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PAPER

A Comprehensive Study on the Relationship between User Experience of Mobile Learning Platforms and Academic Anxiety among College Students

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ABSTRACT

With the rapid advancement of information technology, mobile learning platforms have become essential tools for college students to acquire knowledge and enhance their academic performance. However, the widespread use of these platforms has also introduced potential issues such as academic anxiety, adversely affecting students' learning outcomes and mental health. Existing research indicates a close correlation between the user experience of mobile learning platforms and students' academic performance and psychological states. A thorough exploration of this relationship can aid in optimizing platform design, enhancing student learning efficiency, and alleviating academic anxiety. Current research methods primarily employ descriptive statistics and correlation analysis, lacking systematic quantitative analysis and the application of modern data mining techniques. This paper utilizes advanced clustering analysis methods to systematically investigate the relationship between college students' user experiences on mobile learning platforms and their academic anxiety. The study includes predictive modeling based on clustering analysis and a detailed examination and validation of experimental results. The aim of this study is to unveil the intrinsic link between mobile learning platform user experience and academic anxiety, providing a scientific basis for improving platform design and optimizing user experience, thereby promoting the holistic development of college students and enhancing educational quality.

KEYWORDS

mobile learning platforms, user experience, academic anxiety, clustering analysis, data mining, college students

1 INTRODUCTION

With the rapid development of information technology, mobile learning platforms have gradually become important tools for college students to acquire knowledge and improve their academic performance. Mobile learning platforms are favored

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by a large number of students due to their convenience, flexibility, and abundant resources [1–4]. However, alongside the widespread use of mobile learning platforms, some potential issues have gradually emerged [5–8]. In particular, college students may experience academic anxiety while using these platforms due to various factors, which not only affects learning outcomes but may also have a negative impact on students' mental health [9, 10]. Therefore, exploring the relationship between user experience of mobile learning platforms and academic anxiety is of significant practical significance and research value.

Relevant research indicates that the user experience of mobile learning platforms is closely related to students' academic performance and psychological states [11–14]. In-depth study of this relationship can help optimize the design and functionality of mobile learning platforms, improve students' learning efficiency and satisfaction, and provide scientific evidence to alleviate academic anxiety, promoting the physical and mental health development of students [15, 16]. Through a detailed analysis of the relationship between different user experience factors and academic anxiety, targeted improvement suggestions can be provided for educators and platform developers, maximizing the educational potential of mobile learning platforms and advancing the process of educational informationization.

Although some studies have focused on the user experience of mobile learning platforms and academic anxiety, most research methods are relatively singular, often remaining at the level of simple descriptive statistics and correlation analysis, lacking systematic and in-depth quantitative analysis [17–22]. Some studies also have deficiencies in the application of data clustering and relationship prediction, failing to fully utilize modern data mining and machine learning technologies, which restricts the accuracy and generalizability of the research results. Therefore, there is an urgent need to adopt more scientific and advanced research methods to systematically explore the complex relationship between user experience of mobile learning platforms and academic anxiety.

This paper aims to use advanced clustering analysis methods to explore the relationship between college students' user experience on mobile learning platforms and their academic anxiety. Specifically, the research content is divided into two main parts: the first part is to conduct clustering analysis of mobile learning platform user experience data and academic anxiety data based on the K-medoids algorithm with incrementally optimized centroids, and on this basis, predict the relationship between the two; the second part involves a detailed analysis of the experimental results to verify the effectiveness and reliability of the research methods. Through this study, we hope to reveal the intrinsic connection between mobile learning platform user experience and academic anxiety, providing a scientific basis for improving platform design and optimizing user experience, ultimately promoting the comprehensive development of college students and enhancing educational quality.

2 PREDICTION OF THE RELATIONSHIP BETWEEN USER EXPERIENCE OF MOBILE LEARNING PLATFORMS AND ACADEMIC ANXIETY

With the rapid development of information technology, the application of mobile learning platforms in higher education is becoming increasingly widespread. College students, as the main users of this group, have their learning experiences and mental health issues under close scrutiny. However, the impact of user experience on mobile learning platforms on college students' academic anxiety has not been thoroughly studied. Exploring this study background can not only reveal potential issues in the practical application of mobile learning platforms but also provide valuable references for the development of educational technology. The necessity of studying this issue is reflected in the following aspects: 1) College students are in an important stage of life, facing significant academic pressure and frequent psychological issues. Academic anxiety, as a common psychological problem, seriously affects students' learning outcomes and quality of life. 2) The application of mobile learning platforms in education is continually increasing, and students' frequency of acquiring knowledge, completing assignments, and communicating through these platforms is also rising. However, whether the user experience of these platforms exacerbates or alleviates students' academic anxiety needs to be verified through empirical research. 3) The combination of traditional teaching models with modern technology requires ongoing evaluation of the actual effects of new technologies to ensure their reasonable application in education.

