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International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Counselors use student communities to promote the integration of civic education

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SUMMARY: *Through the construction of "one-stop" student community grid management, counselors integrate the power of civic education into the campus life of students in a comprehensive way, create a new pattern of civic education and enhance the integration of civic education. Based on the common development direction of student community and civic education, this paper brings the grid management model into student community management, and counselors create a grid-based student community management team and structurally integrate the grid management information. With the help of "one-stop" student community to obtain student behavioral information, the use of association rules to establish students' social relationships and social activity degree of students to analyze the factors affecting the proposed density peak clustering algorithm to identify students' abnormal behavioral data, and the safety of students' community activities for abnormal early warning. We analyze the role of counselors in creating a "one-stop" student community grid-based parenting mechanism to enhance the integration of civic education from multiple perspectives. The density peak clustering algorithm with weighted Euclidean distance has a high recognition accuracy of 0.9364, 0.9458, and 0.9622 for student consumption data, access control data, and network data, respectively, and has successfully conducted student community group portrait. The "one-stop" student community grid-based parenting mechanism created by counselors can effectively strengthen ideological and theoretical education and value leadership, with an effectiveness ratio of 86.26%, thus deepening the integration of ideological and political education.*

KEYWORDS: *density peak clustering; association rules; abnormal student behavior; grid-based management; student community; civic education construction*

1 Introduction

Educational reform has made the student dormitory develop in the direction of centralization of accommodation and expansion of scale, and the prototype of student community has initially appeared. At the same time, the rapid development of the market economy, compound, innovative and other talents are in significant shortage, which puts forward a higher demand for students [1]. In this context, the concept of breaking the traditional class group, students learn in a more flexible and diverse way, learning autonomy and development of individualization is increasingly, while students stay in the dormitory space more time, students' education and management work gradually to the dormitory as the core of the transfer of the student community [2-4].

Student community is an important driving force to promote the sustainable and healthy development of the campus, but also the development and embodiment of community culture

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https://doi.org/10.65102/is2026179 Published: 30 April, 2026

and community spirit, which not only shows the cultural cultivation and spiritual outlook of the school staff and students, but also builds a positive teaching environment and growth environment [5-8]. And the work of ideological education and student community has a close relationship, the student community can be a good manifestation of the ideological education, but also allows students to realize the value of ideological education. In the context of the development of the new era, the construction of student communities should be used as a carrier to promote the development of the work of ideological education in depth, through the theoretical depth, ideological connotations, and a variety of forms of community activities, to help promote the community construction of the creativity and cohesion of the students' guidance [9-11]. In addition, community activities can also be organized for the majority of students to enrich the daily activities of students, broaden the channels of civic education and teaching content resources, enhance the fun and attractiveness of civic education, and truly enhance the effectiveness of civic education [12].

As part and parcel of political and ideological guidance, counselors need to be involved in shaping the future of the student community by taking up the initiative of grooming people for the nation and the Party [13, 14]. The role of the counselor in shaping the student community is twofold since the task includes both mental and technical skills; hence, it is important to consider the impact of the counselor on Civic and Political Education.

The aim of this research is to explore the dual impact of student community structure and civic education. In order to achieve integration between civic education, the grid-based management mechanism will be developed together with the establishment of student community administration, creating an effective “one-stop” mechanism for the management and education of the student community. As far as the counselors’ development is concerned, it is suggested that a grid-based student community management group should be set up, and through structural integration of network-management information, thematic similarities would be used for the classification of network data collection; the social networks of students will be drawn out and using density peak clustering algorithm, anomalous behaviors will be detected in the student community. This way, through the practical use of density peak clustering algorithm for detecting the anomaly in relation to the safety of student community activities, we assess the performance of density peak clustering algorithm in identifying the anomalies in student behaviors. On the other hand, the development of ideology and politics education will be assessed by evaluating the grid parenting mechanism of counselors.

2 Pathways for counselors to work in synergy with the student community and civic education

2.1 Synergy between the student community and civic education

(1) Sinking power into the front line of human education

Promoting “one-stop” student community grid management, taking student community governance and student association autonomy as the entry point, guiding students to cultivate their self-management ability, and integrating the power of on-campus service organizations. Leadership, teaching, management and service forces are actively stationed at the front line of the community. Actively organize “face-to-face” activities, so that counselors and other roles have zero-distance communication with students. Promote the refinement of parenting system, with close to the actual way of students, in the communication, to solve the actual problems of students, improve the efficiency, and promote the implementation of the system of whole-person parenting.

(2) Participate in the whole process and serve students' growth

Through the community nodes, we can seize the “period of growth and development” of the students. Utilizing the living qualities of the community, we carry out education for new students to enhance their sense of adaptation, and the first time we utilize the community to carry out education on ideals and beliefs to help students grow. Regularly organize learning sharing sessions to teach students to change their learning concepts and adapt to new learning and teaching methods.

(3) Constructing a platform to “integrate” the power of ideological education in an all-round way

The “one-stop” model shifts the focus of campus community activities from administration to the personal development of students through assigning frontline positions that are responsible for Party-building, cooperative learning, and community development. Through the creation of a new system based on new media within the context of the real-world campus life of students, an innovative tool has been created for ideological and political education. Through expanding its communicative capabilities, the model also increases the availability of Internet-based material, maintains information accuracy, helps achieve the internalization of Civic and Political Education values among the learners, and develops a holistic educational model.

2.2 Construction of a “one-stop” student community grid-based nurturing mechanism

The “one-stop” student community serves as an incubator on the campuses for social involvement, being one of the main means for nurturing and practicing socialist core values, while at the same time participating in Party building along with ideological and political work. Additionally, the community is an important platform for students’ self-education, self-management, self-service, self-discipline, and self-development, which helps in the processes of peer education, helping each other, influencing one another, and moving forward together.

