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Integrating Social Networks and Cluster Analysis to Discuss the Relationship Between College Students' Learning Cliques and Course Selection Decision-making

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Course selection behavior is a decision-making process. In the past, it was pointed out that many factors affect students' selection of course, but their relationship with course selection decision-making has not been explored from the perspective of learning cliques. In a class, there

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are often several small groups of students with good learning relationships who form learning cliques. Therefore, whether the members of each learning clique will form similar behavior groups, whether the course selection process will produce a conformity effect, and whether they will choose the same courses as like-minded members are topics worth exploring. This article thus integrated the methods of social network analysis (SNA) and cluster analysis to explore the correlation between learning cliques and course selection decisions, and further developed prediction models through decision trees to speculate whether members of clique will form a similar behavior group of course selection decision-making in the learning network. This research used the methods of questionnaire survey and secondary data analysis; the research participants were 23 students in a class of the military academy in Taiwan. The research found that: (a) in the overall learning network, there were several large and small cliques in the class, and some members were not affiliated with any clique; (b) compared with the members who were not affiliated with any clique, the behavior of course selection decision-making of members in the learning clique were more consistent.

Keywords: social networks; cluster analysis; learning cliques; course selection decision-making; decision trees

Introduction

Course selection is the starting point of college students' learning process every semester. The seemingly simple behavior is a decision-making process. Although most students select courses by themselves, it does not mean that the behavior of choosing courses is based on their own will. In the past, studies pointed out that many factors affected the selection of courses. For example, Ognjanovic, Gasevic, and Dawson (2016) discussed the factors affecting students' course selection through the analytic hierarchy process and pointed out that the nature of courses, teaching characteristics, grading standards, teaching time, number of students taking courses, self-demand, and so on were used to predict students' course selection behavior. Brown and Kosovich (2015) regarded the reputation of professors as an important factor affecting whether students choose courses or not. Kardan, Sadeghi, Ghidary, and Sani (2013), in predicting students' course selection model by using neural networks, pointed out that students' learning satisfaction and self-interest were very important.

Looking at the above researches, students are indeed influenced by many complicated factors in the process of selecting their courses. However, although the above studies have put forward many contributions and opinions, they seldom discussed the relationship of course selection from the perspective of cliques. In the social relationships of Chinese culture, a phenomenon of tight network and cliques seems to have a great peer influence on relationships among people and can even be above many factors. The differences in cliques often lead to different decision-making behaviors and intention (Grainger, 2011; Murray & Fu, 2016; Pillemer & Rothbard, 2018). For example, Tomás-Miquel, Expósito-Langa, and Nicolau-Juliá (2016) studied the influence of relationship networks on academic performance in higher education and confirmed that students belonged to a dense interconnected cohesive clique; their academic network relationships enabled them to receive multiple sources of support and knowledge, which would help them to better perform academically. Holland (2011) studied educational issues for African American students and found that peers had a significant influence on their friends' academic activities and their postsecondary education plans and experiences. Chuang and Peng (2018) studied the job search pipeline in Chinese labor markets and confirmed that individuals could successfully obtain recommendations for suitable jobs through relationships with members of the clique, particularly that the higher position of the clique member or the social and economic status, the greater the influence. Tan's (2019) research on Taiwan's electoral system confirmed that candidates' affiliation of political cliques and social relationships with the voters would affect the election results. Hsieh (2019) explored the negotiation complexity of environmental politics and regarded the relationship between each other in social networks as an important factor influencing decision-making. Therefore, the importance of cliques is self-evident.

Past studies have successfully measured the relationship of cliques through the perspective of social networks (Coons & Chen, 2014; Hao, Min, Pei, Park, & Yang, 2017; Tasselli & Kilduff, 2018; Yin, Benson, & Leskovec, 2018). All these have indicated that social network analysis (SNA) is widely used and can be used to analyze learning cliques among students. In a class, there are often several small groups of students with good learning relationships. Members of each group have high cohesion, intimacy and some similar behaviors among themselves, thus forming learning cliques. Therefore, how to understand the state of college students' learning network and the composition of learning cliques through SNA? Will each member of a learning clique form similar behavior groups in their course selection decisions? Will the process of selecting courses produce a conformity effect for students to choose the same courses as like-minded members? Is it possible to predict the behavior of course selection decisions by the affiliation of learning cliques? These issues are worth being explored.

Based on the above, this research took the correlation between students' learning cliques and course selection decision-making as the research topic, integrated SNA and cluster analysis methods, and carried out an empirical analysis on the processing of multiple response type relation data and categorical data. Through a clear network diagram and tree diagram, the relationship structure between the data was clearly explained, so that managers can have a clear understanding of the learning patterns of a class, the relationship of cliques, and the behavior groups of course selection decision-making. Furthermore, decision trees were used to develop a prediction model to predict whether each clique members will form a similar behavior group of course selection decision-making based on the cliques to which students affiliated in the learning network. This research was expected to contribute to the improvement of college students' participation quality. The research questions are as follows:

1. Understanding college students' distribution of learning cliques and social networks;
2. Understanding college students' characteristics of course selection decision-making;
3. Constructing a prediction model of the correlation between learning cliques and course selection decision-making.