To reveal the differences in students' academic anxiety under different user experience patterns and to provide a basis for targeted intervention measures, this paper proposes a prediction method based on clustering analysis for the relationship between user experience of mobile learning platforms and academic anxiety. Specifically, the K-medoids algorithm with incrementally optimized centroids is employed to cluster the mobile learning platform user experience data and academic anxiety data. The user experience and academic anxiety data from mobile learning platforms often contain complex and multidimensional features. This algorithm effectively avoids the local optimal problem by proposing a candidate centroid subset and incrementally selecting centroids, compared to the traditional method of simultaneously selecting K centroids, thus better identifying and distinguishing different experience patterns and their corresponding levels of academic anxiety. The selection of the centroid subset and the choice of two initial centroids provide more interpretable clustering results. In this algorithm, the introduction of the candidate centroid subset and the selection of two initial centroids ensure the rationality and diversity of the initial centroids. By making the clustering process more robust while reducing the impact of noise data, we can more accurately identify which user experience patterns are significantly associated with academic anxiety, thereby providing strong support for subsequent relationship predictions and intervention measures.

1. Determination of candidate centroid subset: The determination of the candidate centroid subset requires the exclusion of outliers and isolated points in the data. This is because outliers are typically far from the central area of the data; if these points are selected as centroids, it will lead to isolated clusters in the clustering results, thus affecting the interpretability and accuracy of the results. In the clustering of mobile learning platform user experience and academic anxiety data, outliers may arise from extreme usage behavior of specific users or unusual levels of academic anxiety. To identify these outliers, we need to calculate the variance of each data point. Variance reflects the degree of deviation of a data point from other points in its cluster.

   Assuming a candidate centroid subset is $T \subset F$, and the dimension of the points is represented by l, the distance DIS (a_u, a_k) between points a_u and a_k can be defined as the Euclidean distance:

$$DIS(a_u, a_k) = \sqrt{\sum_{s=1}^{l} \left(a_u^s - a_j^s\right)^2} \tag{1}$$

   The variance of the dataset F can be calculated using the following formula:

$$\delta = \sqrt{\frac{1}{v-1} \sum_{u=1}^{v} DIS(a_u, \bar{a})^2} \tag{2}$$

Assuming the mean of the points is $a^{-} = \sum_{u=1}^{v} a_u / v$, the variance δ_u the point a_u can be calculated as follows:

$$\delta_u = \sqrt{\frac{1}{v-2}\sum_{k=1}^{v} DIS(a_u, a_k)^2} \tag{3}$$

After calculating the variance, a threshold can be defined based on the variance values. Points exceeding this threshold will be considered outliers and excluded from the candidate centroid subset. This process ensures that the points in the candidate centroid subset T tend to be distributed in the central area of the data rather than at the margins or far from other points. Next, by defining the candidate centroid subset T using formula (4), we can ensure it only includes points with smaller variances. Assuming the scaling factor is represented by η, specifically, formula (4) can be formally expressed as:

$$T = \left\{ a_u \mid \delta_u \le \eta\delta, u = 1, \ldots, v \right\} \tag{4}$$

In this way, determining the candidate centroid subset T can effectively exclude outliers in the prediction of the relationship between user experience of mobile learning platforms and academic anxiety, ensuring that the academic anxiety levels of students under different user experience patterns can be accurately represented, making the selection of centroids more rational and representative, thus avoiding biases caused by outlier data points.

2. Determination of two initial centroids: In the proposed algorithm, the determination of initial centroids directly affects the accuracy and interpretability of subsequent clustering results. Figure 1 illustrates an example of selecting two initial centroids. First, we need to calculate the distance measure f_u for each data point a_u. Here, f_u represents the total distance of point a_u to all other points in the dataset. This measurement ensures that the initial centroid p_1 is the most representative point in the dataset, meaning it has the smallest distance to all other points. Specifically, the calculation formula for f_u can be expressed as:

$$f_u = \sum_{k=1}^{v} DIS(a_u, a_k) \tag{5}$$

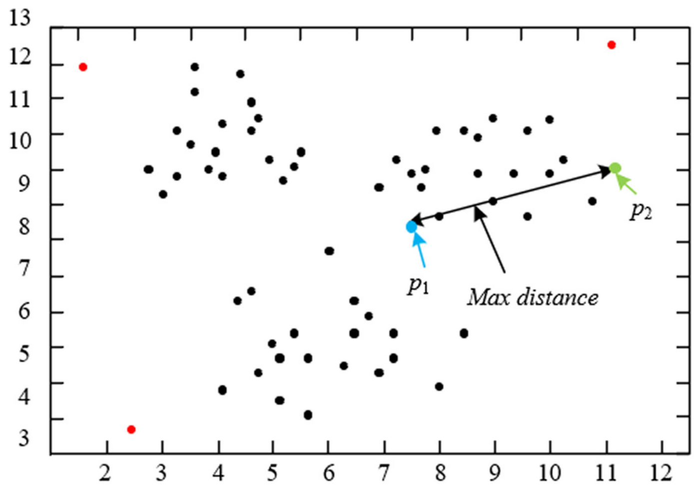

Fig. 1. An example of selecting two initial centroids

By calculating the f_u value for each data point, we can determine the first initial centroid, p_1, which is the point with the smallest f_u. At this point, p_1 can be seen as the centroid of the entire dataset, representing the point closest to all other points. Formally, this can be expressed as:

$$p_1 = \underset{a_u \in T}{ARGMIN}\left\{f_u \mid u = 1, \ldots, v\right\} \tag{6}$$

After determining the first initial centroid p_1, we next need to choose the second initial centroid p_2. To ensure that the selected second centroid p_2 is far from the first centroid p_1, we choose the point that is farthest from p_1 as p_2. This selection strategy ensures that the newly added centroid can maximize dispersion, thereby better capturing the diversity of the data in the early stages. Formally, this can be expressed as:

$$p_2 = \underset{a_u \in T}{ARGMAX}\left\{DIS(a_u, p_1) \mid u = 1, \ldots, v\right\} \tag{7}$$

From the above two formulas, we can see that the total distance of point a_u to all points in the dataset is the variable f_u, and the initial centroid is the point with the smallest f_u, which is p_1. In practical operation, it should be noted that the second centroid p_2 must be selected from the candidate centroid subset. This is because we have previously excluded outliers and isolated points by calculating the variance, ensuring that the points in the candidate centroid subset T are more representative and stable. Therefore, even if some points are farther from p_1 than p_2, they will not be selected as p_2 if they are not in the candidate centroid subset T. In the study of clustering analysis of mobile learning platform user experience data and academic anxiety data, the two initial centroids p_1 and p_2 determined by the above method can effectively reflect the intrinsic structure of the data. The first centroid p_1, as the centroid of the dataset, can represent the typical user experiences and academic anxiety levels of the majority of users. The second centroid p_2, being the farthest point from p_1, can capture another extreme of user experiences and academic anxiety within the user group.

3. Determination of new centroids: Assuming j centroids have been determined, a new centroid needs to be added. First, a candidate centroid p_u is calculated within each cluster such that it satisfies the following equation:

$$p'_u = \underset{a_m \in Z_u \cap T}{ARGMAX}\left\{DIS(a_m, p_u) \mid m = 1, \ldots, v\right\} \tag{8}$$

By using the above equation, a new candidate centroid set $P' = \{p'_1, \ldots, p'_j\}$ can be generated, and the newly added $j+1$-th centroid p_{j+1} needs to satisfy the following equation:

$$p_{j+1} = \underset{p'_k \in P'}{ARGMAX}\left\{DIS(p_k, p'_k) \mid k = 1, \ldots, j\right\} \tag{9}$$

The newly determined centroid p_{j+1} can then be merged with the original centroid set P to form a new set of $j + 1$ centroids.

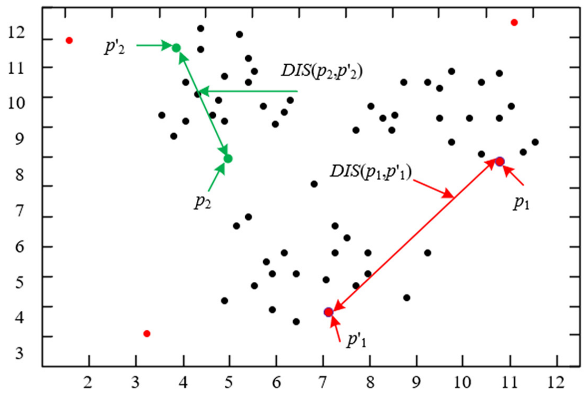

Fig. 2. An example of selecting the third centroid

Following the aforementioned method, by calculating the total distance of each data point to all other points, two initial centroids, p_1 and $p_{2,}$ have been selected. These two points represent the most representative and extreme user experiences and academic anxiety levels within the dataset. In the initial stage, these two centroids divide the dataset into two clusters, Z_1 and Z_2. After completing the preliminary clustering, further optimization of the centroids is needed to improve clustering effectiveness. According to the incremental optimization idea, we first calculate the new candidate centroids within each cluster. Specifically, candidate centroids p_1' and p_2' are generated within clusters Z_1 and Z_2 using equations 8 and 9. These candidate centroids are typically determined by recalculating the median or other representative positions of the points within the clusters. Figure 2 provides an example of selecting the third centroid.