In view of the coordinated development of the “one-stop” student community and ideological education, counselors have proposed a joint education path on this basis, which is based on the idea of forming a specific, effective, comprehensive, and interactive parenting system under the grid.

Grid-based community management represents a new form of social governance that can enhance governance capabilities, promote innovation in governance systems, and promote economic and social development, as well as serve as a very good example of community governance in higher educational institutions. Applying a grid-based method to the management of the “one-stop” student community can help improve the service capability and quality of community education through rational division of grids, improvement of management teams, and improvement of community grid operation mechanisms.

(1) Scientific Grid Division

The primary basis for putting into practice the system of grid management in the "one-stop" community of students is the scientific and rational classification of grids with the purpose of building an integrated community grid system.

Based on the characteristics and current situation of each student community in the school, in accordance with the principles of convenient management, clear definition, and consistent responsibility and authority, different standards and requirements are adopted, and the community grids are set up according to the local conditions, according to people's needs and classifications, so as to make the community grids more scientific, more reasonable and more humanized.

(2) Sound management team

Drawing on the method of social resident community grid management, change the passive and decentralized management into active and systematic management, set the community counselor as a grid member, assume the responsibility of grid management, mainly responsible for the coordination and processing of student affairs in the grid. Dormitory administrators, class teachers, student self-government organizations, etc. are involved as grid management forces.

(3) Improvement of Community Grid Working Mechanism

Strengthen the organization and leadership of the student community grid management service work, strengthen the communication between various departments, hold regular meetings to analyze the problems and deficiencies in the community grid, and study the solutions. Integrate all kinds of resources into the grid, establish the system of school leaders, faculty leaders, and teacher teams to pack the grid, provide categorized guidance, and provide targeted help measures.

2.3 Student Community Management Model by Counselors under the Perspective of Networking

2.3.1 Building a grid-based university student community management team

The university’s civic education programme is incorporated into the grid-based governance of student communities in higher education institutions, and a governance team has been created to assist the formation of a grid-based management approach for university student communities. Grid-based governance can be defined as the approach of community governance that corresponds with the management and service system in the university and involves coordinated linkage.

Figure 1 shows the governance team organizational structure for university student communities based on the grid approach. The main members of the governance team consist of the personnel from the university's functional departments including counselors and student organizations. In the organizational structure, the first-level grid team plays the important leading role in community governance in terms of coordinating the whole situation. The second-level grid team acts as the resource integration center, connecting the grid system of student community governance with the functional ideological and educational team in the school, thus creating the diversified and professional intermediate power on campus. The third-level grid team acts as the executing force in community governance of students in universities.