Literature Review

Learning Cliques and SNA

Members affiliating to cliques have two-way interactions (mutually beneficial intimate relations and high cohesion) with each other, as well as some similar behaviors (Ellis & Zarbatany, 2017). Learning cliques can be defined as relatively tight groups of friends who spend most of the time together and have their own social norms. Because of common social norms and social cognition, good social interaction and mutually beneficial relationship between members, they can contribute to knowledge sharing, mutual learning and exchange with one another (Černe, Nerstad, Dysvik, & Škerlavaj, 2014). Maintaining a good learning relationship between individuals and groups, individuals will be assimilated by the group. Owing to the existence of peer relationship, peer influence and social norms are generated, so that the individual's decision-making behaviors will tend to meet public expectations (Lee & Hong, 2016). Selection and influence processes lead to similarities between members of cliques (Conway, Rancourt, Adelman, Burk, & Prinstein, 2011; Lodder, Scholte, Cillessen, & Giletta, 2016).

Social networks, having the characteristics of pluralism and complexity, are composed of various relationships among groups, formal and informal connections between individuals (White, Currie, & Lockett, 2016). Relationship is an invisible concept with no actual distance and includes many categories, such as political relations between political parties, superior and subordinate relations in the workplace, consanguinity relations between relatives, friendship relations, learning relations among classmates. It is a resulting social structure. Among them, cliques exist in various forms of social structures and are informal groups. Whether it is a country or a class, there are cliques, such as party cliques, clan cliques, economic cliques, learning cliques. From the perspective of social networks, individual behavior will be directly influenced by peers, and individuals located in the center of the network can be regarded as the core or key person with greater influence (Ananthan, 2019; Liou & Daly, 2020).

Using SNA, the network structure and clique characteristics of learning relationships among peers can be concretely presented, and individual behaviors can be predicted in advance. SNA consists of three elements: actors, relationships, and linkages (Luo & Zhong, 2015). The relationship path established between actors includes unidirectional, bidirectional or non-directional links; actors who have a lack of interaction with other members can be regarded as isolate (Liu, Chen, & Tai, 2017). If one does not consider the directionality of the relationship and only cares about whether it exists or not, it is called an undirected relation diagram, which is regarded as weak cliques by the analysis result. In contrast, if the relationship between actors is considered to be a mutually beneficial bidirectional linkage with only one-way linkage not to be included, it is called a directed relation diagram, which is regarded as strong cliques by the analysis result. Compared with the undirected relation diagram, the clique threshold set by the directed relation diagram is stricter (Ma, Zhou, & Zhang, 2016). Therefore, this study strives to be rigorous and sets the standards for students' learning cliques as only when both sides recognize that they have good learning relations with each other can they be regarded as members of the learning cliques, while unilateral recognition is not recognized.

Course Selection Decision-making and Cluster Analysis

The college period is an important stage for students to explore future goals and establish careers. Course learning activities are the main channel for self-integration in the campus experience (Guan et al., 2017). Course input is an important learning experience for college students. The more active individuals are in participating in course activities, the higher their learning satisfaction, professional qualities and career planning ability will have a positive impact on their future developments (Planchard, Daniel, Maroo, Mishra, & McLean, 2015; Webber, Krylow, & Zhang, 2013). From the viewpoint of decision theory, decision-making problems are almost all related to people. The courses to be selected (decision goals) are quite distinct, but there are many subjects that can be chosen. Some decision-makings may be influenced by external factors, so that the final result of course selection is not preset. Conformity seems to explain this phenomenon. Decision-makers are subject to normative or informative social influences, whether on a perceptual or rational level, with the result that they are submissive, identify with the group to which they affiliated, and maintain favorable relationships with their peers (Eggens, van der Werf, & Bosker, 2008). Therefore, students may neglect the course that they originally pre-planned and be influenced by conformity, following similar decisions made by like-minded peers. However, due to the peer influence on course selection decision-making, ignoring personal preference and failing to select a course suitable for the individual, it may marginalize students, reduce the learning effectiveness and satisfaction of the course, and cause the loss of teaching resources (Gao et al., 2014; Kilian, Hofer, Fries, & Kuhnle, 2010).

Because the courses selected by students are discrete data that are difficult to interpret, cluster analysis can be used to analyze the similarity of the behaviors of course selection decision-making and to group them. Individuals in interconnected clusters have similar characteristics and attitudes — a phenomenon known as homophily, indicating that individuals are more likely to form social network connections with others who are similar to them, and to guide the selection of peers (Himelboim, McCreery, & Smith, 2013; Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017). Those with high similarity can be divided into the same cluster, and thus the nature of each cluster is examined. In the past, two-stage clustering was widely used when discussing the topics in various research fields through cluster analysis — that is, combining the aggregation method and non-hierarchical method to make up for each other’s shortcomings (Abdullahi, Schardt, & Pretzsch, 2017; Barbosa et al., 2016; Bharath, Srinivas, & Basu, 2016; Duan, Liu, Dong, & Wu, 2015; Hsu, Ho, Lin, & Kuo, 2017; Larsen, Borrill, Patel, & Fregosi, 2017). The first-stage polymerization method includes the Ward method, farthest neighbor method, inter-group connection method, and center of gravity clustering method, among which the Ward method is most commonly used. First, this article classified individuals through hierarchical cluster analysis and preliminarily observed how many groups they should be divided into. Second, the K-means method of non-hierarchical cluster analysis was used to calculate the distance between individuals by the distance measurement method, mostly using squared Euclidean distance as the basis for cluster attribution. Finally, ANOVA was used to verify the validity of the clustering results and determine the final clustering results.

