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Precise Recognition Model for Mobile Learning Procrastination Based on Backpropagation Neural Network

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The Corona Virus Disease 2019 (COVID-19) epidemic has led to a shift from offline to online learning in universities, with mobile learning becoming the regular learning norm. However, students exhibit procrastination in the mobile learning process, which greatly affects learning outcomes. In contrast to the traditional classroom, teachers are less able to monitor the online learning process and are unable to do so effectively. Therefore, identifying students' procrastination behavior in the mobile learning process and improving teaching efficiency have become issues that need attention and solution. Academic procrastination is an avoidant adaptive behavior that not only affects students' academic performance but also causes stress and anxiety to the procrastinator. An early detection of procrastination and intervention are essential for students to complete their studies. Academic procrastination is mainly identified using subjective scales, which may lead to biased assessment results. In this study, we constructed a mobile academic procrastination recognition model based on a backpropagation neural network, conducted experiments using mobile learning data from 1332 students at a university in China, and evaluated the accuracy of the experiments. The experimental results showed that using students' mobile learning behavior data to make objective judgments on academic procrastination can avoid the bias of results caused by subjective measurement and improve the objectivity and accuracy of academic procrastination measurement; the recognition accuracy of the mobile learning procrastination recognition model reached 0.992, which significantly improved the accuracy and efficiency of academic procrastination recognition.

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1. Introduction

The COVID-19 epidemic, which began in December 2019, limited all forms of human activity to a minimum, particularly in the education sector. The infectiousness, pathogenicity, and other uncertainties of the virus prompted universities to shift entirely to online learning. At the same time, precautionary measures such as isolation and social distance implied an abrupt shift in curriculum and learning styles in the education sector, which led to a shift in relation to student performance, well-being, and academic-anxiety-related issues.

Previous research has investigated the effects of online and distance learning on students and found that the demand for self-control is higher in online and distance learning environments than in traditional teaching environments.(1) Students' lack of motivation and effort exacerbate academic procrastination behaviors as they engage in mobile learning because of inadequate teacher–student interaction, insufficient challenge in online courses,(2) and weak student self-control.(1) The time pressure created by procrastination behaviors can negatively impact academic performance by reducing accuracy and punctuality in submitting tasks. This is followed by emotions such as anxiety, anger, stress, guilt, and restlessness, and in severe cases, sleep problems or other disorders.(3) What is clear is that the extent of procrastination is amplified in an online environment. In contrast to traditional classrooms, teachers only have access to the results of instruction and cannot monitor the teaching process. With online mobile learning, teachers are also unable to provide effective supervision and instruction because they cannot identify students' academic procrastination. Therefore, accurately identifying students' tendency to academic procrastination in the context of mobile learning has become a primary issue for research.

Academic procrastination identification is mainly made using subjective scales, which can easily lead to biased assessment results. A few studies have also attempted to identify procrastination behaviors using diary studies and observation methods. However, such methods have the disadvantage of being too labor-intensive and challenging to be used in a generalized manner. With the development of Internet technology and data mining techniques, students' learning behaviors online can be quantified, and students' learning behavior tendencies can be identified by analyzing their learning behavior data. A backpropagation (BP) neural network is an artificial neural network for classification and prediction tasks. The BP neural network algorithm adjusts the network weights to minimize the difference between the network output and the desired output. The network can learn to produce accurate predictions by iteratively updating the weights. Existing research shows that the BP neural network has high speed, easy training, and powerful generalization ability. Different neural networks are suitable for different tasks and specific application scenarios. The BP neural network algorithm is more suitable for the mobile learning delayed recognition scenario studied in this thesis, with higher recognition accuracy.(4)

Therefore, we investigate the construction of a mobile academic delay recognition model based on a BP neural network. The online learning behavior data of 1332 students in a Chinese university on the mobile learning platform Chaoxing App were used for mining. The mined data were input into the mobile academic procrastination identification model of the BP neural network for experiments, and the model's accuracy was evaluated. The experimental results showed that using students' mobile learning behavior data to make objective judgments on academic procrastination can avoid the bias of results caused by subjective measurement and improve the objectivity and accuracy of academic procrastination measurement; the recognition accuracy of the mobile academic procrastination recognition model reached 0.992, which significantly improved the accuracy and efficiency of academic procrastination recognition.