Furthermore, it is necessary to compare the distances between the existing centroids and the new candidate centroids. The specific steps involve calculating $DIS(p_1, p_1')$ and $DIS(p_2, p_2')$, which represent the distances between the existing centroid p_1 and its cluster's new candidate centroid p_1', as well as the distance between the existing centroid p_2 and its cluster's new candidate centroid p_2'. Based on the comparison results, the candidate centroid that exhibits the greatest distance change is selected as the new centroid. Assuming in our study that $DIS(p_1, p_1') > DIS(p_2, p_2')$, then according to equation 9, the newly added third centroid should be p_1'. This indicates that among the existing two clusters, the position of the centroid within cluster Z_1 has changed more significantly, and the newly added centroid p_1' better represents the data characteristics within that cluster.

This incremental optimization method for centroids is very effective in revealing the relationship between user experience on mobile learning platforms and academic anxiety. The initial two clusters have already indicated the distribution of certain users regarding their experience and academic anxiety levels, while the newly added third centroid p_1' further segments the user group, uncovering more intrinsic connections. For example, p_1 represents users with high user experience and low academic anxiety, p_2 represents users with low user experience and high academic anxiety, while the newly added p_1' reveals a new group, such as users with high user experience but moderate academic anxiety. The following is a detailed description of the algorithm process:

1. Data preprocessing: First, collect data on user experience with the mobile learning platform and data on academic anxiety. This data typically includes users' frequency of platform use, satisfaction, and functionality usage, as well as their anxiety levels and learning pressures as psychological health indicators. Before clustering, standardize the data so that different dimensions can be compared on the same scale.

2. Selection of initial centroids: After data preprocessing, select the initial two centroids, p_1 and p_2, as the starting point for clustering. The selection of initial centroids can be done by calculating the total distance of each data point to all other points and selecting the point with the smallest total distance as the centroid. These two centroids represent the most representative and extreme levels of user experience and academic anxiety in the dataset.
3. Preliminary clustering: Using the initial centroids p_1 and p_2, partition the dataset into two clusters, Z_1 and Z_2. Each data point is assigned to the cluster of the nearest centroid based on its distance to the centroid.
4. Generation of candidate centroids: After the preliminary clustering is complete, a new candidate centroid needs to be generated for each cluster. The specific method is to recalculate the median or other representative positions of the points within each cluster to produce candidate centroids p_1' and p_2'.
5. Comparison of candidate centroid distances: Next, calculate the distances between the existing centroids and the newly added candidate centroids $DIS(p_1, p_1')$ and $DIS(p_2, p_2')$.
6. Selection of the new third centroid: Based on the distance comparison results, select the candidate centroid that shows the greatest distance change as the new centroid. Assuming in our study that $DIS(p_1, p_1') > DIS(p_2, p_2')$, then the newly added third centroid should be p_1'. This indicates that within the existing two clusters, the centroid position in cluster Z_1 has changed more significantly, and the newly added centroid p_1' better represents the data characteristics within that cluster.
7. Update clustering and iterative optimization: After adding the new centroid, reassign the data points and update the cluster divisions. Each data point is reallocated to the cluster of the nearest centroid based on its distance to the new centroids. This process iterates continuously until the centroids no longer show significant changes, and the allocation of data points within the clusters stabilizes.
8. Application to relationship prediction