Decision Trees

This study used SNA and cluster analysis to integrate the relation data of the learning cliques with the categorical data of course selection decision-making and explained clearly the distribution and classification of cliques through network and tree diagrams. Furthermore, decision trees were used to verify the correlation of the similarity between the cliques to which students affiliated and the behavior groups of course selection decision-making.

Decision tree is a widely used classification and prediction tool and presents a tree structure diagram. Each node of the tree represents a test attribute and each branch represents a test result. The end node represents the final decision and category distribution situations, which can be called the decision-making node. Its function is to determine the category of the final prediction — that is, the result of classification (Farid, Zhang, Rahman, Hossain, & Strachan, 2014). Common algorithms of decision trees include ID3, C4.5, classification and regression trees (CART), and Chi-square automatic interaction detection (CHAID), among which ID3 and C4.5 are suitable for categorical variables. This study used C4.5 algorithm (an improved version of ID3) and greedy algorithm to construct a classification model (Quinlan, 1993) of tree structure by top-down recursive and divide-and-conquer methods. It is characterized by classification rules that are easy to understand and with high accuracy, and it can make classifications according to specific data and its category attributes in order to establish the judgment basis of decision logic (Guo & Jiang, 2015; Kudla & Pawlak, 2018). Therefore, it can be used to explain the relationship between cliques and decision-making and to construct prediction models.

Research Method

Research Design

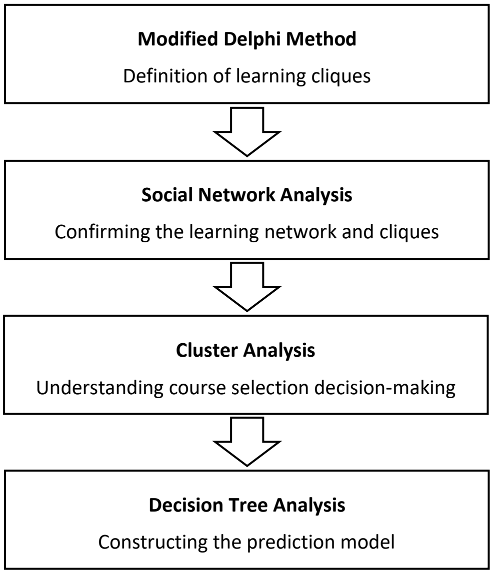
The acquisition of relation data and categorical data is of great importance. There are two answer methods: single choice and multiple choices. In order to describe in detail some of the characteristics of the interviewees, the multiple-choice answer method is usually used to collect data. However, when the number of variables in the multiple-choice answer method is large, the obtained data matrix will become disorganized and difficult to observe, or the relationship structure between the variables will be explained by simple statistical analysis techniques. In the past, most analysis methods used repeated cumulative answers and cross-over analysis to process. However, these methods can only understand a small part in a segmented way. For example, they are limited to probing into pair variables and the degree of relationship between variables, and it is necessary to have a deeper understanding of the relationship between variables (Tseng, 2005). Therefore, the special analysis method for relation data and categorical data is especially important.

Different from the past, this study focused on using easy-to-read and easy-to-understand graphs to describe and analyze the relationship between relation data and categorical data. First, this study adopted the modified Delphi method to confirm the definition of learning cliques. In order to confirm whether there is a learning relationship between students, this study used a simple multiple response relation data tick method, replacing a lengthy scale with one that avoids the burden or impatience of the interviewees, thus obtaining more authentic data. Through SNA, the distributions of learning cliques and network structures of students' affiliation were depicted. Researchers converted the data of students' course selection into categorical data according to the existing list of course selection, and used two-stage clustering to classify and group the behavior of course selection decision-making according to their similarities. Next, decision trees were used to develop the prediction model to explain the relationship between learning cliques and the course selection decision-making, as shown in Figure 1. Finally, based on the research findings, this article compiled conclusions and suggestions for reference for planning educational policies.

Participants and Data Collection

Course selection can be regarded as a decision-making process and experience in a college career. This study takes a military academy as a case. Although military academies provide non-mainstream education, in the past few pieces of research on military academies engaged in similar topics. After graduating from military academies, students served as troop leaders and managers, and they need to make decisions constantly. Compared with a general university, military academies are more important for the development of

Figure 1: Research Design



decision-making ability, which is related to the professional quality and future development of students of military academies. Understanding the distribution of learning cliques of students and the behavior of course selection will contribute to the quality of course participation and learning. Indeed, it has particularity and necessity. Therefore, participants consisted of students who were recruited from a population of students enrolled in Management Science at a military academy in Taiwan. Before initiation of this study, all research procedures were approved by the institutional review board of administration. In addition, the questionnaire survey of this study was implemented anonymously.

Military academies have many restrictions on the use of the Internet and are relatively closed. It is not easy to collect information about the relation data of their students through community Websites or media. Therefore, in a semester, this study conducted a questionnaire survey on a class by purposive sampling, using the class as the network boundary to verify the correlation between learning cliques and the course selection decision-making.

Questionnaire Design

In the questionnaire design, with the modified Delphi method, the first- and second-level unit managers, professors, administrative personnel, and student representatives of the military academy and civilian universities formed an expert group to confirm the integrity of the definition of learning cliques. The verification standard must conform to the threshold set by the average mean (*M*), mode (*MO*), standard deviation (*SD*), and quartile deviation (*QD*) in order to reach consensus and consistency (Murry & Hammons, 1995). The Delphi method verification standard is shown in Table 1.