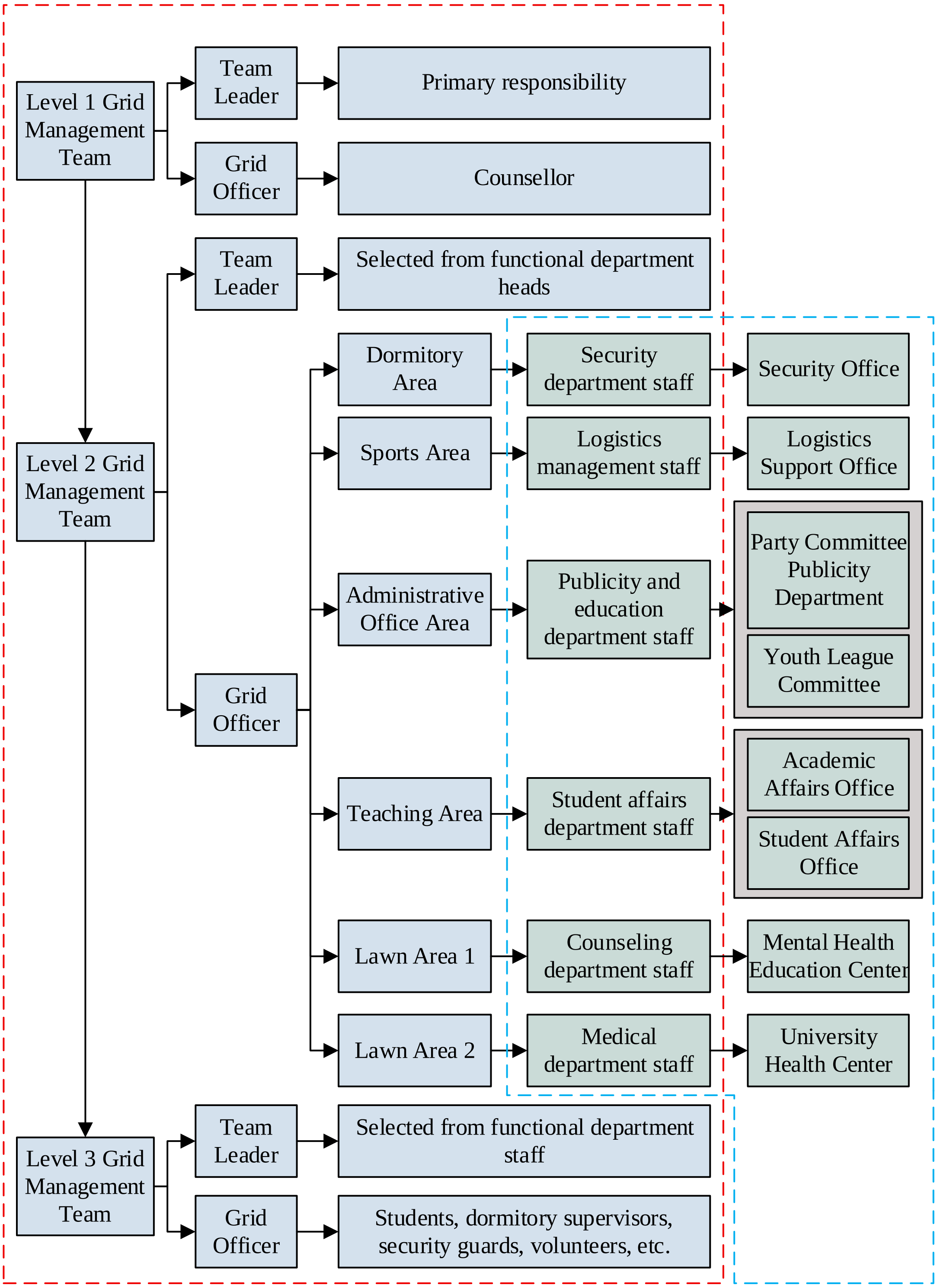


Figure 1: The community management team of the university student community

2.3.2 Structural integration of grid management information

Based on the digital school construction project, the original student information data platform is integrated, including the teaching affairs system and the student information portal, the campus one-card system, the student management information system, and the dormitory access control system. Afterwards, structural integration is carried out for these information data systems to realize system integration and information sharing for the grid-based management of college students, with the Education Technology Center taking the lead.

2.3.3 Student Social Characteristics and Abnormal Behavior Detection

1) Student Information Mining

By judging the data crawled by the web crawler through the degree of theme similarity, using competitive intelligence methods to prioritize the mining of student information resources under the most valuable URLs, to get the mining hierarchy in the theme attribute F_{ij} expressed as:

$$F_{ij} = \frac{\alpha_{ij}}{\sum \alpha_{nj}} \tag{1}$$

In the formula, n denotes the subject word of student information, α_{ij} denotes the number of times j that any subject word i appears within the crawled resource, and $\sum \alpha_{nj}$ denotes the total number of times that all the subject words appear within the crawled resource.

Since some of the subject attributes belong to public words, which have a high frequency of occurrence but little usefulness for student information, in order to reduce the weight of these public words and improve the quality of the resource collection, the reverse data mining frequency I_{DF_i} is set to denote:

$$I_{DF_i} = \log \frac{|D|}{\left|\left(j : n_i \in d_j\right)\right| + 1} \tag{2}$$

where D denotes the total number of resources after crawling and integration, $j : n_i \in d_j$ denotes the number of resources with the presence of student information topic attributes, and d_j denotes the student information mining results.

The weight of keywords is set to $T_F \cdot I_{DF}$, where T_F indicates the frequency of any word appearing in the crawler crawling process, and T_F and I_{DF} are fused to sort the weights of the crawled data again, and the dimension of the vector space of the stored resources is q, and the weight value of the keyword k is set to the same dimension, assuming that P denotes the user expectation topic, C_{kq} denotes the attribute keyword weight in the expectation topic, then it can be obtained:

$$P = \sum_{k \in d} C_{kq} = \left(w_1, w_2, \cdots, w_q\right) \tag{3}$$

Then calculate the ratio between the frequency of keywords appearing in the target topic and the total number, set $x_i = 1$ to indicate that the keyword is the reference value of the high-frequency word, then the topic within the crawling resource can be described as:

$$V = \sum_{k \in p} C_{kp} = \left(x_1 w_1, x_2 w_2, \cdots, x_i w_q\right) \tag{4}$$

Set the threshold r according to the actual requirements, if r is satisfied, the crawled resource is judged to have high similarity with the desired topic and can be mined.

2) Students' Social Relationship Establishment and Behavioral Characterization

This section uses the way of association rules to determine the best friend, in the campus, it is considered that two students who are best friends will often appear together in the same place, such as eating or consuming together, which is in line with the mode of college students' friends getting along with each other, which is called common behavior in this paper. When two people appear in the same place in a smaller time interval Δt, this paper defines it as co-occurrence.

In order to obtain the student's school friend relationship, it is necessary to calculate the co-occurrence dataset between student pairs as:

$$U = \left\{ \left(i, j, \tau(i \cup j) \right) \middle| i, j \in u_{1,2,3 \cdots N} \right\} \tag{5}$$

where i and j are students and $\tau(i \cup j)$ is the number of simultaneous occurrences of students i and j.

To rule out chance, a threshold T is assigned to each location when discovering student i's buddies through student behavioral records. It means that when the number of co-occurrences of students A and B is greater than T, the two students are considered as buddies. Considering that the threshold value for each location is related to the total number of times, it is defined as:

$$T_i^l = \frac{sum_i^l}{\alpha^l} \tag{6}$$

where T_i^l is the threshold of co-occurring buddies of student i at location l, sum_i^l refers to the total number of times that student i has appeared at location l, and α^l is the ratio coefficient at location l, and the number of times that students i and j co-occur is denoted as $\tau(i \cup j)$, when $\tau(i \cup j) > T_i^l$, student j is considered to be a buddy of i at location l, denoted as $G(i \rightarrow j)$.

On the basis of co-occurring data pairs, the association rule is used to determine the scaling factor α^l, where the use of mining relationships in the form of $i \rightarrow j$ is used, i.e., if there is an association rule of $i \rightarrow j$, then student i and j have a buddy relationship. Support $S(i \rightarrow j)$ and confidence $C(i \rightarrow j)$ are defined here, and the support is:

$$S(i \rightarrow j) = \frac{\tau(i \cup j)}{D}, i \neq j \tag{7}$$

Confidence is defined as:

$$C(i \rightarrow j) = \frac{\tau(i \cup j)}{\tau(i)}, i \neq j \tag{8}$$

where D denotes the total number of swipe records in the entire dataset, $\tau(i \cup j)$ is the number of co-occurrences of students i and j, and $\tau(i)$ is all swipe record entries of student i. Support $S(i \rightarrow j)$ denotes the frequency of co-occurrence of student i and student j in all datasets, and confidence $C(i \rightarrow j)$ can be used to denote the degree of association between student i and j.