2. Literature

2.1 BP neural network

The BP neural network, a type of artificial neural network, is a multilayer feed-forward neural network trained according to the error BP algorithm. It is currently one of the most widely used neural network models. BP was first proposed to solve the XOR problem. The "Hopfield network" neural network model can be used to solve combinatorial optimization approximation solutions and pattern recognition, such as text recognition and image recognition. BP neural networks have the advantages of strong nonlinear processing capability and flexibility to set the network structure of the hidden layer.

The BP neural network is a structure consisting of an input layer, a hidden layer, and an output layer. The hidden layer is in the middle of the input and output layers. The hidden layer can be one or more layers, also called neurons. Each neuron is isolated from the outside world, but it changes the relationship between the input and the output, and each layer has several nodes. The BP neural network algorithm is composed of forward and backward computation processes. The data samples are input from the input layer and processed by the hidden layer, and the samples are output from the output layer. Neurons in each layer may only affect the state of neurons in the next layer, and this computational path constitutes the forward computation process; the backward computation (BP) process means that when the result of the output layer fails to achieve the expected effect, the error signal is returned along the original computational path, and the error is reduced gradually in turn by modifying the weight of neurons (see Fig. 1).

2.2 Academic procrastination

Procrastination behaviors are prevalent in everyday life. Procrastination is considered a behavior of unnecessarily postponing or delaying tasks.(5) Furthermore, academic procrastination is a specific manifestation of procrastination behavior in the field of learning. Scholars at home and abroad have conducted much research on academic procrastination. They have obtained rich research results, but many research findings are still controversial, especially the definition of academic procrastination.

Academic procrastination is "the behavior of individuals who irrationally delay academic tasks". Procrastinators intend to complete their academic tasks but keep delaying them for various reasons, resulting in their inability to meet the deadline.

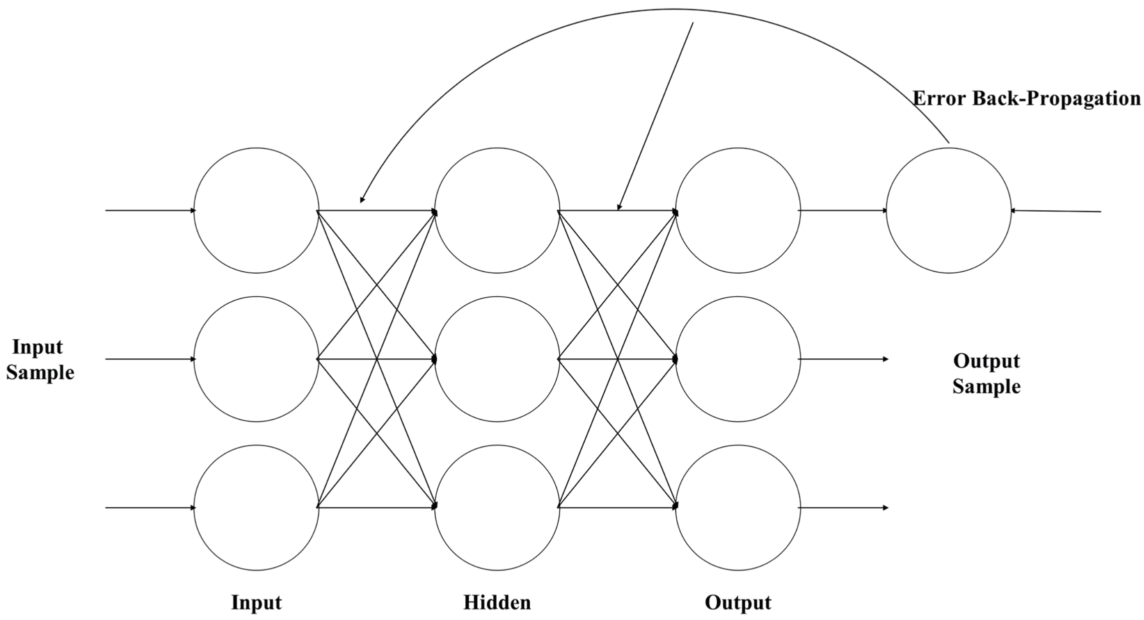

Fig. 1. BP neural network structure.

In addition, scholars consider academic procrastination an irrational behavior. Procrastinators are aware of the consequences and effects of procrastination but still delay performing tasks. This leads to the development of undesirable emotions and behaviors in individuals.

