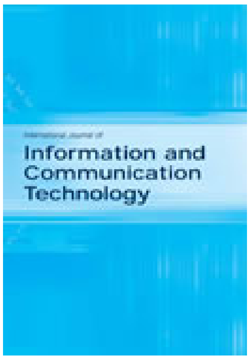

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Exploration of English learning mode based on mobile learning platform assisted by data mining

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Abstract: As information technology develops, the use of mobile learning tools in English instruction is spreading rather rapidly. This study combines data mining techniques to explore effective methods for optimising English learning modes on mobile learning platforms. Firstly, using K-means clustering analysis to identify students' learning behaviour characteristics and identify student groups with different learning styles. Then, the Apriori algorithm is applied to mine the association rules between learning behaviour and learning outcomes, further revealing the key factors that affect learning outcomes. In addition, tracking students' learning progress and emotional changes through time series analysis provides a design basis for personalised learning paths for the platform. The research results indicate that optimisation strategies based on data mining can help improve learning effectiveness and support teachers and platform developers to provide more targeted learning suggestions.

Keywords: K-means; Apriori; data mining; time series analysis.

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1 Introduction

In recent years, mobile learning has gradually gained popularity among students and educators as a flexible and convenient way of learning. With the popularisation of mobile devices and the rapid development of mobile Internet, the learning model based on mobile platform has shown great potential in foreign language teaching (Pegrum, 2016). Mobile learning can better meet the individual needs of students by means of personalised push notifications, real-time feedback, and other features than conventional classroom teaching, which breaks the constraints of time and space and gives students learning chances anytime and anywhere (Troussas et al., 2020). But the present teaching strategies on mobile learning platforms sometimes lack in-depth study of learning data, which reduces the value of tailored services. Consequently, a major problem of relevance in the present academic and educational domains is using data mining approaches to mobile learning platforms to maximise learning modes.

Particularly in personalised learning and analysis, the application of data mining technology in the field of education has resulted in many successes that provide strong theoretical and technical support for customised teaching design and improvement of educational effectiveness. To create individualised learning routes for educational platforms, numerous studies have lately tried to examine student learning behaviour data using methods such clustering, association rule mining, and time series analysis. Chen et al. (2024), for instance, suggested an intelligent learning system based on K-means clustering, which uses clustering analysis to identify student groups with distinct learning styles, so attaining varied instruction and greatly enhancing learning results. Furthermore, Nkomo and Nat (2021) segmented student groups using fuzzy clustering algorithms, so producing more exact personalised learning suggestion mining applications. Using Apriori technique, Palacios et al. (2021) exposed the natural link between learning behaviour and learning results, therefore enabling educational platforms to offer more focused intervention plans. Using data mining methods, Shen et al. (2009) found in a similar study the link between classroom engagement and academic success, therefore supporting individualised teaching design. Simultaneously, Matzavela and Alepis (2021) used association rule mining in mobile learning systems to raise course recommendation performance and hence maximise learning efficiency.

Further employed in educational data analysis is time series analysis. Nabizadeh et al. (2020b) for instance used time series analysis to analyse students' learning development and emotional changes, thereby enabling teachers to quickly modify their curricula and provide notable teaching outcomes. In a similar vein, Vialardi et al. (2011) confirmed the accuracy of time series analysis in forecasting learning outcomes and tracked students' knowledge mastery using time series prediction models. Dynamic tracking of the psychological state during the emotional learning process by Nabizadeh et al. (2020a) offers a platform for customising counselling plans.

Furthermore highly appreciated is the use of data mining in forecasting and intervention in educational results. Gupt creates prediction models using a decision tree algorithm, for instance, which analyses the link between learning paths and final grades thereby supporting educational interventions in real-time. Arora et al. (2019) also predicted students' learning intentions by means of Bayesian networks in educational big data research. By use of the random forest algorithm, Kukkar et al. (2023) developed a learning path recommendation system to enhance student learning outcomes.

In addition, Ezaldeen et al.'s (2022) study further improved the prediction of learning progress and emotional changes by analysing learning behaviour sequences through LSTM models. A fusion of data mining and natural language processing analysis framework was proposed, which can effectively capture emotional and behavioural characteristics during the learning process, providing more comprehensive support for the education system. This indicates that the application of data mining technology in the education field not only helps to achieve personalised learning, but also provides broad prospects for learning effect prediction and behavioural intervention.