Here there are four thresholds, Δt, T_{s_1}, T_{s_2} and T_c. The Δt is the co-occurrence time interval threshold, so based on the investigation and experience here the time threshold Δt interval is determined as 1min.

T_{s1} and T_{s2} are the support thresholds, where T_{s1} is used to screen the students who seldom have swipe records, and it is defined by the experimental calculations and verifications:

$$T_{s1} = 0.01 \times \bar{D}_l^i \tag{9}$$

where $\bar{D}_l^i$ is the average student consumption record in a location.

The threshold value T_{s2} is to remove pairs of students with lower frequency of occurrence, i.e., if the number of times two students co-occur is lower than T_{s2}, the two students are considered to be completely unrelated. Since the number of co-occurrences of friends in different locations is different, an adaptive threshold is used here, where $\sum_{j=1} \bar{\tau}(i \cup j)$ is the average of the total number of co-occurrences as:

$$T_{s2} = 0.01 \times \sum_{j=1} \bar{\tau}(i \cup j) \tag{10}$$

T_c is the confidence threshold for extracting high confidence rules. Taking student i as an example, students i and j are considered to have a strong rule connection only if the confidence level $C(i \rightarrow j)$ is not less than T_c, and then j is called as a buddy of i. Here $\{\hat{\tau}_{i,j}\}_{j=1}^{N-1}$ is used to denote the ranking result between student i and all other students $\tau(i \cup j)_{j=1}^{N}$. In the general case there are points of very clear convergence to equilibrium, here called k points. There are only a few students who co-occur with student i with high frequency above the k point, then these students are considered to have a strong association with student i, i.e., they are close friends. Below the point k, these co-occurrences are considered to be the result of randomness. So T_c is defined here as:

$$T_c = \frac{\hat{\tau}_{i,l}}{\tau(i)} \tag{11}$$

where $\hat{\tau}_{i,l}$ is satisfied:

$$\begin{aligned} \hat{\tau}_{i,l} - \hat{\tau}_{i,(l+1)} &\geq \frac{\tau(i)}{\lambda} \\ \hat{\tau}_{i,(l-1)} - \hat{\tau}_{i,l} &\leq \frac{\tau(i)}{\lambda} \end{aligned} \tag{12}$$

Here λ is the threshold parameter. The expectation $E(X)$ of the number of friends to find is calculated by adjusting λ. The expectation is calculated as:

$$E(X)=\begin{cases}\sum_{i=1}^{N}\frac{1}{N}\times\left(\frac{f_i-\overline{f_i}}{F_i}\right) & f_i\neq 0\\ 0 & f_i=0\end{cases} \tag{13}$$

Here N is the total number of students, F_i is the actual number of buddies of the i th student, f_i is the number of buddies identified by the confidence rule, and $\overline{f_i}$ is the number of buddies identified wrongly for this student. When the model does not identify any buddy of student i, i.e., $f_i=0$, then the number of misidentified buddies is ignored, and the expected value of the model identifying this student is 0. According to this formula, if the right student's buddy can be identified completely, the expected value is 1.

Eventually, the de-weighted accumulation of the buddies obtained from different locations is the number of buddies of the student at school as:

$$F_i=\sum_{l}G\left(i\rightarrow R^l\right) \tag{14}$$

F_i is the number of buddies of the student and is the number of buddies at the location. If the friends at multiple locations are the same person, they are counted only once. The entire flow of student social relationship mining is shown in Fig. 2.

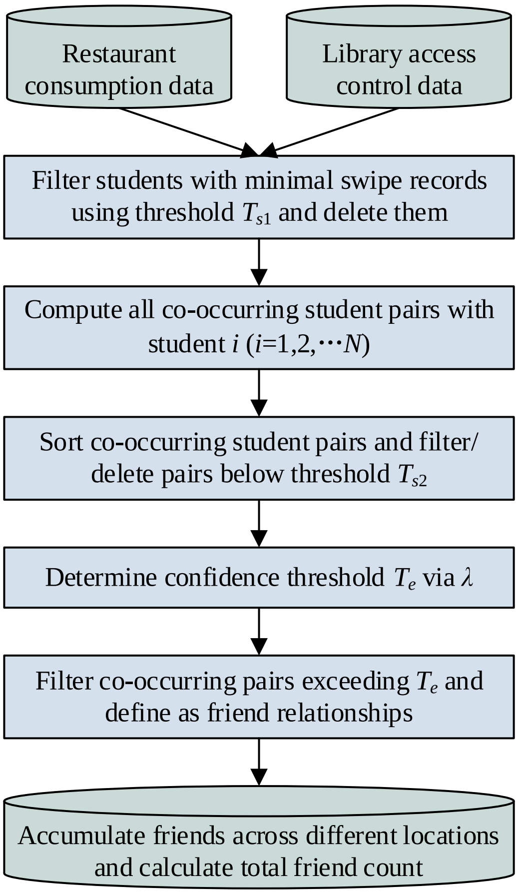


Figure 2: The process of the whole student social relationship mining

3) Anomaly Detection Algorithm for High School Students

(1) Density peak distance algorithm

Density peak clustering algorithm belongs to an unsupervised learning algorithm that can find non-convex cluster classes, which can find the number of clusters intuitively, and it is also easy to find abnormal sample points. The cluster centers of this algorithm have two characteristics

a. Sample points are surrounded by neighboring sample points of lower relative density.

b. Sample points have relatively large distances from higher density sample point objects.

To facilitate in-depth analysis of college student group behavior, assume that the student sample set X includes m objects with n attribute features for each data object, then $X=\left\{x_1,x_2,x_3,\cdots,x_m\right\}$, $x_i=\left(x_{i1},x_{i2},\cdots,x_{in}\right)$.