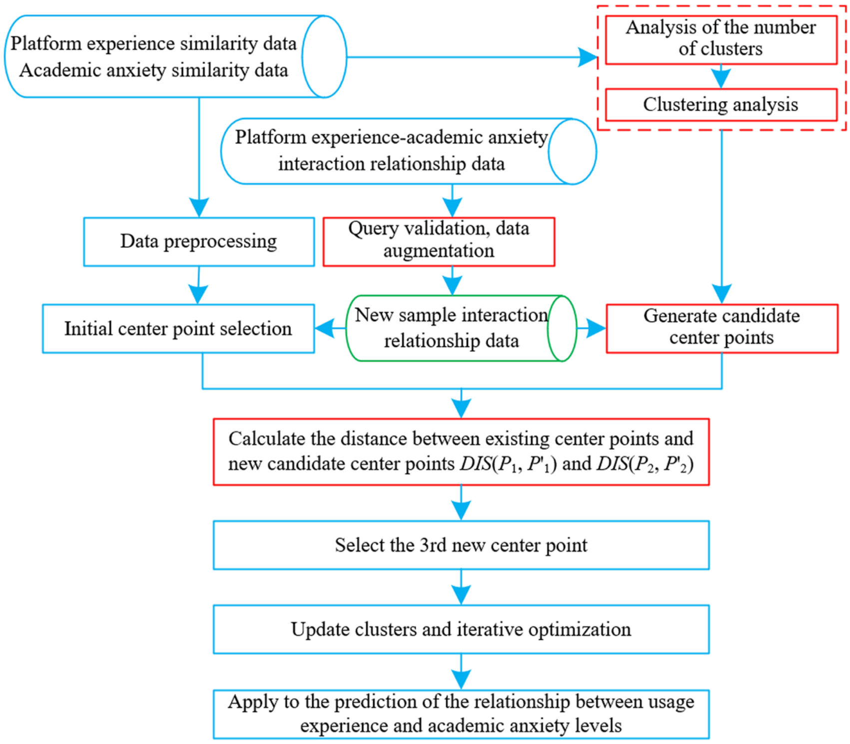

Fig. 3. Specific process of the proposed algorithm

Through the incremental optimization method for centroids using the K-medoids algorithm, the final multiple centroids and clustering results can effectively reveal the relationship between user experience on mobile learning platforms and academic anxiety. The clustering results show the distribution of different user groups concerning their experience and academic anxiety levels, helping researchers identify typical user behavior patterns and psychological characteristics. Figure 3 illustrates the specific process of the algorithm described in this paper.

Other centroid optimization algorithms, such as FastK, DPK, and DPNMK, all involve the calculation of a distance matrix, which has a complexity of $P(v^2)$, where v represents the number of points in the dataset. The method proposed in this paper optimizes the selection and updating of centroids in several ways. First, the complexity of calculating the distance matrix is $P(v^2)$, which is the same as other algorithms. Next, the complexity of calculating variance is also $P(v^2)$, which is used to assess the representativeness of each data point to determine a more suitable subset of centroids. Then, in determining the candidate centroid subset and selecting the initial centroids, the complexity is $P(v)$, ensuring the efficiency of the algorithm in the initial phase. The complexity of the entire centroid updating process can be calculated using the following formula:

$$P\left(sv\sum_{j=2}^{J} j\right) = P(svJ^2) \tag{10}$$

The complexity of the proposed algorithm can be calculated using the following formula:

$$P\left(v^2 + v + v^2 + v + v + sv\sum_{j=2}^{J} j\right) = P(v^2 + svJ^2) \tag{11}$$

The key aspect of this algorithm lies in the process of incrementally increasing centroids from 2 to J. Assuming that the maximum number of iterations for K-medoids clustering with J centroids is s, its complexity is $P(svJ)$. This process is relatively complex because each time a centroid is added, clustering and optimization need to be redone to ensure that each new centroid effectively partitions the data, improving clustering results.

3 EXPERIMENTAL RESULTS AND ANALYSIS

In the experiment, we subdivided the quantitative data from the participants into two categories: usage behavior data and academic performance data, and performed clustering analysis using the K-medoids algorithm with incrementally optimized centroids. The usage behavior data includes students' frequency of platform use, duration of use, and functionality usage rates, while the academic performance data includes students' grades, completion rates for assignments and quizzes, as well as academic anxiety scores. Since the dataset has multiple attributes, it cannot be directly visualized in 2D or 3D graphs; thus, we used multidimensional scaling analysis for data transformation and extracted 2D data, plotting the clustering results scatter plots for usage behavior data and academic performance data (see Figures 4 and 5). In Figure 4, the marked points represent non-candidate centroids in this algorithm, where point p_1 is chosen as the optimal centroid by both algorithms, representing the cluster containing all the black marked points in the upper left area of the figure. However, there are significant differences in the clusters represented by the other two centroids, p_2 and p_3, across the two algorithms. The proposed algorithm nearly splits the first cluster into two (red and blue points in Figure 5), and these points are closely distributed in the central area of the graph, suggesting they should belong to the same cluster rather than being split.