Table 1: Delphi Method Verification Standards

Verification index	Definition
Average mean (*M*)	Indicating the concentration trend of experts' degree of agreement, with > 4 points as the screening boundary
Mode (*MO*)	Indicating the most frequently selected value that experts agree to choose
$MO-M$	≥ 1 represents a high degree of agreement among experts, < 1 means disagreement
Standard deviation (*SD*)	< 1 means the degree of dispersion of experts' agreement is low; the closer the value is to zero, the more concentrated the opinion is
Quartile deviation (*QD*)	< 0.6 indicates a high degree of consensus among experts; $0.6 < QD \leq 1$ indicates a moderate consensus; > 1 indicates a lack of consensus

The peer comparison determined whether there was a good learning relationship with each other. There was no limit to the number of people ticked, so as to avoid missing information. Both parties ticking each other could be considered as members of a learning clique, while unilateral ticking was not considered. If individuals believed that there was no learning relationship with other peers at all, they could choose not to tick (see Table 2). The list of course selection provided by the school for the students of this class during the semester was then used as the source of secondary data to ensure accuracy and objectivity of the statistical analysis data.

Table 2: Multiple Response Type Relation Data Questionnaire

Student number	S1	S2	S3	S4 - S23
Please tick your student number				
Which fellow students take the initiative to care about you, often study with you, often consult about academic problems, and are willing to share knowledge with you?				

Application Example and Analysis

Descriptive Statistical Analysis

This study adopted purposive sampling, taking military students in a military academy in Taiwan as the research participants, and selected a class from the management science department as the research case. The class is made up of 23 high school students from three different backgrounds: 7 students direct from military schools, 13 students from private high schools, and 3 students being international exchange students. In the part of the list of course selection, there are 6 courses (A, B, C, D, E, and F) for selection in the class. While Course C is the most popular elective course, Course B is only selected by one student. On average, one student takes 1 to 3 courses. Statistics of basic data, the courses for selection, and the number of students are shown in Tables 3 and 4.

Table 3: Basic Data Statistics

Gender		Source of enrollment			Total
Male	Female	Direct from military schools	Private schools	Exchange student	
22	1	7	13	3	23

Table 4: Statistics on Courses for Selection and Number of Students

Course	Course A	Course B	Course C	Course D	Course E	Course F	Total
Number of students selecting the course	2	1	16	6	4	10	39

Data Analysis

Modified Delphi method

In order to confirm the definition of the learning clique, 11 experts and scholars were invited to implement the two-round modified Delphi method. A total of 22 questionnaires were sent out, and 22 were recovered, with a recovery rate of 100%. The analysis results showed that through the search of expert opinions, the two rounds of questionnaires both passed the verification standard, and some textual descriptions were modified. In addition, all the verification values in the second round were better than those in the first round, indicating that the expert group agreed with the modified definition of learning clique and had a high degree of consensus. Therefore, "which fellow students take the initiative to care about you, often study with you, often consult about academic problems, and are willing to share knowledge with you" indicates that there is a good learning relationship between them, which can be used as the definition of learning clique and for implementing formal questionnaires. The analysis results are detailed in Table 5.

Table 5: Results of Two Rounds of Analysis on the Questionnaire With the Delphi Method

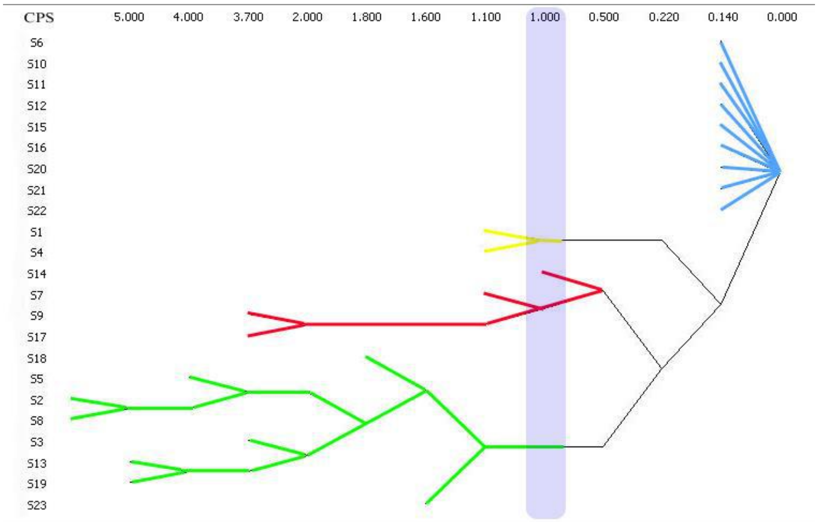
Definition of learning relationship	Degree of agreement (M)	$MO-M$	Quartile deviation (QD)	Standard deviation (SD)
Round 1	4.50	0.50	0.53	0.68
Round 2	4.57	0.45	0.50	0.55

SNA

This study used SNA software UCINET to construct a learning relationship matrix among students in each class and analyzed the learning relationship among students by clique. Each student's Clique Participation Score (CPS) indicates the probability of belonging to the clique. As long as the value is > 1, it indicates that the student belongs to the clique; the larger the value is, the more important the student's position is in the clique. Therefore, from Figure 1, the learning relationship of the students in the class can be divided into three different cliques (all values > 1) of yellow, red, and green, along with the independent blue individuals who do not belong to any clique (value = 0.14). There are 2 members of the yellow clique: S1 and S4. There are 4 members of the red clique: S14, S7, S9, and S17. There are 8 members of the green clique: S18, S5, S2, S8, S3, S13, S19, and S23. The scores of the clique participation of S2 and S8 are the highest (both values = 5), which means those two members are most influential in the green clique. The blue individuals without cliques are S6, S10, S11, S12, S15, S16, S20, S21, and S22, totaling 9 people.