The local density and high-density distance for a sample point x_i are defined as follows:

Definition of local density:

$$\rho_i=\sum_{i\neq j}\varphi(d_{ij}-d_c) \tag{15}$$

where i is the ith sample point, j is the jth sample point, d_{ij} is the distance between the points x_i and x_j, the parameter d_c is the truncation distance, and $\varphi(x)$ is the segmentation function, $\varphi(x)=1$ when $d_{ij}<d_c$, otherwise $\varphi(x)=0$. . From the formula can be derived, the local density of the sample point indicates that the distance from the sample point does not exceed the truncation distance of the set of all sample points.

Definition of high-density distance: greater than its own local density of sample points, and the distance between the closest sample point. The high density distance δ_i for any point x_i can be expressed as:

$$\delta_i=\begin{cases}\max\left\{d_{ij}\,\middle|\,j\in x\right\} & if\ \ \forall j\in x,\rho_i\geq\rho_j\\ \min\left\{d_{ij}\,\middle|\,\rho_i<\rho_j,\,j\in x\right\} & \text{otherwise}\end{cases} \tag{16}$$

(2) Distance metric for feature weighting

In density-peak clustering, the distance metric directly affects the results of the clustering algorithm. Euclidean distance, also known as Euclidean distance, can calculate the similarity of two samples by the distance between the samples, the closer the distance, the more similar. In n-dimensional space, the Euclidean distance between x_i and x_j can be expressed as:

$$d(i,j)=\sqrt{\sum_{k=1}^{n}(x_{ik}-x_{jk})^2} \tag{17}$$

The attribute-weighted distance measure proposed in this paper works directly on the dimensions by satisfying the standard normal distribution for each dimension. The weighted Euclidean distance of two sample points is expressed as:

$$d_{new}(i,j)=\sqrt{\sum_{k=1}^{n}\left(\frac{x_{ik}-x_{jk}}{s_k}\right)^2} \tag{18}$$

where s_k denotes the standard deviation of the k th dimension.

(3) Identification of cluster centers and anomalies

Cluster class center is a sample point with both large local density and large high density distance, which can be expressed as:

$$\gamma_i = \rho_i * \delta_i \tag{19}$$

As can be seen from the definition of cluster class center, when the sample point i becomes the cluster center point, it is bound to have a larger density ρ and distance δ, and according to the above formula, at this time, the sample point should also have a larger value of γ.

In order to identify outlier samples, the set of sample points belonging to a cluster but not more than d_c away from other clusters is defined as the boundary region, and the point with the highest local density in the boundary region is also defined as ρ_b. The sample points in the cluster with local density equal to or less than ρ_b are separated as anomalous points.

3 Effectiveness of counselors' work in building student communities and civic education

3.1 Characterization of student community groups

3.1.1 Data cleansing

In the case of data collection in higher education institutions, the sources of information vary widely, leading to different formats of data. Therefore, there are different pre-processing steps that should be undertaken depending on the source of information. There are different cleaning processes based on the source and category of information collected. In this current study, the collected data is first pre-processed based on the category of information. Next, each category of cleaned data is carefully checked for any anomalies. The data used in this section includes:

(1) Completion of missing data

(2) Redundant data deletion

(3) Data normalization

(4) Multi-source data integration

3.1.2 Identification of data anomalies

Figure 3 shows the accuracy in recognizing anomalies from university data by comparing four different methods: K-means clustering, hierarchical clustering, density peak clustering with unweighted Euclidean distance, and density peak clustering with weighted Euclidean distance. These assessments are made using consumption log data, access control log data, and network log data. Since the performance of such methods should be evaluated within the university environment, labeled data samples are needed. In our experiment, we obtain labeled data samples according to the pre-set rules and annotations by domain experts.

The recognition accuracies of the density peak clustering algorithm with weighted Euclidean distance for consumption data, access control data and network data are 0.9364, 0.9458, 0.9622, which are higher than K-Means clustering by 0.1781, 0.1629, 0.1937, and 0.0559, 0.0522 than the unweighted Euclidean distance density peak clustering algorithm, respectively, 0.0433, the density peak clustering algorithm with weighted Euclidean distance has better effect on the anomaly identification of university data.

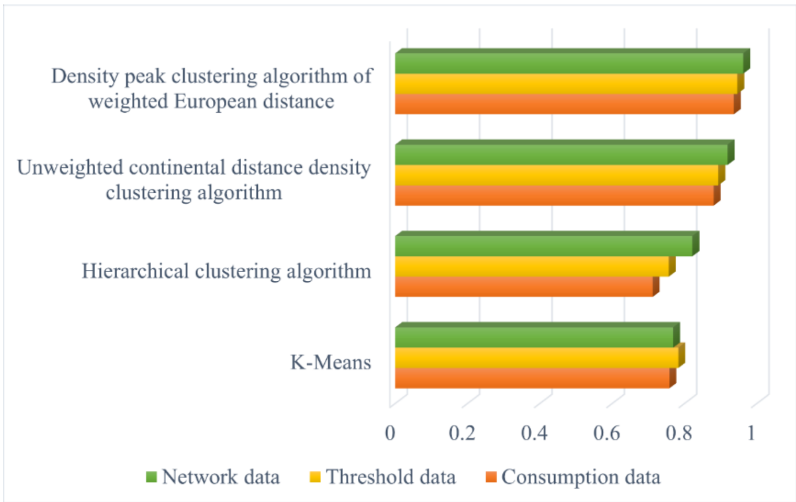
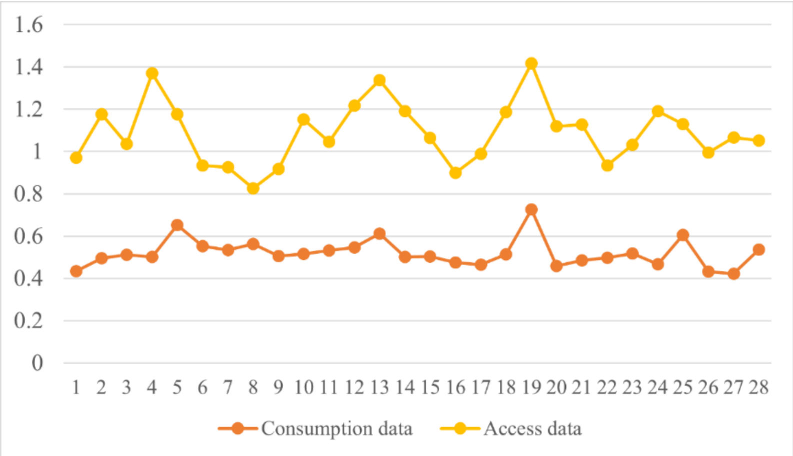