In summary, scholars have analyzed the concept of academic procrastination mainly from cognitive, behavioral, and emotional perspectives. They agree that academic procrastination is a "purposeful behavior of delaying or postponing learning tasks." In this study, academic procrastination is defined as an irrational behavior in which individuals always purposefully postpone or delay learning tasks, which leads to changes in their emotions and health.

2.3 Mechanisms of procrastination behavior

Many researchers have established that academic procrastination hurts individuals' academic performance and physical health, among other things. However, as research has progressed, scholars have realized that academic procrastination can also positively affect an individual's behavior.

2.3.1 Negative effects of academic procrastination

Academic procrastination often affects students' academic performance, and it is significantly and negatively associated with poor academic performance.[6] In addition, the time pressure caused by procrastination can cause individuals to develop adverse emotions such as stress and anxiety.[7] This adverse emotional experience can also affect students' academic performance. In addition, poor academic performance and bad emotional experiences, in turn, lead to procrastination behaviors, thus creating a vicious circle. Chronic procrastination has important implications for an individual's physical health. This is because procrastinators can delay treatment, thus making physical conditions worse.

Moreover, procrastination significantly and negatively affects students' self-development, especially self-esteem, self-efficacy, and self-identity. Namely, the higher the level of procrastination, the lower the self-esteem, self-efficacy, and self-identity.(8)

2.3.2 Positive effects of academic procrastination

Academic procrastination has been found to have a positive side. It is demonstrated by the fact that procrastinators can experience a sense of challenge and accomplishment by studying before the end of their academic tasks. Academic procrastination is a peak experience.(9) It stimulates the procrastinator's potential to concentrate on academic tasks and complete them promptly and efficiently.

2.4 Relationship between academic procrastination and academic performance

Academic performance is the intrinsic motivation that drives and sustains an individual's activities. It is the output of students in the field of learning. Specifically, individuals with higher academic performance are more motivated and persistent, devoting themselves to learning activities and trying to complete academic tasks. In contrast, individuals with lower academic performance lack interest in learning activities and tend to be perfunctory, and their academic procrastination is more severe. Academic performance has a significant effect on students' motivation. Some people identified academic performance as an internal motivator that leads to learning activities and makes them more purposeful and directed, including both endogenous and exogenous motivation dimensions.(10)

Numerous studies have shown a strong relationship between academic performance and academic procrastination behavior. They confirmed that academic performance is significantly and negatively related to academic procrastination. Namely, the more interested and motivated an individual is in the learning process, the less likely he or she is to exhibit procrastination behavior. This is in line with the findings of some scholars.(11)

Furthermore, several scholars have determined the relationship between academic procrastination and two dimensions of academic performance. It was revealed that endogenous motivation negatively affects academic procrastination, whereas exogenous motivation positively affects it.(12) According to the classification of academic performance dimensions, the researchers concluded that students with high endogenous motivation tend to choose challenging learning tasks, and their interest influences them in completing the tasks. Their academic procrastination behavior is less. In contrast, students with high exogenous motivation tend to choose more manageable learning tasks to seek rewards, win the evaluation of others, and win the competition. They are more influenced by external triggers and have difficulty experiencing the interest and pleasure of learning. Only after completing the task do they experience the value of learning when they are rewarded or appreciated by others. Compared with endogenously motivated students, exogenously motivated students are prone to engage in academic procrastination unconsciously.

2.5 Mobile academic procrastination

Mobile learning is a new way of learning that uses technologies such as mobile devices and wireless networks to conduct education and learning activities. Over the past decades, with the rapid development of mobile device and wireless network technologies, mobile learning has been widely used and popularized in education and work, and mobile learning has become one of the leading learning methods nowadays. Mobile learning brings many advantages, such as portability, universality, and flexibility, allowing students to learn anytime and anywhere to meet personalized learning needs.