The NETDRAW software was used to draw a network diagram to show the connection between the learning network appearance and the students' relationships. The students (S*) are represented by ■. From Figure 2, it can be more clearly observed that apart from student S20, the learning network of the students in this class is widely connected. The students belonging to the red and green cliques have close learning relationships with each other, and the number of students belonging to the green clique is the largest. Blue individuals without cliques are scattered on the edge of the network diagram, and their learning relationship with other peers is relatively distant. Further observation shows that members S2 and S8 are at the center of the network diagram, the shape of the ■ point being the largest; there are many

Figure 1: Distribution of Learning Clique Tree



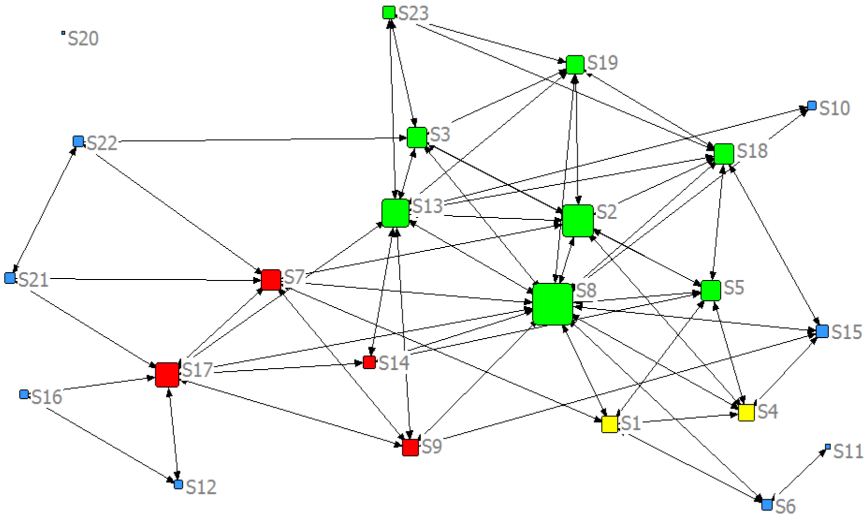
links with other peers, showing that these two students not only have influence on cliques, but also occupy an important position in the overall learning network of the class and are the core or key figures of the class. On the other hand, the blue individuals' ■ points are small in shape and sparsely connected (Grunspan, Wiggins, & Goodreau, 2014). Managers can grasp the learning relationship and distribution among students in real time by using the tree distribution map and learning network map of cliques.

An interesting phenomenon was found: as almost all students in the class are male, the only female student (S8) is the most influential core figure. It is obvious that the female student seems to have a unique position in the military academy dominated by male. Observing the differences in enrollment sources, it was found that the yellow clique is composed of students directly from military schools. The red clique is made up of students admitted from private schools. The green clique is made up of half of the students admitted from military schools and half from private schools. It is noteworthy that all international exchange students are blue individuals without cliques. Managers should pay more attention to their learning conditions.

Cluster analysis

According to students' decision-making on course selection, the courses for selection in this class include six courses A, B, C, D, E, and F, of which Courses A, B, and D are in the

Figure 2: Learning Network



field of management, and Courses C, E, and F in the field of mathematics. This study adopted the two-stage clustering analysis method to confirm the number of groups. In the first stage, the Ward method was adopted to observe the number and similarity of groups of students' course selection through hierarchical cluster analysis. Figure 3 shows that clusters can be roughly divided into 3 to 4 groups. In the second stage, K-means, a non-hierarchical cluster analysis, was used to assign students with more similar course selection decision-making behaviors to the same group using Euclidean distance as the calculation standard (as shown in Figure 4). Variance analysis (ANOVA) was carried out for clusters that are divided into 3 groups and 4 groups respectively to verify the validity of the clustering results. As can be seen from Tables 6 and 7, the errors among the groups divided into 4 groups are relatively large, the errors within the groups are relatively small, and significant differences are reached. The results of the examination are superior to those of the group divided into 3 groups. Therefore, it is better to divide the course selection decision into 4 groups (I, II, III, IV).