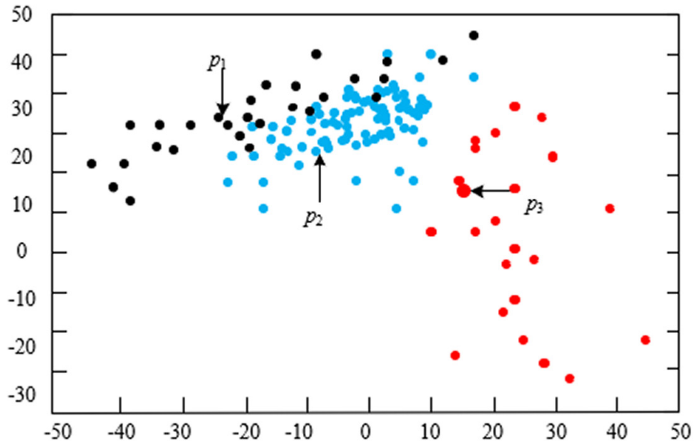

Fig. 4. 2D Distribution of clustering results for usage behavior dataset

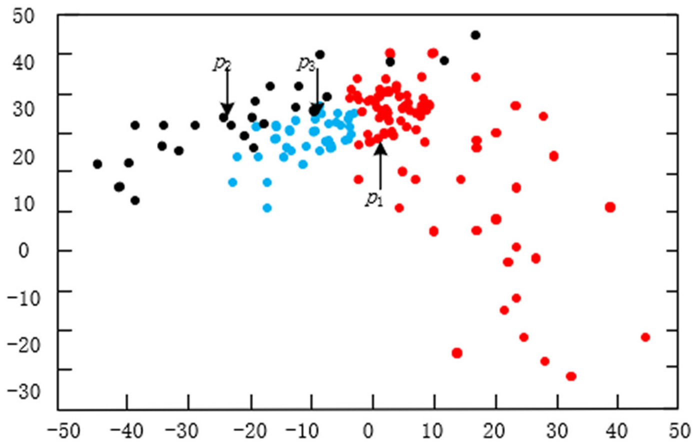

Fig. 5. 2D distribution of clustering results for the academic anxiety dataset

From the analysis conclusions, the K-medoids algorithm with incrementally optimized centroids shows good performance in clustering usage behavior data and academic performance data. The experimental results indicate that although some clusters exhibit splitting phenomena under different algorithms, the selection of candidate centroid subsets and the incrementally optimized centroids achieved the expected clustering effect overall, particularly in identifying and optimizing representative centroids. Point p_1, as the common optimal centroid of both algorithms, further validates the robustness and consistency of the algorithm. However, for the phenomenon of cluster splitting, it may be necessary to further optimize algorithm parameters or introduce more complex clustering methods to ensure that tightly clustered areas of points are not incorrectly split. Overall, this study provides a powerful tool for understanding the relationship between user experience on mobile learning platforms and academic anxiety, laying a data foundation for developing targeted intervention measures.

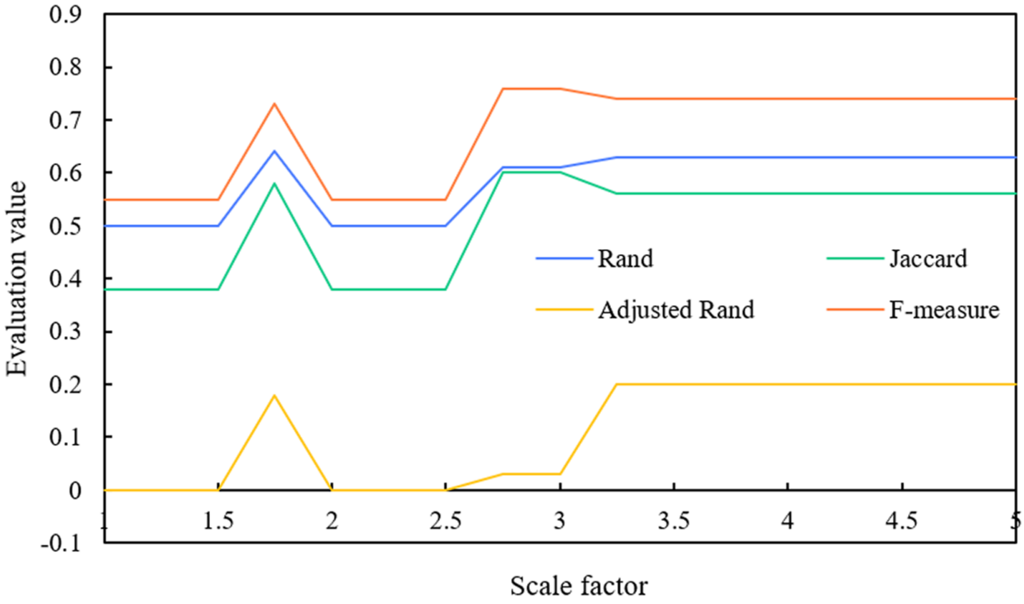

Fig. 6. Evaluation curve for predicting the relationship between mobile learning platform usage experience and academic anxiety