However, some studies have shown that students sometimes experience mobile learning procrastination. Mobile learning procrastination refers to the procrastination behaviors that arise during students' online learning. Although mobile learning can theoretically help students learn more effectively, many factors such as technology availability, the nature of the learning task, and users needing proper training impose limitations on mobile learning. In recent years, many researchers have explored the causes of mobile learning procrastination behavior and how to reduce it. In this study, some of the main reasons include a lack of technical knowledge, the poor quality of the device, and unclear learning goals. Some studies suggest that personality traits such as procrastination tendencies and a lack of self-efficacy contribute to mobile learning procrastination behaviors. To reduce mobile learning procrastination behaviors, some researchers have proposed some solutions, which include improving users' technical knowledge, improving device quality, setting specific learning goals, and increasing self-efficacy. Mobile learning procrastination behavior is a complex issue that requires the integration of multiple factors. In the future, we need more research to explore this issue and propose better solutions to enhance the practical application of mobile learning.

3. Precise Recognition Model of Mobile Learning Procrastination Based on BP Neural Network

3.1 Recognition model of mobile learning procrastination

With the popularity of mobile Internet and education informatization, mobile learning has become one of the main daily learning methods for Chinese college students. Mobile learning procrastination is a common phenomenon that occurs in the process of mobile learning with the help of mobile information systems. It refers to the irrational tendency to deliberately delay or postpone necessary tasks, resulting in negative emotions and adverse psychological states when the results do not meet expectations. In mobile learning, procrastination can negatively affect students' learning outcomes and can indirectly predict mobile learning engagement. Students with procrastination behaviors fail to complete tasks within the prescribed time frame or complete them ineffectively, which ultimately manifests itself as a decrease in academic performance.

In a mobile learning environment, most students fail to adhere to course schedules owing to poor self-control or procrastination, which ultimately affects course performance. In addition, research has shown that procrastination negatively affects students' self-efficacy, academic mood, and many other academic performances. Furthermore, procrastination's distress and psychological burden can result in dysfunctional or maladaptive behaviors. Chronic academic procrastination can hinder students' ability to learn and cause psychological barriers to learning, which can lead to boredom, truancy, and dropping out of school, which in turn can lead to unsatisfactory academic performance, increase student stress, and affect students' health.(13) Therefore, it is imperative to identify students' learning procrastination behaviors in mobile learning and help students understand and perceive it.

Current methods for assessing and identifying students' tendency to procrastinate typically use self-report, behavioral observation, logbooks, and others' ratings.(14) The self-report method is the most used approach and uses scales as a measurement tool. The currently used academic procrastination scales are Academic Procrastination Inventory (API),(15) Procrastination Assessment Scale-Students (PASS),(16) General Procrastination Scale (GPS),(17) and Tuckman Procrastination Scale (TPS).(18) The behavioral observation method is used to determine whether students tend to procrastinate by observing learners' progress in time management and task completion during learning (Moon and Illingworth, 2005).(19) The logbook method uses a diary to record the completion of tasks over time in the learning process to determine whether students are procrastinating.(20) Finally, an evaluation method is used to determine if a student tends to procrastinate through a third-party observer, and the third party is usually rated by the teacher.(21)

The self-report scale uses standardized problem process measurement, which is irrelevant for specific scenarios. The observation method can systematically observe individual procrastination behavior, but it spans an extended period, is subject to external influence, and is difficult to operate. The logbook method takes a small sample size, and conclusions can be more generalizable. The evaluation method is highly subjective and more difficult to implement. In this study, we employed the behavioral observation and evaluation methods to identify students' procrastination behaviors and construct a mobile learning procrastination identification model, as shown in Fig. 2.

Under the mobile learning delay recognition model, students' learning process on the mobile learning platform generates educational big data information. On the basis of the generated educational big data, students' learning behavior and learning log data in the learning process are collected by combining the relevant data and finally applying the observation method to identify students' mobile learning delays. We also distinguish severe, mild, and no procrastination behaviors. The other observation method under the mobile learning delay recognition model uses the BP neural network algorithm under artificial intelligence.

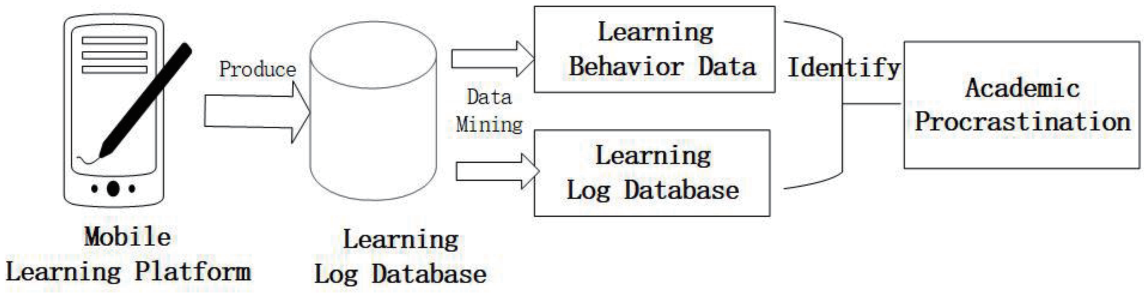

Fig. 2. Identification model of mobile learning procrastination.