Figure 5 shows the course selection situations of the 4 groups. It is further known from Figures 4 and 5 that there are 4 members in Group I, S13, S23, S1, and S4 in order, whose common characteristics are that they have all selected Courses C and E in the field of mathematics (the probability of simultaneous course selection = 1); Group II consists of 10 members, including S16, S20, S11, S12, S8, S18, S2, S3, S5, and S6, which is characterized in that most members have selected two courses in mathematics — Course C (the

Figure 3: The First-stage Ward Method Tree Distribution

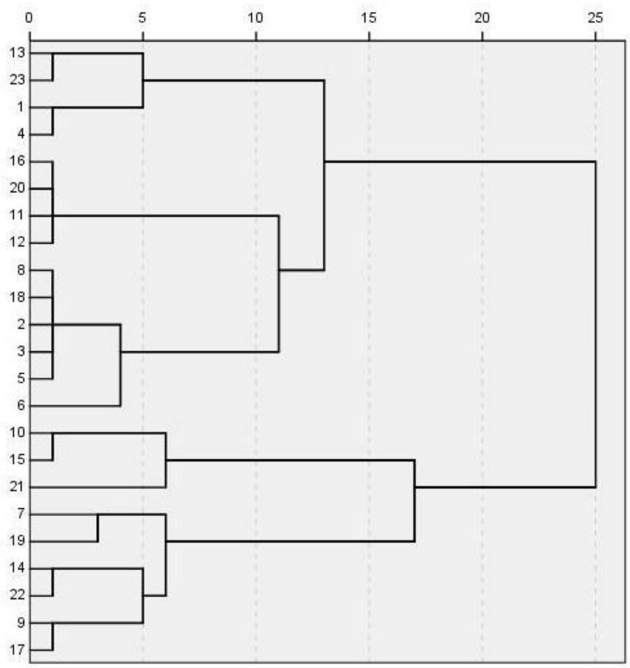


Table 6: Variance Analysis (ANOVA) for Decision-making of Course Selection Divided into 4 Groups

	Cluster		Error		*F* test	Significance
	Average square sum	Variance	Average square sum	Variance		
Course A	0.386	3	0.035	19	11.014	.000
Course B	0.097	3	0.035	19	2.754	.011
Course C	1.105	3	0.082	19	13.493	.000
Course D	0.571	3	0.143	19	3.984	.023
Course E	0.361	3	0.117	19	3.084	.050
Course F	1.069	3	0.129	19	8.311	.001

Table 7: Variance Analysis (ANOVA) for Decision-making of Course Selection Divided into 3 Groups

	Cluster		Error		*F* test	Significance
	Average square sum	Variance	Average square sum	Variance		
Course A	0.580	2	0.033	20	17.391	.000
Course B	0.145	2	0.033	20	4.348	.027
Course C	2.035	2	0.040	20	50.870	.000
Course D	0.951	2	0.127	20	7.506	.004
Course E	0.186	2	0.147	20	1.265	.304
Course F	0.359	2	0.247	20	1.457	.257

Figure 4: The Second-stage K-means Tree Distribution

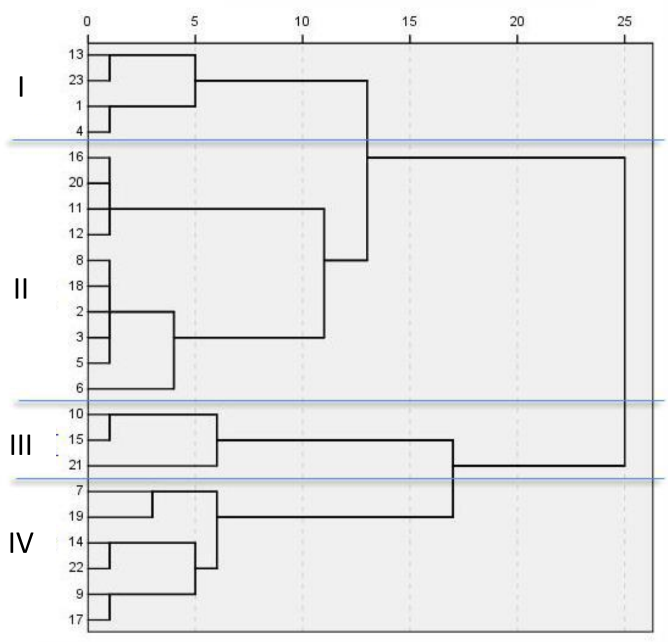
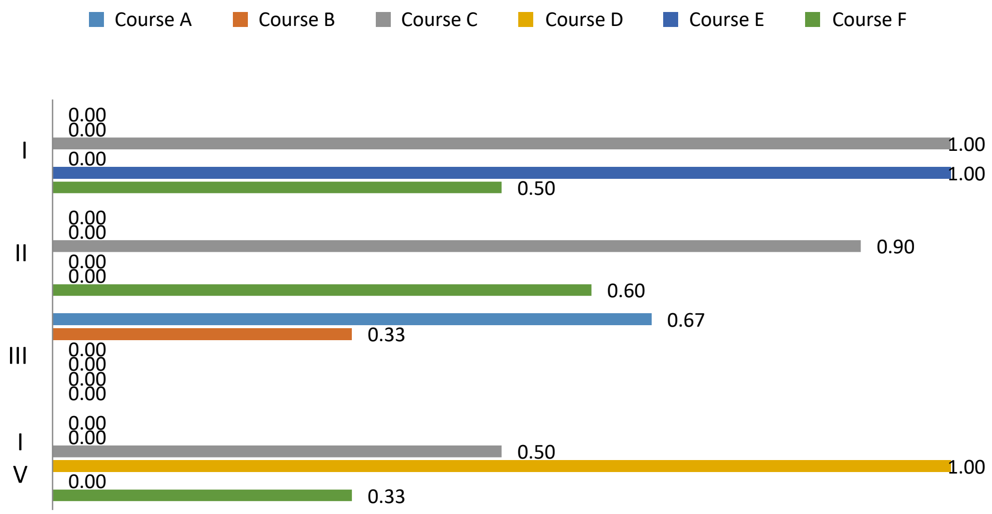