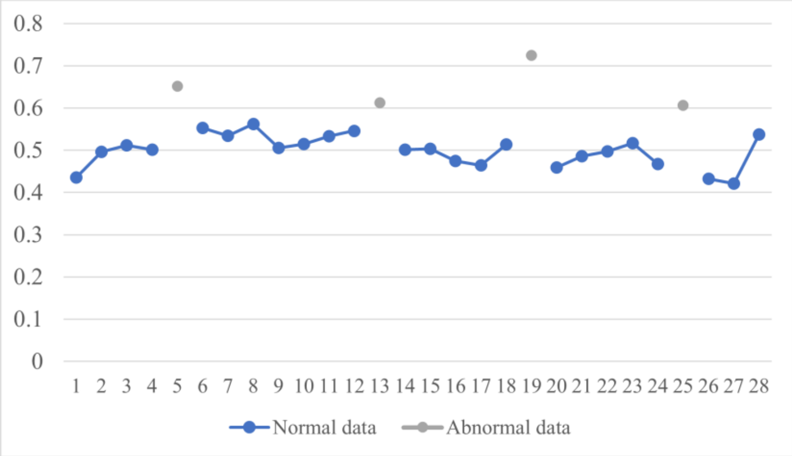
Figure 3: Data anomaly recognition accuracy

The irregularities in the consumption records and access control records for one student are shown in Fig. 4. Fig. 4(a), 4(b), and 4(c) show the consumption record, the access control record, and their corresponding normal and abnormal behaviors. Moreover, the variation of these two records over a period of four weeks is shown in the same figure. The density peak clustering algorithm was used to determine anomaly scores, which helped identify anomalies based on score distributions.

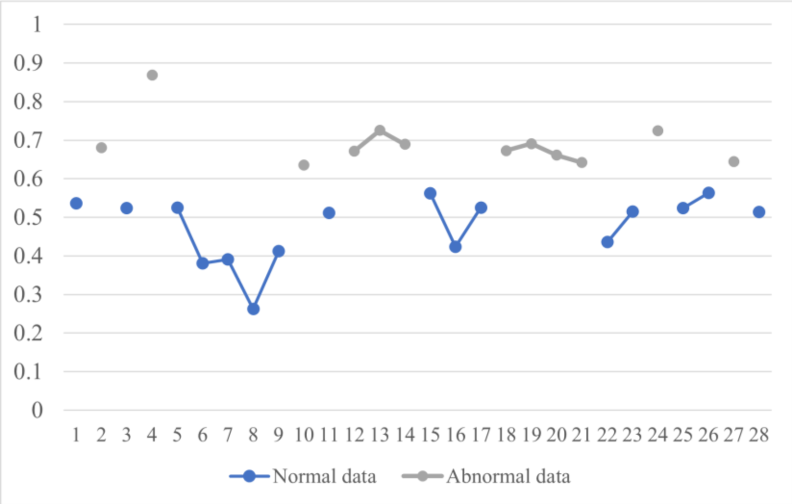
From the experimental results, it can be concluded that the fluctuation of the access control data is greater than the consumption data, and the student's consumption data has anomalies on the 5th, 13th, 19th, and 25th days, with anomalous values of 0.652, 0.612, 0.725, and 0.606 in turn.The access control data has more anomalies, and there are consecutive anomalies, in which there are consecutive anomalies on the 13th, 14th, and 15th days, with anomalous values of 0.672, 0.725, and 0.689.



(a) Consumer data and access data



(b) Normal and abnormal data of consumption



(c) Normal and abnormal data of the access data

Figure 4: A student's consumption data and the abnormal distribution of the portal data

3.1.3 Student Community Group Profiling and Analysis

In this paper, students are selected as disciplinary infractions (S1), whether they participate in evening study (S2) and total monthly consumption amount (S3) as the features for cluster integration.

Before using the clustering integration method, it is necessary to use the MinMaxScaler method in the Scikit-learn library to standardize the maximum and minimum values of the selected features, in order to reduce the differences between the features.

The density peak clustering algorithm was used to conduct k-clustering with a center point of 3 for the students, and the results were integrated to obtain three different groups of students with distinct characteristics. To facilitate teachers in identifying the student community groups, different student groups were named based on their specific characteristics and learning outcomes. The three groups were respectively called "autonomous learners", "conventional learners", and "consumption-oriented learners".

Statistical analysis found that there are 37 students with serious abnormalities in the behavior of autonomous learners, which are designated as outliers in this paper and made deletion. The results of the cluster analysis of the student group portrait are shown in Table 1.

There are 124 autonomous learners, accounting for 12.80% of the total number of students. They are excellent in all indicators, have the lowest frequency of disciplinary violations, the lowest level of monthly consumption, and participate in evening self-study in school accommodation, indicating that this type of learners are better in life and school discipline, with stronger self-control and higher commitment to learning.

Routine learners, totaling 711, accounting for 73.37% of the total number of learners, were average in all indicators, had the highest school discipline among the three types of learners, did not participate in evening self-study, and had an intermediate level of consumption.