3.2 BP neural-network-based mobile learning procrastination recognition model

The BP neural network is an effective multilayer neural network learning approach. It is characterized by the forward transmission of signals and the backward propagation of errors, after which these errors are used to adjust the weights of neurons, thus generating an artificial neural network system that can simulate the original problem. Using this network system to identify mobile learning delays can get rid of self-reported scale flaws. At the same time, the information of educational big data generated by mobile learning can be processed by artificial intelligence to detect students' academic delays in a more accurate and timely manner. Therefore, we construct the recognition model of mobile learning procrastination based on the traits of the BP neural network, as shown in Fig. 3.

The BP neural-network-based mobile learning delayed recognition model requires three stages. The first stage is the raw data processing stage. In this phase, data mining techniques are needed to mine students' learning behavior and learning log data for the big educational data generated by learners in the mobile learning platform. These two data are then preprocessed to form the initial data set of samples. The second stage is the BP neural network training stage. The initial dataset is input into the BP neural network model and training during this stage. The neurons' weights are adjusted by calculating errors to finalize the recognition model. This process is the most critical link related to the accuracy of the delay recognition. The third stage is the procrastination recognition stage. According to the second-stage BP neural network model calculation, the behavior is classified as severe, moderate, mild, or no procrastination.

4. Example of Mobile Learning Delay Recognition Application Based on BP Neural Network

To test whether the BP neural-network-based mobile learning procrastination identification model can measure students' academic procrastination behaviors and determine their academic procrastination levels, we used online learning behavior data from 1332 students at a Chinese university as experimental data. In Chinese universities, online teaching is commonly carried out using Chaoxing App, which is a convenient and easy-to-use platform to operate, can record and save students' online learning behavior data, and is convenient for teachers and researchers

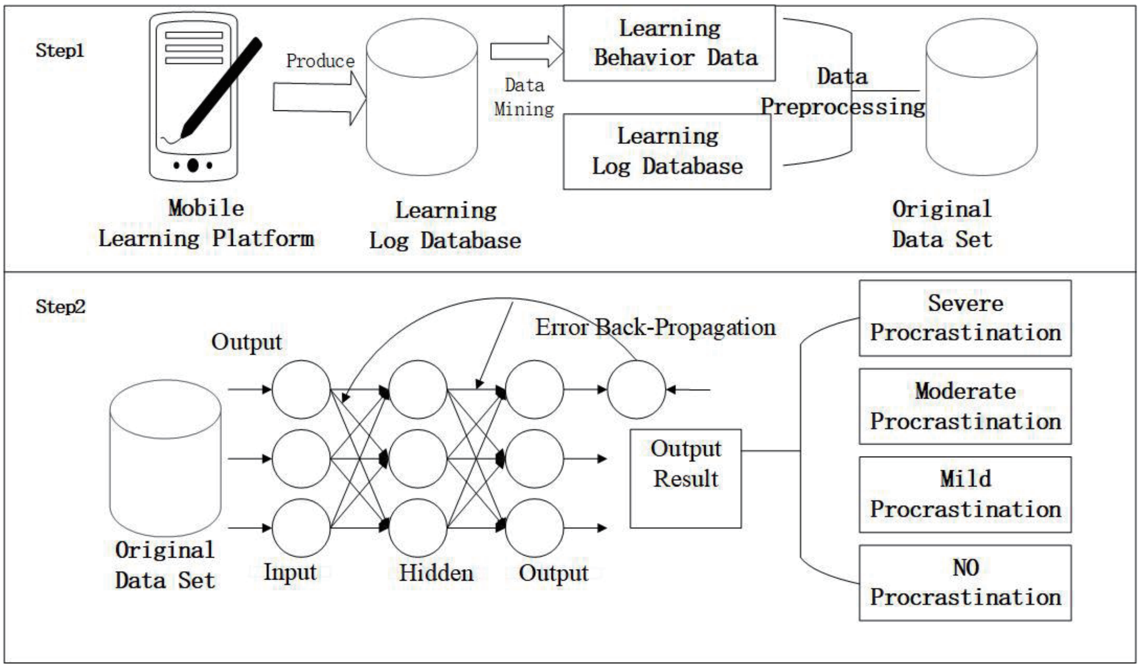

Fig. 3. Recognition model of mobile learning procrastination based on BP neural network.