Although previous studies have shown that data mining techniques can effectively support the intelligent development of educational platforms, there are still shortcomings in research on mobile learning platforms, especially in the field of foreign language learning, where there is a lack of systematic pattern optimisation exploration. Therefore, this study will be based on data mining techniques, using K-means clustering, association rule mining, and time series analysis methods to deeply explore students' behaviour data on mobile learning platforms, in order to optimise English learning modes and improve learning effectiveness. I hope to provide theoretical support and practical reference for the personalised teaching mode of mobile learning platforms through this study.

The main contribution of this article is to propose a personalised learning recommendation model based on data mining to optimise English learning modes on mobile learning platforms. The specific contributions are as follows:

1 Multi method fusion personalised recommendation model: Combining K-means clustering, Apriori association rule mining, and time series analysis techniques, a multi-level recommendation framework was systematically constructed. By identifying students' learning behaviour characteristics, mining key influencing factors of learning effectiveness, and tracking changes in learning emotions and progress, personalised learning path design was achieved from multiple dimensions to improve learning effectiveness.

2 Accurate identification of learning style groups: Through K-means clustering analysis of students' learning behaviour, different learning style groups can be segmented, laying a precise foundation for personalised recommendations in the future.

3 Mining the correlation between learning behaviour and effectiveness: Based on the Apriori algorithm, this article delves into the association rules between learning behaviour characteristics and learning effectiveness, revealing the key behavioural factors that affect learning effectiveness and providing data support for optimising learning patterns.

4 Personalised emotion and progress tracking: Through time series analysis, students' learning progress and emotional changes are dynamically monitored, providing emotional and progress support for the design of personalised learning paths, making the recommendation system more humane and intelligent.

2 Relevant technologies

2.1 K-Means clustering

Widely applied in clustering analytic activities in data mining, K-means clustering is a partition based unsupervised learning technique (Ahmed et al., 2020). Dividing the dataset into K clusters will help to ensure that the data points in each cluster are comparable to one another while the data points between many clusters have notable variations. K-means minimises the squared distance between data points inside each cluster and the cluster centre (Likas et al., 2003) therefore reaching this aim.

K-Means seeks to reduce the total of squared Euclidean distances between every data point and their cluster centres. The defined objective function is:

$$J = \sum_{k=1}^{K} \sum_{i \in C_k} \left\| x_i - \mu_k \right\|^2 \tag{1}$$

where, x_i represents the data point, μ_k represents the centre of cluster k, J is the set of all data points in cluster k, and K is the number of clusters.

At the beginning of the K-means algorithm, K data points are chosen at random to form the first cluster centres. Assuming these initial cluster centres are:

$$\left\{ \mu_1^{(0)}, \mu_2^{(0)}, \ldots, \mu_K^{(0)} \right\} \tag{2}$$

Assign every data point to the closest cluster every iteration. Calculate the distance of any data point x_i from every cluster centre and allocate it to the cluster denominated by the closest cluster centre. The cluster allocation equation for data point x_i is:

$$C(x_i) = \arg\min_k \left\| x_i - \mu_k \right\|^2 \tag{3}$$

where, $C(x_i)$ represents the cluster index to which the data point x_i belongs.

After the data point allocation is completed, recalculate the centre position of each cluster to be equal to the average of all data points in that cluster. For the data point set C in cluster k, the new cluster centre μ_k is defined as:

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \tag{4}$$

where, $|C_k|$ represents the number of data points in cluster k.

Usually, K-means evaluates clustering efficacy by techniques of within cluster sum of squares (WCSS), the total of squared distances between every data point inside a cluster and its centre. Its definition is:

$$WCSS = \sum_{k=1}^{K} \sum_{i \in C_k} \left\| x_i - \mu_k \right\|^2 \tag{5}$$

The iterative process of K-means algorithm can be stopped when one of the following two conditions is met:

The cluster centre no longer changes, i.e.: $\mu_k^{(t)} = \mu_k^{(t+1)}$, reaching the maximum iteration count T.