Consumption-based learners totaled 134 students, accounting for 13.83% of the total number of students, and performed poorly in all indicators. Although they participated in evening self-study in school accommodation and the frequency of school disciplinary cases was low, the total monthly consumption amount was the highest, indicating that this group of students did not form the correct concept of consumption due to the long-term accommodation and the lack of parental care and teaching.

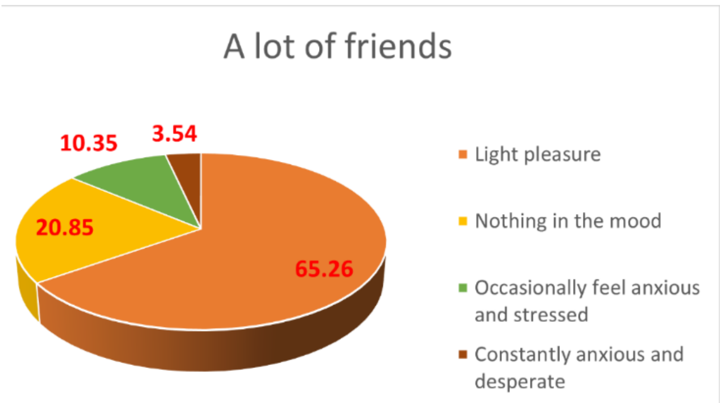
Table 1: Analysis of the student group portrait cluster analysis

Type name	Cluster center			Term average Total score	Student population	Percentage ratio/%
	S1	S2	S3			
Autonomous learner	0.15	1	314.33	1563	124	12.80
Conventional learner	1.20	0	526.95	1408	711	73.37
Consumer learner	0.34	1	720.18	1331	134	13.83

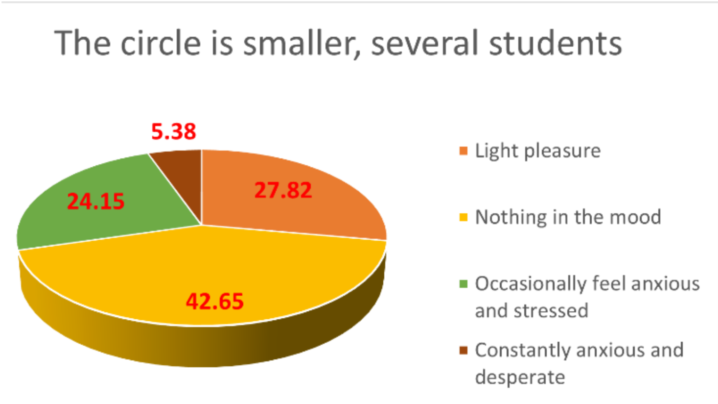
3.1.4 Factors influencing students' social activeness

The correlation between the degree of social activeness and students' mindset is shown in Figure 5, with Figures (a), (b), and (c) as having many friends, a small circle, only a few classmate relationships, and not many friends, respectively. The more socially active the students are, the higher the percentage of relaxed and happy.

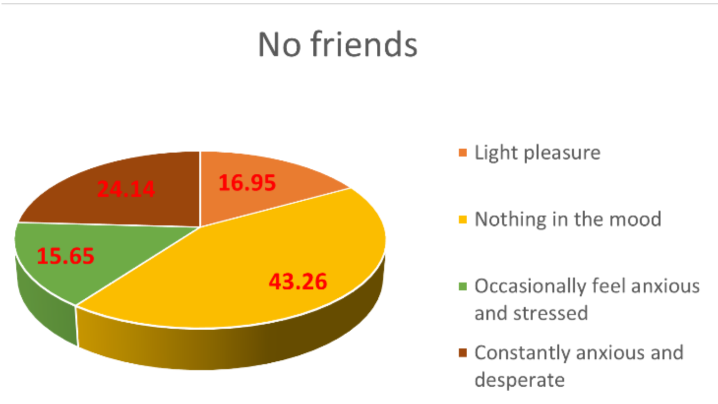
In figure (a), students have many friends, the percentage of relaxed and happy is 65.26%, nothing mood ups and downs, occasionally feel anxious, and frequently anxious are 20.85%, 10.35%, and 3.54%, respectively. The percentage of relaxed and happy decreased in Figure (b) and Figure (c), which were 27.82% and 16.95% respectively. The overall mindset of students with many friends is significantly better than that of the student group with smaller circles and few friends, i.e., active socialization has a positive impact on students' mindset to a certain extent.



(a) A lot of friends



(b) Small circle



(c) No friends

Figure 5: The correlation between social activity and student mindset

3.2 Application of Early Warning Model for Student Community Activity Anomalies

A school is a field study school with 6 grades, 80 classes, 4,263 students, 521 teachers, and 18 subjects. In the first semester of 2024-2025, the accuracy rate, F1-score, and the average value of the weekly statistics were calculated according to the correct and incorrect abnormalities in the teacher's abnormal alert processing. Score comprehensive evaluation indicators, and according to the weekly statistical averages organized into statistical tables. The results of a key university's application of evaluation indicators are shown in Figure 6, where ①, ②, ③ and ④ are the accuracy rate of academic performance anomaly early warning, academic performance anomaly early warning F1-score, the accuracy rate of student community activity safety anomaly early warning, and the F1-score of student community activity safety anomaly early warning, respectively.

The accuracy rate of student community activities and academic alerts and F1-score values can reach more than 85% on average throughout the semester. After retraining the student abnormal behavior recognition model in the sixth week, the recognition accuracy rate of the big data mining analysis of student community activities and academic performance have been significantly improved, and the F1-score can reach 88.15% at the end of the semester after retraining.

Counselors use the grid management method to promote the construction of student community and improve the student community management team. With the help of big data technology and abnormal student behavior identification model to analyze abnormal student community activities, they pay attention to student community development and student behavior performance from daily life.