to export students' learning behavior data. In this experiment, the online behavioral data of students exported from Chaoxing App were processed, and data indicators that can be used to identify academic procrastination were selected. Mobile academic procrastination behavior variables were constructed, the variables were input into the BP neural network algorithm for calculation, and the calculated results were used to judge students' academic procrastination behavior. The following are the specific practical steps.

4.1 Data source and data preprocessing

The mobile learning platform chosen for this study was Chaoxing App. The experimental data came from the "New Media Operation and Promotion" of an e-commerce course at a Chinese university. The course was taught online on Chaoxing App from March to July 2022, and it lasted 16 weeks, with a total of 1332 students studying online. The students' learning behavior data generated by Chaoxing App included viewing teaching resources, learning and teaching tasks, and completing tasks and other activities.

Teaching resources were prepared for the students according to the course content, including lecture PPT, learning videos, and case materials. The teaching tasks were mainly to participate in online discussions and complete post-course tasks, which mainly tested the effectiveness of students' learning. Acquiring data on students' learning behaviors was the first stage of identifying academic delays. Therefore, the learning behavior logs generated by students in Chaoxing App were filtered, screened, and aggregated to be used to identify students' procrastination behaviors. The educational big data generated from students' learning processes were diverse and voluminous. Therefore, drawing on the Hooshyar design algorithm, four variables, namely, the start time of instructional activity release, the time students first viewed and the time they completed the instructional activity, and the deadline of the instructional activity, were used to constitute the student learning behavior dataset.(6) The instructional activities selected for this study consisted of learning the instructional content, participating in class discussions, and completing post-class assignments, and the specific data types are shown in Table 1.

4.2 Ranking of mobile learning delay recognition

Mobile learning procrastination was used to identify students' procrastination behaviors through their academic behavior data. For this purpose, we disaggregated students' academic procrastination behaviors. Mobile learning procrastination was classified into four levels on the basis of students' academic behavior data. The categories were severe procrastination, moderate procrastination, mild procrastination, and no procrastination. Severe procrastination refers to academic delaying behaviors that are so severe that they seriously impede the completion of school and have a significant impact on academic performance, even leading to academic failure; moderate procrastination refers to academic delaying behaviors that are more pronounced and have some impact on academic performance and progress but can still be resolved through self-adjustment and willpower; mild academic procrastination is usually described as the occurrence of episodic delaying behaviors, but the outcome of the delay does not have a significant impact on the individual's learning and life, nor does it lead to obvious negative consequences. No procrastination is defined as the timely completion of the online instructional content, the submission of instructional tasks, and active participation in the content of instructional activities during learning.

Table 1
Description of data categories and symbols.

Tier 1 indicators	Secondary indicators and descriptions
x: indicator description: x stands for course content	x^o: Course content release time x^f: Initial viewing time of course content x^s: Completion of course content time x^d: Course content cut-off time
y: indicator description: y stands for course discussion	y^o: Course discussion release time y^f: Initial viewing time of course discussion y^s: Completion of course discussion time y^d: Course discussion cut-off time
z: indicator description: z represents post-course assignment	z^o: Post-class assignments release time z^f: Initial viewing time of post-class assignments z^s: Completion of post-class assignments time z^d: Post-class assignments cut-off time

4.3 Construction of mobile learning procrastination behavior variables

According to the learning behavior data of students shown in Table 1, the four variables assigned to each teaching activity were further calculated and transformed to construct three variables as mobile learning procrastination behavior variables, namely, inactive time, active time, and idle time. The calculation method and symbols of inactive time, active time, and free time for each teaching activity are shown in Table 2.