If t represents the current number of iterations, then:

$$\Delta\mu = \sum_{k=1}^{K} \left\| \mu_k^{(t)} - \mu_k^{(t+1)} \right\|^2 \tag{6}$$

If $\Delta\mu$ is less than the preset threshold ε, the algorithm converges.

In some applications, to evaluate the degree of cluster separation, inter cluster distances can be calculated, such as the Euclidean distance between cluster centres. The distance between cluster centres μ_i and μ_j is defined as:

$$d\left(\mu_i, \mu_j\right) = \left\| \mu_i - \mu_j \right\| \tag{7}$$

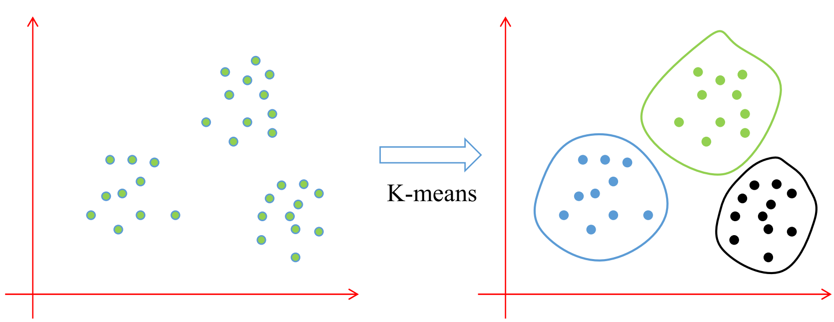
Calculated based on the average distance between each data point and other data points inside its cluster as well as the average distance from the closest cluster, contour coefficient is a measure of clustering quality. The contour coefficient for each data point x_i is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max\left(a(i), b(i)\right)} \tag{8}$$

where, $a(i)$ represents the average distance between data point x_i and other data points within its cluster, and $b(i)$ represents the average distance between data point x_i and the nearest data point within the cluster. The contour coefficient falls between [–1, 1], hence the clustering effect improves with increasing proximity to 1.

The K-means algorithm achieves effective grouping of data by continuously minimising the distance between data points within the cluster and the cluster centre. The schematic diagram of K-means algorithm is shown in Figure 1.

Figure 1 Schematic diagram of K-means algorithm (see online version for colours)



2.2 Apriori algorithm

Apriori is a venerable association rule mining method in classical computing, mainly used to mine frequent itemsets and their association relationships from large amounts of data. The core idea is to utilise the property that 'all subsets of frequent itemsets are also frequent' (i.e., 'anti monotonicity') to gradually construct candidate itemsets, reduce search space, and improve computational efficiency. The Apriori algorithm is widely used in fields such as shopping basket analysis and recommendation systems, and can help reveal potential patterns and relationships in data (Aflori and Craus, 2007).

In the Apriori algorithm, frequent itemsets refer to itemsets with support greater than or equal to the minimum support threshold (Singh et al., 2013). Support refers to the frequency at which a certain item set appears in all transaction records, defined as:

$$Support(X) = \frac{Count(X)}{N} \tag{9}$$

where, X represents an itemset, $Count(X)$ represents the number of times itemset X appears in all transaction records, and N is the total number of transaction records.

Confidence measures the probability of itemset Y appearing when itemset X appears, and is used to evaluate the reliability of association rules. For association rule $X \Rightarrow Y$, its confidence level is defined as:

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \tag{10}$$

where, $X \cup Y$ represents transaction records that contain both itemsets X and Y.

Frequent itemsets help to develop association rules that highlight item relationships. An association rule is usually written as $X \Rightarrow Y$, indicating a higher likelihood of including Y when X is included. From frequent itemsets satisfying the minimum confidence criterion, the Apriori algorithm constructs association rules.The core of the Apriori algorithm is to use support pruning. The Apriori algorithm generates common itemsets using layer by layer iterative approach. In each round, a candidate set is generated by combining the frequent itemsets from the previous round. The process of generating frequent itemsets is as follows:

Firstly, generate candidate itemsets: merge frequent itemsets L_{k-1} to generate candidate k-itemsets C_k. After that, prune: delete from the candidate k-itemsets those fall short of the support level. Create frequent itemsets at last. Frequent item L_k sets consist of the candidate itemsets that satisfy the support criterion. Equation for generating candidate itemsets:

$$C_k = \{X \cup Y \mid X, Y \in L_{k-1}, \mid X \cap Y \mid = K - 2\} \tag{11}$$

While creating association rules from frequent itemsets, high confidence rules are selected through confidence pruning to improve the quality of the rules. Specifically, for each frequent itemset F, divide it into non-empty subsets X and $Y = F - X$, generate association rule $X \Rightarrow Y$, and only retain rules that meet the confidence requirement.