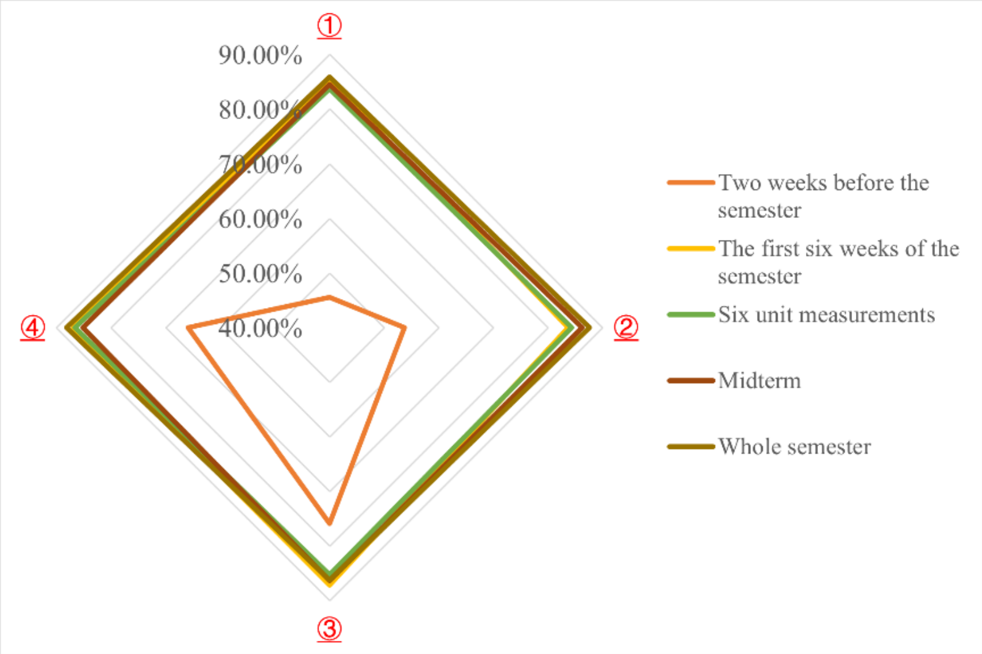


Figure 6: The results of the evaluation of the application of a key university

3.3 Development of Student Community Civics

Figure 7 illustrates counselors' use of the student community in promoting ideological and political education, which includes ideological and theoretical education, as well as value guidance, Party and class building, academic culture building, student life management, mental health education and counseling, online ideological and political education, campus crisis management, career and employment guidance, theory and practice research, and other aspects. Interestingly, ideological and theoretical education, in conjunction with value guidance, had the most prominent impact, which was 86.26%. Party and class building, along with academic culture building, made up 62.57% and 53.69%, respectively. Student life management had a percentage of 48.75%, while mental health education and counseling amounted to 56.91%. Online ideological and political education contributed 63.26%, campus crisis management 31.25%, career and employment guidance 43.77%, theory and practice research 55.97%, and other aspects 8.58%.

Counselors will be able to strengthen ideological and theoretical guidance, enhance the development of the Party and class, and foster a learning environment through the grid-based educational system of the integrated “one-stop” student community. Moreover, when combining this system with the information gathering and analysis of students in the “one-stop” community, counselors and university officials can gain more direct and comprehensive knowledge about campus activities. In addition, the use of the weighted-Euclidean density-peak clustering algorithm will help to identify anomalies in student behavior and activities in order to respond appropriately to any potential campus crises. Thus, through the construction of the grid-based educational system within the “one-stop” community as well as the refinement of the counselor-led student-community management model, civic education can be better integrated into theory and practice.

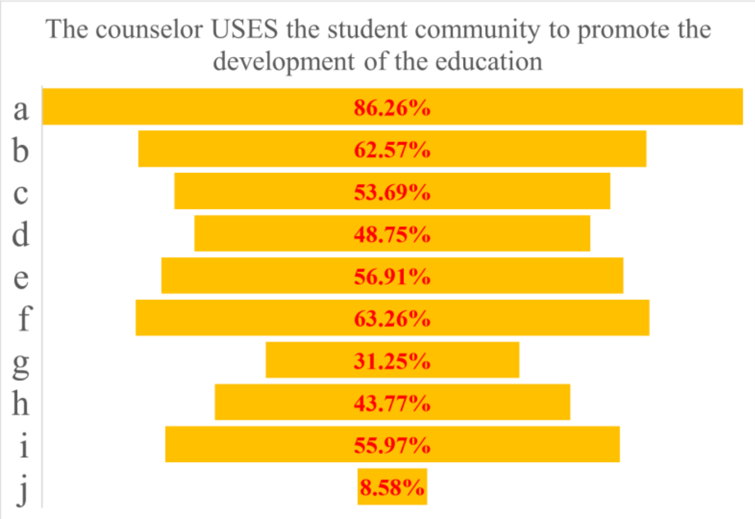


Figure 7: Use the student community to promote the development of the education

4 Conclusion

In this study, the researchers explored the construction of civic education in the context of "one-stop" student community. The counselors employed a grid-based educational approach along with a matching governance model in order to collect and analyze the behaviors of the students. With the help of the density peak clustering algorithm, the model increases the ability of detecting anomalous behaviors of the students and enhancing the efficiency of the management of community grids, which makes possible the combination of community grid governance and civic education.

By means of using weighted-Euclidean density-peak clustering, the counselors were able to find the anomalies in the consumption records, access-control records, and network logs of the students, with the accuracy rate of 90%. In total, three types of clustered data about students' behavior were classified as "autonomous learners," "regular learners," and "consumer learners." For predicting and responding to any abnormalities in the students' community, the accuracy rate was over 80%, thus allowing the counselors to react quickly to any crisis on campus and determine important aspects of "one-stop" community development and enhance the interaction between community building and civic education.

By integrating the grid governance with the concept of "one-stop" student community, the counselors managed to create an integrated system of student development, in which the introduction of civic education was facilitated.

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