4.4 Identification of mobile learning procrastination behavior

In the experiment, the BP neural network operation in the mobile delay recognition model based on the BP neural network was run using Weka software, which is a free, open-source, powerful, and easy-to-use machine learning software program. One only needs to set the relevant parameters about the BP neural network algorithm in the software, and the software can quickly complete the data set training and output the results.

4.4.1 Data normalization to maximum value

Mobile learning procrastination variables are time-type data. In this study, we performed transformations and normalization on temporal data to restore diverse data representations to a uniform scale, thereby standardizing variables within the [0,1] range. Owing to the evident boundary conditions of the data values in this study, the employed normalization formula (Eq. 1) is used for Min–Max normalization. Here, 'min' and 'max' represent the minimum and maximum values of a certain feature, while V and V' represent the new normalized and original values, respectively.

$$V = \frac{V' - min}{max - min} \tag{1}$$

Table 2
Behavioral variables of mobile learning procrastination.

Course tasks	Symbols	Explanation	Calculation formulas
Course content (x)	x^a	inactive time	$x^a = x^f - x^o$
	x^b	active time	$x^b = x^s - x^f$
	x^c	idle time	$x^c = x^d - x^s$
Course discussion (y)	y^a	inactive time	$y^a = y^f - y^o$
	y^b	active time	$y^b = y^s - y^f$
	y^c	idle time	$y^c = y^d - y^s$
Post-class assignments (z)	z^a	inactive time	$z^a = z^f - z^o$
	z^b	active time	$z^b = z^s - z^f$
	z^c	idle time	$z^c = z^d - z^s$

4.4.2 Setting of experimental parameters

The number of neurons and network depth are essential parameters in designing the BP neural network algorithm in the mobile learning delay recognition model based on the BP neural network.

In the BP neural network, each neuron receives inputs from all neurons in the previous layer and produces a new output value. The network's training capability and prediction accuracy can be improved by increasing the number of neurons. When the number of neurons is very small, the network may not be able to adapt to the complex input–output mapping, resulting in underfitting. At the same time, when the number of neurons is very large, the network may overfit and decrease prediction performance. In the experiment, the mobile learning procrastination behavior variables were used as neuron inputs, and there were nine variables in the mobile procrastination recognition model of the BP neural network, so the number of neurons for the experiment was set to 9.

Increasing the network depth in BP neural networks can increase the network's expressiveness and learning ability, and improve the network's adaptability to complex mappings. However, increasing the network depth can also make the complex network structure more prone to gradient disappearance. Therefore, to ensure the model performance and recognition accuracy, we used the empirical formula $2^X > N$ (X: number of nodes in the hidden layer; N: number of samples).

Initially, we set a relatively small number of nodes for the hidden layer for training. If the number of training iterations is excessively high or no convergence is achieved within the defined number of iterations, we terminate the training. Then, we incrementally increase the node count of the hidden layer and initiate the training anew. Throughout the experiments, we trained the hidden layer using four distinct numbers of nodes: 10, 12, 14, and 16. Ultimately, it was determined that a hidden layer comprising 12 nodes yielded the best results.

In the context of the BP neural network for mobile learning procrastination recognition, the output node of the neural network is set to 1. By further assessing the value of the output node, we can discern the level of procrastination behavior. Hence, the BP neural network structure we use in this experiment is 9*12*1.

4.4.3 Dataset training

After setting the BP neural network parameters of the experimental model in the Weka software, the sample data were trained for learning. In the experiment, we divided the learning behavior data of 1332 students into training and test samples (1000 students' learning behavior data as training samples and 332 students' learning behavior data as test samples). By completing the training of the dataset in the Weka software, the training process neural network structure output values were divided into delayed behavior levels. Moreover, the input data was normalized to the highest value, and the output values of the BP neural network in the model were at [0,1] intervals. The output values correspond to the procrastination levels, as shown in Table 3.

Table 3
Delay levels.

Output	Delay level
[0.75,1]	Severe procrastination
[0.5,0.75)	Moderate procrastination
[0.25,0.5)	Mild procrastination
[0,0.25)	No procrastination

Table 4
Identification results of mobile learning delays.

Output	Number	Percentage (%)	Delay level
[0.75,1]	85	25.60	Severe procrastination
[0.5,0.75)	168	48.49	Moderate procrastination
[0.25,0.5)	58	17.47	Mild procrastination
[0,0.25)	21	8.43	No procrastination

Completing the BP neural network data training for the research model requires the delayed identification and testing of the test samples of the mobile learning behavior data.