Lift measures the scale of the actual likelihood of happening of rule $X \Rightarrow Y$ to the probability of independent occurrence, representing the degree of correlation between X and Y. The improvement degree is defined as:

$$Lift(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X) \times Support(Y)} \tag{12}$$

Should the degree of improvement surpass one, there is a positive association between itemsets X and Y. Should the degree of improvement be less than 1, there is a negative association between them; Should the degree of improvement equal one, the two are independent.

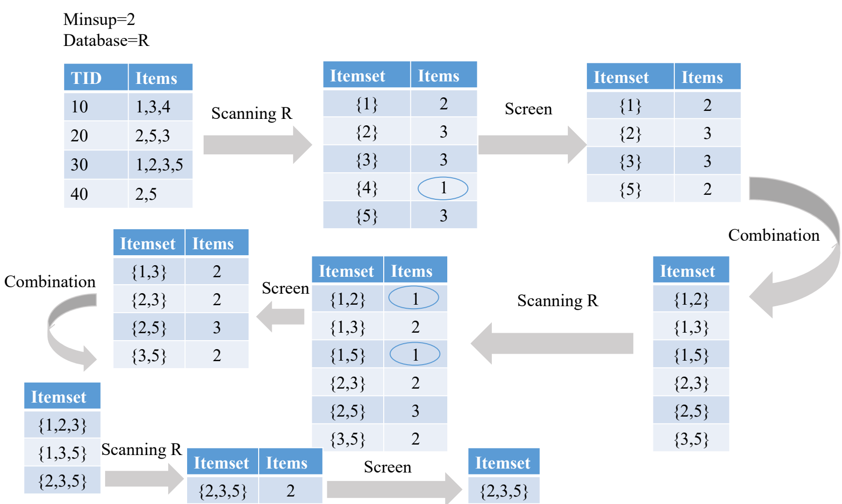
Create strong association rules satisfying minimum support and confidence criteria from regular itemsets. In particular, for every frequent itemset F, create subsets X and $Y = F - X$ containing at least two elements, form association rule $X \Rightarrow Y$, and satisfy the following conditions:

$$Support(X \cup Y) \geq MinSupport \tag{13}$$

$$Confidence(X \Rightarrow Y) = \geq MinConfidence \tag{14}$$

The Apriori algorithm achieves association rule mining by iteratively generating candidate itemsets and filtering frequent itemsets. The framework diagram of Apriori algorithm is shown in Figure 2.

Figure 2 Apriori algorithm framework diagram (see online version for colours)



2.3 Time series analysis

Time series analysis is a technique applied in data analysis and prediction, with the basic goal of discovering patterns in time series data and using these patterns for prediction (Esling and Agon, 2012). The core theory of time series analysis includes modelling features such as stationarity, trends, and seasonality (Fu, 2011).

A time series is collection of observations arranged in chronological order, denoted as Y_t, where $t = 1, 2, ..., n$ are time indices. A simple time series model can be represented as:

$$Y_t = T_t + S_t + R_t \tag{15}$$

where, T_t represents the trend component; S_t represents seasonal components; R_t represents the random component.

The statistical properties of stationary time series, such as mean, variance, and autocovariance, do not vary over time. A time series Y_t is stationary if:

$$E(Y_t) = \mu \tag{16}$$

$$Var(Y_t) = \sigma^2 \tag{17}$$

$$Cov(Y_t, Y_{t+k}) = \gamma(k) \tag{18}$$

where, μ is the mean, σ^2 is the variance, and $\gamma(k)$ is the covariance of the lagged k.