Figure 5: Proportion of Courses Selected by Members of Each Group

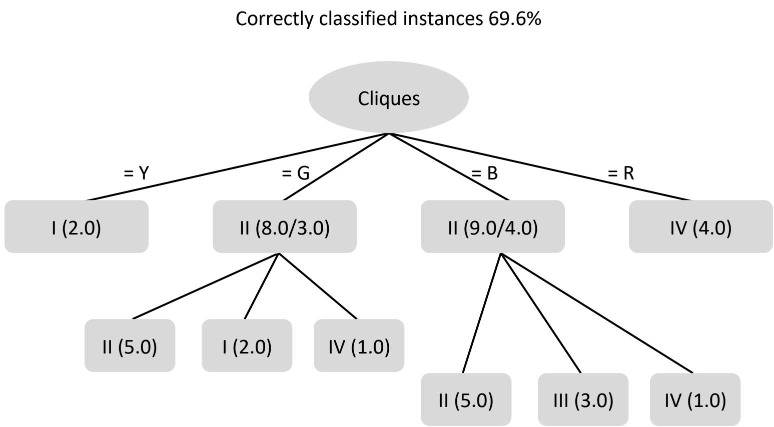


probability of simultaneous course selection = 0.9) or Course F (the probability of simultaneous course selection = 0.6); Group III consists of three members, S10, S15, and S21, and is characterized by a tendency to take courses in two courses in the management field, Course A or Course B; Group IV consists of 6 members, including S7, S19, S14, S22, S9, and S17, and is characterized in that all members have selected Course D in the field of management (the probability of simultaneous course selection = 1) and some members have selected Course C or F in the field of mathematics. Therefore, the members of Group I and Group II focused on courses in the field of mathematics, the members of Group III tended to choose courses in the field of management, and the members of Group IV attached equal importance to courses in the fields of management and mathematics. From the points of views of social networks, the individual behavior is related to peer influence, especially individuals located in the center of the network in the class. There are many connections between other individuals, who can be regarded as the core or key people and have great influence. Because members S2 and S8 in Group II have a very important influence in the overall learning network, it is easy for them to call on more peers to choose the same courses, making Group II the largest group among the four.

Correlation Between Learning Cliques and Course Selection Decision-making

The purpose of this study was to understand the relationship between the learning cliques among students and the decision-making of course selection. Therefore, the similarity between a student's clique and the group decision-making behavior for course selection was verified by using decision trees classification models. The analysis results show that the accuracy rate of the prediction sample classification is 69.6%, indicating that the two are indeed related to a certain extent. Figure 6 illustrates that members of the yellow clique (Y) and the red clique (R) respectively belong to Group I and Group IV, indicating

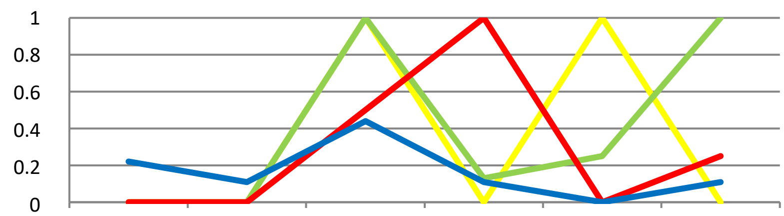
Figure 6: Classification Model of Learning Cliques and Course Selection Decision-making



that their decision-making behavior for course selection is quite consistent. The green clique (G) has 8 members, with 5 assigned to Group II for course selection decision-making, 2 assigned to Group I, and 1 assigned to Group IV, and so most members still have similar behaviors. There are 9 blue individuals without cliques (B), with 5 assigned to Group II for course selection decision-making, 2 assigned to Group III, and 1 assigned to Group IV, and their behaviors are mostly scattered.

The elective characteristics of each clique are shown in Figure 7. Members of the yellow clique (Y) all have selected Courses C and E in the field of mathematics; members of the green (G) clique all have selected Courses C and F in the field of mathematics; and members of the red clique (R) all have selected Course D in the field of management (simultaneous selection rate = 1). Only the blue individuals without cliques (B) have not selected the same courses, and their behaviors are more dispersed (simultaneous selection rate is < 1), with courses selected in the fields of both management and mathematics. In summary, this result can infer that members of smaller cliques approach the same decision-making decision; on the contrary, independent individuals who are less in contact with other members are not subject to group behavior and make their own decisions without being influenced by the group, and so their decision-making of course selection is quite different. There is a positive correlation between clique and decision-making.

Figure 7: Proportion of Course Selection by Cliques



	Course A	Course B	Course C	Course D	Course E	Course F
Clique (Y)	0	0	1	0	1	0
Clique (G)	0	0	1	0.13	0.25	1
Clique (R)	0	0	0.5	1	0	0.25
Clique (B)	0.22	0.11	0.44	0.11	0	0.11

Discussion

Observing the distribution of learning cliques and social networks, we find that the behavior of a class member is related to the influence of peers who have close interaction and reciprocal relationships with themselves, thus forming several learning cliques. In addition, there are several members who are not affiliated with any clique and are on the borderline of the overall learning network. In terms of the research participants of this study, military academy students have a large number of male students and a few female students. The female student in this class is at the center of the class. Causes could be further explored as to whether this is related to factors such as personal charm, characteristics, or academic performance. The composition of each clique is related to the background conditions of the members, especially the exchange students from abroad. Whether the differences in language, cultural customs, and other background conditions with students in their own countries, the learning relationship with their peers may be relatively distant, and further research is needed. Observing the characteristics of course selection decision-making, members of the same group of course selection will be affected by the learning cliques they affiliated, resulting in more consistent behavior of decision-making. In a class learning network, members who are at the center of the learning network have many connections with other peers. They are key figures with important influence and can be regarded as class leaders. How can educators effectively use and manage them is also an important topic. Through the prediction model constructed in this study, there is a prediction accuracy rate of nearly 70%. It can be used to explain the high correlation between the affiliation of learning cliques and the behavior of course selection.