4.5 Mobile academic delay identification and testing

The learning behavior data of the 332 students used as test samples were used as input values. The BP neural network model was run in the Weka software to relate the output values to the delay levels. The results of the operation are shown in Table 4.

To verify the accuracy of the mobile learning delay recognition model, accuracy, sensitivity, precision, false positive value, and F-measure were used as evaluation metrics to assess the accuracy of the mobile learning procrastination model.(22) The evaluation indexes of the model effect were mainly derived from the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) calculations.(23) TP refers to the number of observations for which the model predicts positive (1) and is positive (1). TN refers to the number of observations for which the model predicts positive (1) but is negative (0). FP refers to the number of observations for which the model predicts positive (1) but is negative (0). Finally, FN is the number of observations for which the model predicts positive (1) but is negative (0), as shown in Table 5. Specific indicator descriptions and calculation equations are shown in Table 6.

To further illustrate the accuracy of the BP neural-network-based mobile learning procrastination recognition model, the same research sample was run in the Weka software to verify the accuracy of the mainstream algorithms such as support vector machine, decision tree, and Bayesian network for the classification of students' procrastination tendency. The evaluation indexes of the BP neural network model were compared with the current mainstream algorithms, and the results are shown in Table 7. The BP neural network model outperformed other models in all five evaluation indexes, and the indexes of accuracy, sensitivity, precision, and F-measure were above 0.8, indicating that the BP neural-network-based mobile academic procrastination identification model is adequate and the accuracy is the highest.

Table 5
Four basic definitions of categorical response models for binary target variables.

		Categories of predictions	
		1	0
Actual categories	1	TP	FN
	0	FP	TN

Table 6
Evaluation indicators.

Evaluation indicators	Description of indicator	Calculation formula
Accuracy	Ratio of number of objects that can correctly identify 1 and 0 to total number of objects identified	$\frac{TP+TN}{TP+FP+FN+TN}$
False positive value	Ratio of number of objects incorrectly identified as positive (1) to total number of observed objects that are actually negative (0)	$\frac{FP}{TN+FP}$
Sensitivity	Ratio of number of objects correctly identified as positive (1) to number of objects that are actually positive (1) among all observed objects	$\frac{TP}{TP+FN}$
Precision	Ratio of number of objects correctly identified as positive (1) to total number of observed objects identified as positive (1) by the model	$\frac{TP}{TP+FP}$
F-Measure	Comprehensive model evaluation metrics and sensitivity and accuracy reconciliation metrics	$\frac{2TP}{2\times TP+FP+FN}$

Table 7
Performance evaluation of mobile recognition model based on BP neural network.

Evaluation indicators	BP neural network	Support vector machine	Decision tree	Bayesian network
Accuracy	0.837	0.822	0.785	0.831
False positive Value	0.132	0.143	0.253	0.165
Sensitivity	0.923	0.876	0.792	0.892
Precision	0.922	0.854	0.786	0.902
F-measure	0.943	0.895	0.759	0.897

5. Conclusion

In this study, the BP neural-network-based mobile learning procrastination recognition model was constructed to classify academic procrastination into four levels: no procrastination, mild procrastination, moderate procrastination, and severe procrastination. Furthermore, the study model was trained and tested using the data of 1332 students' academic behaviors on the Learning Pass platform from a university in China, and was compared with support vector machine, decision tree, and Bayesian network, which are the current mainstream algorithms, using accuracy, sensitivity, precision, false positive value, and F-measure as evaluation metrics.

The results showed that the model could identify students' academic procrastination behaviors. The accuracy of the model was also verified with good identification results.

Follow-up studies can be conducted in the direction of intervening in students' academics after procrastination identification and urging them to complete their studies in a timely manner. The research results better identify students' academic delays and help teachers monitor the learning process and promote the high-quality development of online education.

The limitations of this study are as follows: Future research should further expand the sample size to more comprehensively validate the effectiveness of the method. In addition to the assignment submission data, other online learning activity data, such as the delay time for reviewing the learning content and the time for the mutual evaluation of students' assignments, may also affect the characterization of academic procrastination behavior, and future studies may focus on the role of these activity data. The complete system architecture of the research model still needs to be built, and future studies can consider the system architecture of the research model and develop the research model into a separate software system.

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