Under various lags, the autocorrelation function is applied to evaluate the correlation of time series defined as:

$$\rho(k) = \frac{Cov(Y_t, Y_{t+k})}{Var(Y_t)} \tag{19}$$

where, $\rho(k)$ is the autocorrelation coefficient of lagged k. If $\rho(k)$ decays rapidly, the time series may be stationary.

The autoregressive model assumes that the current value of Y_t is linearly correlated with the values of the previous few moments, that is:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \tag{20}$$

where, ϕ_1, ϕ_2,..., ϕ_p are model parameters, and ε_t is white noise.

The moving average model presumues that the current value of Y_t combines the first few white noise terms linearly, defined as:

$$Y_t = \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{21}$$

where, θ_0, θ_1,..., θ_q are model parameters.

The ARMA model combines autoregression and moving average models and is suitable for stationary time series:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{22}$$

where, ϕ_i and θ_j are model parameters.

Differential operations let non-stationary time series to become stationary. First-order difference has a broad definition as:

$$Y_t' = Y_t - Y_{t-1} \tag{23}$$

Regarding second-order variation:

$$Y_t'' = Y_t' - Y' = Y_t - 2Y_{t-1} + Y_{t-2} \tag{24}$$

Represented as ARIMA (p, d, q), the ARIMA model is relevant to non-stationary time series where d denotes the number of variations:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) Y_t = \left(1 + \sum_{i=1}^{p} \phi_j L^j\right) \varepsilon_t \tag{25}$$

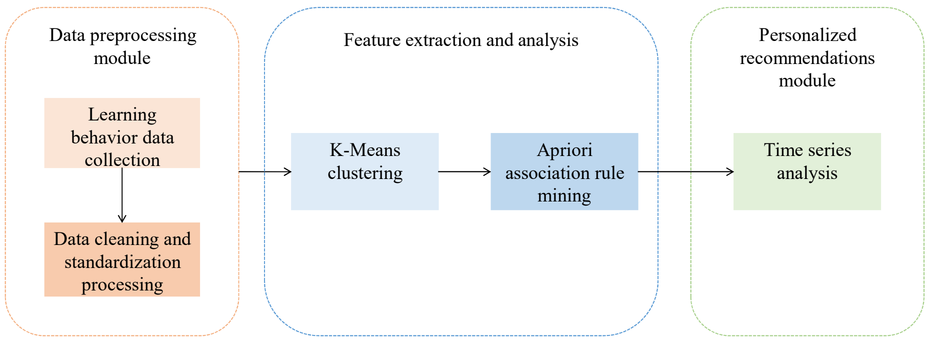
where L is the lag operator.

The above concepts provide a foundation for time series modelling and analysis. Through model selection and parameter estimation, future time series values can be predicted.

3 Exploration model of English learning mode based on data mining

On mobile learning platforms, by combining data mining techniques, it is possible to more accurately identify students' learning behaviour characteristics and effectiveness relationships, thereby effectively optimising the English learning mode. The optimisation methods are divided into three parts: K-Means clustering, Apriori association rule mining, and time series analysis. The model framework of this method is shown in Figure 3.

Figure 3 Model framework diagram (see online version for colours)



K-means clustering aims to segment students' learning behaviour characteristics and identify different learning style groups, in order to provide more targeted learning resources or feedback. By analysing students' behavioural data, students can be divided into several learning style groups. The behavioural patterns of each group have significant differences, representing unique learning preferences or habits. Through cluster analysis, the platform can identify student groups that tend towards 'self-directed learning', 'passive learning', or 'high-frequency interaction', thereby achieving more accurate learning content recommendations. For developing their own learning paths, for instance, 'self-directed learning' pupils could be appropriate; 'passive learning' children could need more robust outside direction and motivation.

Based on the several learning styles, investigate the relationship between learning behaviour and learning results and expose the main determinants of learning outcomes. The Apriori method can examine how often occurring behavioural patterns and learning results interact. Setting support and confidence criteria in association rule mining helps the platform disclose important learning path design aspects by filtering out behaviour combinations with great influence. These association rules give data basis for platform optimisation of learning techniques, such as adding effective learning behaviour guidance or creating critical nodes in learning plans to improve students' English learning efficacy.