Conclusion and Suggestions

Conclusion

College students' distribution of learning cliques and social networks

From the observation of the learning network diagram and clique distribution diagram, this article finds that there are several large and small cliques in each student's learning relationship and non-clique members are scattered in the fringe area in a class. Members of the cliques have a very close learning relationship with each other, while members who do not affiliate to any clique have a relatively distant learning relationship with other peers. The conclusion is consistent with the findings of the research by Grainger (2011), Liu et al. (2017), Murray and Fu (2016), and Pillemer and Rothbard (2018).

College students' characteristics of course selection decision-making

Through the tree distribution chart of cluster analysis, we observe similarity of student behavior groups of course selection decision-making and analyze the characteristics of course selection in each group. If there are key members in the group, due to their considerable influence, it is easy to call on more peers to make the same course selection decision-making, which is consistent with the explanation of Ananthan (2019) and Liou and Daly (2020). In addition, the behavior groups of course selection decision-making formed by members in each clique is relatively consistent, which confirm the viewpoint of Himelboim, McCreery, et al. (2013), Himelboim, Smith, et al., (2017), and Lee and Hong (2016), while members without cliques are not affected by the conformity effect. Moreover, the difference in the behavior of course selection decision-making is relatively large. From this, we can see that the relationship between the affiliation of cliques and the decision-making of individuals is inseparable. This phenomenon deserves further attention.

The prediction model of the correlation between learning cliques and course selection decision-making

This research integrated SNA and cluster analysis and took the correlation between student learning cliques and course selection decision-making as a case study for empirical research. The traditional questionnaire with dozens of questions was excluded from data collection, while a simple relation data tick method was used to conduct the survey. The existing list of course selection was used as the source and converted into categorical data. The analysis method focused on a graphic description of the relationship between cliques and decision-making, and then the prediction model of the course selection decision-making of each learning clique member was constructed through decision trees. The analysis result was quite effective and offers value for reference.

Implications

Attach importance to the relationship between students' learning relationship and selection of courses

In a class, peer learning relationships affect the overall learning environment and atmosphere of the class. It is suggested that school managers should make good use of the class learning network diagram to observe the learning cliques and distribution among students. In addition, students who are isolated from the class are typically on the borderline. Managers should take the initiative to pay attention to their learning interaction with other peers so that all students can become more cohesive. There is a positive correlation between the learning cliques and course selection decision-making. Special consideration should be given to the characteristics of different learning cliques in the field of course design and teaching so as to make it more in line with the needs of students and to optimize the allocation of teaching resources and benefits.

Future Research Directions

Through simple questionnaires and existing course selection materials, this study discussed the relationship between students' learning cliques and course selection decision-making. It is suggested that continuous follow-up surveys can be carried out for specific groups each semester to grasp their learning status in real time, obtain relation data and categorical data over different periods, further implement longitudinal analysis, and provide managers a reference for future planning of education policies.

This study took a class in a military academy as the case sample and empirically discussed the relationship between students' learning cliques and course selection decision-making. It is suggested that future research can further extend to other classes using the prediction model developed by this study and even take students from other non-military academy and universities as research participants to verify the research results. In fact, various cliques exist around the lives of nearly all people. Future research can adopt diversified research methods to discuss the relevant issues of the influence of cliques on decision-making, such as the influence of cliques on decision-making in the selection of departments, employment orientation, and whether cliques have an influence on students' learning performances. This would help to fully generalize the causal relationship between cliques and decision-making or organizational performance.

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整合社會網絡和集群分析探討大學生學習派系與選課決策的關係

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摘 要

選課行為是一種決策過程。過去研究指出，有諸多因素會影響學生選課的結果，然而卻鮮少以學習派系的角度來探討與選課決策之間的關係。在一個班級之中，往往存在着學習關係較良好的數個小團體，進而組成學習派系。每個學習派系的成員是否會形成相似的行為群組，選擇課程的過程是否會產生從眾效應，以及他們是否會與志趣相投的成員選擇相同的課程，都是值得探討的主題。因此，本研究整合應用社會網絡分析和集群分析方法，探討學習派系與選課決策的關聯，進一步透過決策樹發展預測模式，由學生在學習網絡中所隸屬的派系，推測各派系成員是否會組成相似的選課決策行為群組。本研究採用問卷調查法和次級資料分析法，研究對象為台灣某軍事院校的 23 名學生。研究結果如下：（1）在班級之中存在着數個大、小派系，以及不隸屬任何派系的成員；（2）相較於不隸屬任何派系的成員，學習派系內的成員選課決策行為較為一致。

關鍵詞：社會網絡；集群分析；學習派系；選課決策；決策樹

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