In this study, the clustering results of mobile learning platform usage experience data and academic anxiety data were evaluated using the Rand index, Jaccard index, adjusted Rand index, and F-measure under different scale factors. According to the data in Figure 6, as the scale factor increases, the Rand index peaks at 0.64 at a scale factor of 2.5, while it remains around 0.5 at other scale factors (such as 1, 1.5, 2, 3, and 3.5). This indicates that when using the K-medoids algorithm and optimizing the centroids, the clustering results can better reflect the similarity between samples at a specific scale factor (e.g., 2.5). The Jaccard index also shows a significant increase at 2.5 (0.58), while the values at other scale factors are relatively low, suggesting a higher overlap between clustering results and actual categories at this scale. The adjusted Rand index shows an overall lower level, peaking at 0.2, indicating that there is still room for improvement in the accuracy of clustering results. The F-measure reaches 0.76 at scale factors of 4 and 4.5, indicating relatively high precision and recall for clustering at these two scales, reflecting an overall ideal clustering effect. Combining the above experimental results, we conclude that the K-medoids algorithm with incrementally optimized centroids can effectively improve the clustering effect of mobile learning platform usage experience data and academic anxiety data at specific scale factors. Especially at scale factors of 2.5 and 4, 4.5, the clustering performance is quite excellent, reflecting the effective separability of the data and the similarity between samples. However, the relatively low adjusted Rand index suggests that improvements are still needed in separating different clusters.

Table 1. Relevant metric measurements for predicting the relationship between mobile learning platform usage experience and academic anxiety

Statistic Item	Usage Behavior	Academic Performance
Sample Size of Mobile Learning Platform Usage Experience	444	211
Sample Size of Academic Anxiety	663	203
Number of Interactions	2925	1475
Sparsity Value	0.011	0.033
Interaction Relationship Coefficient for Usage Experience Samples	6.56	7.01
Interaction Relationship Coefficient for Academic Anxiety Samples	4.42	7.22

Based on the data in Table 1, we can observe the relevant metric measurements between mobile learning platform usage experience and academic anxiety. The sample size for usage behavior data is 444, while the sample size for academic performance is 211. For academic anxiety, the sample size is significantly higher, reaching 663. This indicates that in this study, the collection of academic anxiety samples is more comprehensive, potentially reflecting the general psychological state of students during the use of mobile learning platforms. The number of interactions shows that the interaction relationships for usage behavior amount to 2925, while academic anxiety has 1475, indicating that students have a relatively high frequency of interaction while using the platform. In terms of sparsity values, the sparsity for usage behavior is 0.011, and for academic anxiety, it is 0.033, suggesting that academic anxiety samples exhibit relatively higher sparsity in interaction relationships. The interaction relationship coefficient for usage experience samples is 6.56, while for academic anxiety samples, it is 4.42, further demonstrating that usage behavior is more interactive, while academic anxiety samples appear more conservative in interaction relationships. From the analytical conclusions, these data suggest that there is a complex relationship between students' academic anxiety levels and usage behavior under different usage experience modes. The high sample size of academic anxiety data implies that the study can better capture students' emotional responses in different learning environments. However, the lower number of interaction relationships for academic anxiety and higher sparsity values imply that, although the impact of academic anxiety may be widespread, students' level of interaction while using mobile learning platforms may be low, potentially leading to relatively small fluctuations in anxiety levels. Therefore, targeted intervention measures should consider enhancing students' sense of participation on mobile learning platforms to reduce the impact of academic anxiety.