At last, the platform can dynamically monitor students' emotional trends and learning development by means of time series analysis. By means of this study, the periodicity and long-term trends of learning behaviour can be captured, therefore exposing students' involvement and emotional fluctuations during the educational process. Analysing the time series of learning progress, for instance, helps the platform to detect which times during the learning process have slower progress or more emotional fluctuations and offers individualised feedback design support for it. Should it be discovered that students' emotional state of learning has dropped over a given period of time, the platform can offer motivating cues or tailored resource recommendations at this point to assist in the rebuilding of learning motivation; should learning progress prove to be stationary, the platform can promptly modify the recommended learning path to support the ongoing increase of learning effectiveness.

By combining K-means clustering, Apriori association rule mining, and time series analysis, not only can students' learning characteristics be comprehensively identified, but deep relationships between behaviour and effectiveness can also be revealed, and learning status can be dynamically monitored. This helps the platform to offer more flexible personalised learning support, optimise learning routes, and so improve students' English learning experience and efficacy.

First, several learning style groups are found by means of K-means clustering algorithm analysis of student behaviour. This method compiles student learning behaviour data – including learning frequency, learning length, activity kind, etc., – into many groupings, each reflecting a learning style.

Given K initial cluster centre points C_1, C_2,..., C_K, get the distances from every student x_i to the cluster centre:

$$d\left(x_i, C_j\right)=\sqrt{\sum_{m=1}^{n}\left(x_{im}-C_{jm}\right)^2} \tag{26}$$

where, x_{im} and C_{jm} respectively represent the value of the m-th feature.

Assign each student to the nearest cluster centre and update the centre point C_j of every cluster to the mean of every other data point in that cluster.

$$C_j=\frac{1}{\left|S_j\right|}\sum_{x_i\in S_j} x_i \tag{27}$$

This process is repeated until the centre point no longer changes significantly, thereby generating different learning populations, each corresponding to a learning behaviour characteristic.

After clustering analysis, the Apriori algorithm is used to analyse the association rules between learning behaviour characteristics and learning outcomes, revealing key influencing factors. Apriori's fundamental ideas are developing rules and mining frequent itemsets.

Set a minimum support threshold then search for any itemsets with support higher than that threshold. The itemset X support computation equation is:

$$Support(X)=\frac{Count(X)}{N} \tag{28}$$

Create association rules with a minimum confidence threshold and in frequent itemsets.

$$Confidence(X\Rightarrow Y)=\frac{Support(X\cup Y)}{Support(X)} \tag{29}$$

This stage can help the platform identify which learning behaviour patterns are more fit to enhance learning outcomes by revealing the relationship between particular learning behaviours and great effectiveness.

Time series analysis helps one to track changes in students' emotional states and learning progress, therefore supporting the building of individualised learning paths. One might consider emotional shifts or learning progress as a time series:

$$Y_t = T_t + S_t + R_t \tag{30}$$

where, T_t represents the trend of learning progress or emotional changes; S_t represents seasonal components, reflecting the cyclical fluctuations of emotions; R_t represents a random component.

If the time series is stationary, an ARMA model can be used for modelling:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{31}$$

where, ϕ_i and θ_j are model parameters, and ε_t is white noise.

By means of time series analysis, students' learning patterns or emotional swings over a period of time may be found, so offering data basis for the building of individualised learning routes for the platform. When the emotional condition is low, the platform can offer motivating comments; when the progress is slow, it can suggest appropriate learning activities, therefore optimising the students' educational process.

The joint application of K-means clustering, Apriori algorithm, and time series analysis can identify students' learning style groups, mine key learning behaviour characteristics, and track learning progress and emotional changes, providing strong support for personalised path design for mobile learning platforms.

4 Experiment

4.1 Dataset

This work planned an experiment based on the publicly accessible EdNet dataset in order to investigate how best to maximise the learning experience and improve the outcomes, using K-means clustering, Apriori association rule mining, and time series analysis methods to deeply analyse students' learning behaviour, effectiveness, and emotional changes, providing a basis for personalised learning paths for the platform. The EdNet dataset contains learning records of over 10,000 students, covering behavioural data such as online learning frequency, interaction frequency, and test scores. It also includes multiple changes in test scores during the learning process, which can comprehensively reflect students' learning progress and effectiveness. It is suitable for conducting multi-faceted data mining experiments.

4.2 Experimental results and comparison

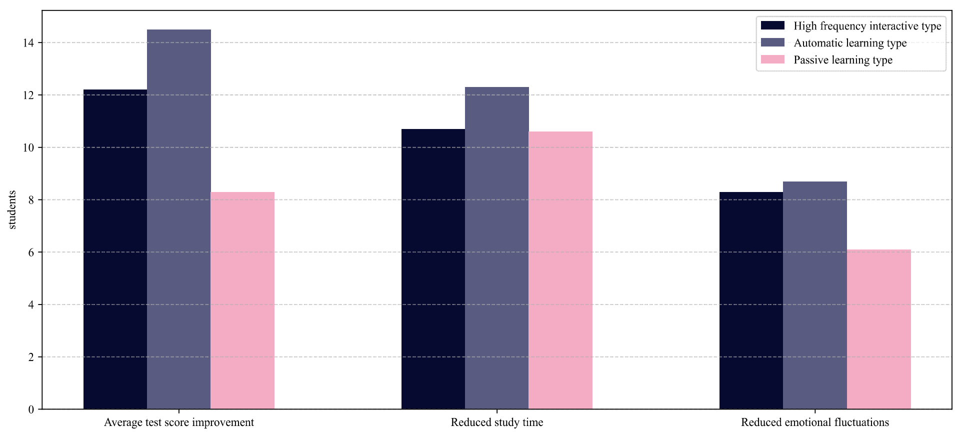
The methodology of this study consists of three core steps. Firstly, the K-means clustering algorithm is used to perform clustering analysis on students' learning behaviour data, in order to identify different learning style groups of students. By clustering variables such as learning frequency, learning duration, and interactive behaviour, students are divided into three learning groups: 'high-frequency interactive', 'self-directed learning', and 'passive learning'. The behavioural characteristics and learning preferences of each group are significantly different. High frequency interactive students exhibit strong initiative and high-frequency interactive behaviour, while self-directed learning students tend to learn independently, while passive learning students have a lower learning frequency and show less learning autonomy. This allows the platform to offer unique learning materials and resource recommendations for several kinds of pupils to satisfy individual demands.

Analysed were changes in students' test scores, learning length, emotional fluctuations, and other variables before and after personalised learning path suggestions to assess the efficacy of the model in this paper. Table 1 and Figure 4 both illustrate the outcomes.

Table 1 Model test results

Student group	*Average test score improvement (%)*	*Decreased learning duration (%)*	*Decreased emotional fluctuations (%)*
High frequency interactive type	12.2	10.7	8.9
Self directed learning type	14.5	12.3	10.6
Passive learning type	8.3	8.7	6.1

Figure 4 Experimental result chart (see online version for colours)



With high-frequency interaction students demonstrating the most notable gain in scores, up to 12.2%, the experiment revealed that the customised suggestion learning path employing the model suggested in this article greatly enhanced the average test scores of different groups. Concurrently, the marks of students engaged in passive and self-directed learning rose by 8.3% and 14.5% respectively. Furthermore lessening of the learning period and emotional oscillations suggests that the model also helps to improve learning efficiency and emotional stability.

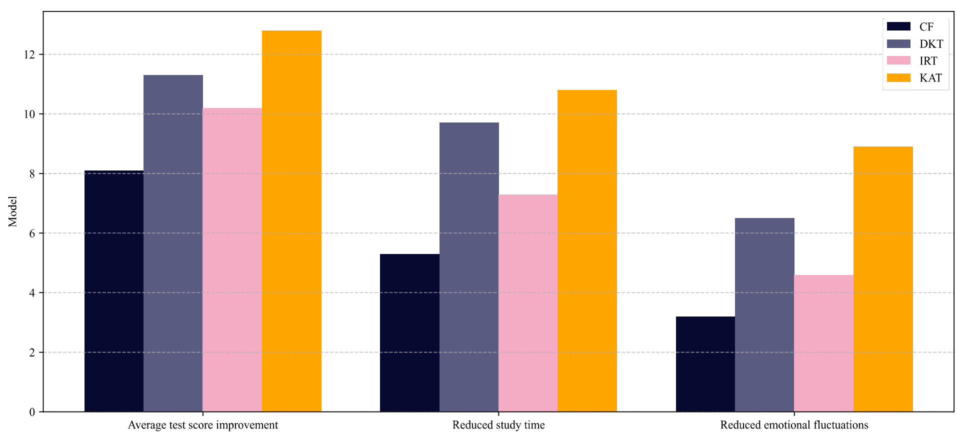
The model combining K-means clustering, Apriori association rule mining, and time series analysis was compared with various particular models usually used in the field of personalised learning recommendation in order to validate the efficacy of the strategy suggested in this work even further. Figures 5 shows the comparing results.