Table 2. Top N evaluation of usage behavior data ($\lambda = 44.52$)

Top N	10	20	30	50	100	200	300
KNN	3	5	8	11	16	21	32
Ridge Regression	2	2	3	5	13	25	28
Variational Autoencoders	3	10	12	16	33	58	78
Deep Hashing	5	8	8	12	12	14	31
Multi-Task Learning	5	9	12	18	32	53	78
The Proposed Method	6	10	14	23	33	56	81

(Continued)

Table 2. Top N evaluation of usage behavior data ($\lambda = 44.52$) *(Continued)*

Top N	400	500	600	700	800	900	1,000
KNN	35	34	34	37	41	42	42
Ridge Regression	36	46	52	57	64	71	71
Variational Autoencoders	105	124	145	161	177	184	192
Deep Hashing	42	47	48	52	62	63	71
Multi-Task Learning	100	115	131	136	143	146	154
The Proposed Method	150	144	187	157	147	169	174

Table 3. Top N evaluation of academic performance dataset ($\lambda = 42.14$)

Top N	10	20	30	50	100	200	300
KNN	4	11	18	31	57	95	101
Ridge Regression	4	9	11	22	37	85	121
Variational Autoencoders	6	11	14	21	37	65	88
Deep Hashing	4	6	15	21	42	57	73
Multi-Task Learning	4	10	15	22	37	71	95
The Proposed Method	5	11	17	23	45	88	108
Top N	**400**	**500**	**600**	**700**	**800**	**900**	**1,000**
KNN	122	131	141	143	144	144	146
Ridge Regression	153	165	201	215	218	218	221
Variational Autoencoders	112	135	157	178	203	215	231
Deep Hashing	85	100	123	143	151	161	181
Multi-Task Learning	125	158	181	198	208	218	242
The Proposed Method	132	172	193	201	226	245	273

Based on the data in Table 2, we can observe the performance of different algorithms in the top N evaluation of usage behavior data. The top N evaluations for KNN, ridge regression, variational autoencoders, deep hashing, multi-task learning, and the proposed method change with the increase in sample size. In smaller samples (such as top 10 and top 20), KNN and the proposed method perform relatively well, with scores of three and six, respectively. In larger samples (such as top 1000), the proposed method achieves a score of 174, which is significantly higher than other algorithms. This indicates that the proposed method demonstrates strong adaptability and effectiveness across various sample sizes when handling usage behavior data. Overall, the proposed method outperforms traditional algorithms across multiple evaluation metrics, especially when dealing with large sample sizes, effectively improving clustering performance.

From the data in Table 3, we can see the differences in performance among various algorithms in the top N evaluation of the academic performance dataset. The proposed method performs relatively consistently in smaller samples (e.g., top 10 is 5, top 100 is 45) and shows a significant improvement in larger samples, reaching 273 in top 1000, far exceeding other algorithms. In contrast, KNN and ridge regression perform better in small samples, but in larger samples (e.g., top 1000), their performances are 146 and 221, respectively, which are noticeably lower than the proposed method. Moreover, variational autoencoders and multi-task learning perform well at moderate sample sizes but gradually fall behind the proposed method at larger sample sizes. Overall, the proposed method shows superiority across various sample sizes, especially in effectively capturing data characteristics when processing large academic performance datasets. The analysis suggests that the proposed K-medoids-based prediction method demonstrates good predictive capability across different sample sizes in academic performance datasets, particularly exhibiting strong adaptability and robustness in large samples. Compared to traditional methods such as KNN and Ridge Regression, the proposed method better identifies the complex relationships between academic performance and academic anxiety, providing precise data support for targeted intervention measures. This result indicates that the incrementally optimized K-medoids algorithm contributes to improving the processing effectiveness of academic performance data, leading to more accurate predictions of academic anxiety in a big data environment, facilitating deeper research into the relationship between mobile learning platform usage experience and student academic anxiety.

4 CONCLUSION

This paper employed an advanced K-medoids clustering analysis method to explore the relationship between college students' experiences using mobile learning platforms and their academic anxiety, aiming to reveal the intrinsic connection between the two. The research is divided into two main parts: first, clustering analysis of mobile learning platform usage experience data and academic anxiety data using the K-medoids algorithm, and second, a detailed analysis of the experimental results to verify the effectiveness and reliability of the research method. The experimental results include the 2D distribution of academic anxiety and usage behavior datasets, relationship prediction evaluation curves, and relevant metric measurements, demonstrating that the proposed method outperformed traditional algorithms across different datasets, providing a scientific basis for optimizing platform design and enhancing user experience. However, this study also has certain limitations, such as the potential impact of sample selection on the generalizability of the results and a focus only on usage behavior and academic anxiety without considering the influence of other psychological factors. Future research directions could expand data sources and integrate multidimensional factors such as mental health and learning motivation for a comprehensive analysis, enabling a more thorough understanding of the relationship between college students' learning experiences and psychological states in mobile learning environments. This would contribute to improving mobile learning platforms and enhancing educational quality, providing stronger support for the holistic development of college students.

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