1 One often used recommendation system that suggests learning materials depending on student similarity is collaborative filtering (Ekstrand et al., 2011). Usually applied in situations with rich user behaviour data, this approach does not depend on explicit labels. In this experiment, test results and learning behaviour of the students guide the collaborative filtering model's recommendations.

2 Deep knowledge tracing (Piech et al., 2015): DKT is a deep learning model that forecasts learning success from behavioural history of individual students. By means of training and dynamically recommended appropriate learning materials, the DKT model may effectively represent students' knowledge level.

3 Item response theory (Cai et al., 2016): IRT is a classic personalised learning recommendation model mainly used to evaluate students' ability levels and infer their knowledge mastery based on their performance on different difficulty test items. This model can adjust the recommended content based on students' abilities to maintain adaptability and challenge in learning.

Figure 5 Model comparison results (see online version for colours)



While somewhat outperforming the DKT model in most indicators, the experimental results suggest that the model proposed in this paper outperforms the CF and Item IRT models in improving test scores, lowering learning time, and managing emotional fluctuations. The particular investigation follows this:

Test score improvement: The test score improvement effect of the model in this article is relatively significant, reaching 12.8%, which is higher than collaborative filtering and item response theory. In contrast, the score improvement of DKT is close to that of our model, reaching 11%. This article uses clustering to identify learning style groups, and then combines association rules to mine the relationship between key learning behaviours and outcomes, in order to provide more accurate customised content for students.

Reduced learning time: In terms of learning efficiency, the model in this article reduces learning time by 10.8%, which is better than collaborative filtering and item response theory, and comparable to DKT. The model in this article takes into account both student behaviour characteristics and learning outcomes in the recommended learning path, making the learning content more targeted and thus improving learning efficiency.

The model in this article has an effect of 8.9% in lowering emotional fluctuations; this is better than both item response theory and collaborative filtering and somewhat better than DKT. Using time series analysis, this model analyses and forecasts students' emotional shifts, therefore supporting them when emotional variations are notable and enabling them to keep a constant emotional state.

All things considered, the approach suggested in this paper based on K-means clustering, Apriori association rule mining, and time series analysis has major impacts in enhancing learning effectiveness, optimising learning duration, and controlling emotional fluctuations. The model suggested in this research shows more practicality and adaptability in practical applications than models including collaborative filtering, DKT, and IRT; it can also more fully maximise students' learning paths and experiences. This customised recommendation system combining several techniques offers a better way to maximise mobile learning environments.

5 Conclusions

Aiming to maximise the English learning mode on mobile learning platforms, this paper suggests a customised learning suggestion methodology based on data mining technologies. This work identifies various learning style groups based on students' learning behaviour characteristics by combining K-means clustering, Apriori association rule mining, and time series analysis and investigates the relationship between learning behaviour and learning outcomes, so revealing the main elements influencing learning outcomes. Furthermore, time series analysis supports the platform to create customised learning routes by tracking students' learning development and emotional transformations. Validating its efficacy in personalised learning suggestions, the experimental results reveal that our model beats often used models including collaborative filtering, DKT, and IRT in enhancing student test scores, lowering learning time, and emotional fluctuations. By means of multidimensional data analysis, this approach not only offers efficient learning path recommendations but also provides customised emotional support, so assisting students to stabilise their learning emotions and increase learning efficiency and effectiveness compared with other models. This article presents a model that shows great relevance in the use of learning recommendation systems and educational data mining, therefore offering a fresh approach for maximising tailored recommendations on English learning environments. Future research could take into account combining more behavioural traits and emotional feedback data to improve the accuracy and flexibility of tailored recommendations even more.

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