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Exploration of the Management Mode and Quality Evaluation of Entrepreneurship Education in Colleges and Universities Based on Data Mining

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Abstract: China has also continuously applied it to practice in its development process, and has carried out a lot of research and practice. Experiments and promotion have been carried out in major colleges and universities, which has laid a solid foundation for college students' entrepreneurial education thoughts and management methods. This paper used data mining technology to evaluate the teachers in entrepreneurship teaching, so as to improve the entrepreneurial quality of college students and promote their transformation from entrepreneurship to employment. The results in this paper showed that teachers in the age group A2 (31-35) had the highest proportion of excellent teaching quality evaluation results among all age groups, accounting for 47%; teachers with the title of J3 (associate professor) had the highest proportion of excellent teaching quality evaluation results among all teacher titles, accounting for 82%; teachers with E2 (master's degree) education had the highest proportion of excellent teaching quality evaluation results among all teachers' qualifications, accounting for 71.4%. According to the data, teachers of moderate age with associate professor or above and master's degree or above are more likely to teach excellent students, thereby promoting the further improvement of the entrepreneurial management education models in colleges and universities.

1. Introduction

Since the enrollment expansion of higher education in China in 1999, its management scale has expanded rapidly. However, with its rapid expansion, the supply and demand of college graduates have gradually become unbalanced. College students face the dilemma of unemployment after graduation, which is a reality that cannot be ignored. Employment of labor force is the biggest difficulty in China's economic development. The biggest problem is that a set of effective entrepreneurial management models and systems has not been established. To this end, China’s high education must change the concept of education and reform the way of personnel training, so as to strengthen college students' entrepreneurial management and cultivate innovative talents with strong social competitiveness. Therefore, based on data mining, this paper constructed a teacher

team management system suitable for university entrepreneurship education. By educating them on entrepreneurship and strengthening their management, they can improve their management decision-making level.

At present, the establishment of a scientific, effective and systematic entrepreneurship education management system are of great significance. Zhu Hai-Bo looked back on the development of innovative and entrepreneurial education in China during 2010-2015. He reflected on the deficiency of the present innovative and entrepreneurial education, and made some suggestions [1]. Nwambam Aja Sunday suggested that the institution should regularly train and re-train the trainers to enhance the teaching ability of entrepreneurship education. Universities, governments and individuals provide the necessary facilities and materials to make teaching more efficient and effective. It was also proposed that governments and private organizations should work together to provide university graduates with the necessary resources to apply their entrepreneurial skills to employment [2]. Badri Lin selected Tunisian students aged 22 to 25 from Sfax University and Sousse University and used ordered logistic regression to investigate college students' entrepreneurial willingness. The results showed that students' profile of theoretical knowledge and practical knowledge in entrepreneurship education, as well as their personal characteristics, are the most decisive variables influencing their entrepreneurial willingness [3]. Yu Min-Chun's university-based entrepreneurial ecosystem applied a novel approach to comparative educational research and evaluation projects. He put forward an important enlightenment in the process of exploring entrepreneurship education, which promoted the perfection and development of entrepreneurship education [4]. The development of entrepreneurial education is rapid, but it lacks efficient management models and systems, and data mining technology can establish an effective management model and system.

The technique of data mining has been deeply researched in university students' education. Yang Huirong mainly introduced the application of data mining technology in the education management information system. In order to better manage students' information, a data mining system was constructed [5]. Li Yu uncovered a way to hide knowledge from educational data. It can mine interesting patterns from educational data. Therefore, he used two-dimensional and three-dimensional clustering to evaluate students' grades. Educators can better understand students' grades and provide basis for teaching decisions. Students can also get some suggestions about their performance from the mining results [6]. Draksler Tanja Zdolsek argued that there is a lack of research on the impact of entrepreneurship education on entrepreneurial ability and entrepreneurial intention. A new conceptual research model was established to study the impact of entrepreneurship education on entrepreneurial ability and entrepreneurial intention [7]. Although data mining has achieved a lot in the education of university students, it has not touched on the management model and system of enterprise education. Therefore, from this point of view, this article aimed at improving the management decision skills of the students in different colleges.

2. Exploration of the Evaluation System of Entrepreneurship Education Management in Colleges and Universities

Carrying out entrepreneurial education is actually looking for ways to enhance the quality and creativity of university students. Entrepreneurial education in higher learning brings enormous benefits to both schools and students [8].

2.1 Data Mining

Data mining techniques refer to the process of discovering and mining new knowledge in an object database [9]. Data mining has three steps: preparation of data, mining of data, evaluation and

presentation of the data results. In the third step, it can also be divided into four parts.

2.1.1 Data Preprocessing Technology

The so-called data preprocessing technology is to analyze and extract the relevant data after recognizing and identifying the mining object, and then reasonably detect it according to its restrictions, so as to generate the corresponding data information. Data preprocessing technology mainly includes four aspects, which are as follows:

(1) Data integration

Data redundancy is a prominent issue in data integration. Data information redundancies can be formed or detected when there are inconsistencies in dimensions or attributes [10]. In this article, attributes *A* and *B* are given and their correlations are written:

$$r_{AB} = \frac{\sum(A-\bar{A})(B-\bar{B})}{(n-1)\delta A \delta B} \tag{1}$$

In Formula (1), *n* represents the number of tuples, and $\bar{A}$ represents the average of *A*. $\bar{B}$ represents the average of *B*, and δA represents the standard deviation of *A*; δB represents the standard deviation of *B*.

If r_{AB} is larger, the greater its correlation. Therefore, a large value of r_{AB} means that *A* or *B* can be removed as redundancy. When $r_{AB} = 0$, *A* and *B* are independent of each other.

(2) Data cleaning

The so-called data cleaning is to eliminate irrelevant information in the target data information database. Data type conversion is achieved by cleaning up missing information, and taking into account changes in data and chronological adjustments.

(3) Data transformation

There are many operations in data transformation, mainly reduction, normalization, and projection. The goal of data transformation is to find the feature representation of information and use the transformation method to find the invariant of the data. There are several ways to normalize the above operations, and the maximum-minimum normalization is mainly used [11-12].

Maximum-minimum normalization is a basic linear transformation of the original data set. It is supposed that the minimum value in attribute *A* is *minA* and the maximum value is *maxA*. The specific formula is shown in Formula (2):

$$v' = \frac{v-minA}{max_A-min_A}\sigma_X(new\_max_A - new\_min_A) + new\_min_A \tag{2}$$

By mapping the value *v* in attribute *A* to the interval $[new\_min_A, new\_max_A]$, v' can be obtained. The formula for calculating v' is shown in Formula (3):

$$v' = \frac{v-\bar{A}}{\sigma A} \tag{3}$$

If the value *v* of *A* is normalized to v', then v' is calculated as:

$$v' = \frac{v}{10^j} \tag{4}$$

The formula for *j* can be expressed as:

$$j = \max(|v'|) \tag{5}$$

(4) Data simplification

In the process of data preprocessing, data simplification is a very critical link. In the actual process of processing data, not every piece of data can play a good role. Useless information not only cannot support the mining results, but also reduces the overall computing efficiency. Therefore,

it is required to fully recognize the characteristics of the data in the database. It is necessary to reduce the mining scope of the database as needed and remove unnecessary information so that the mining data set can be simplified as much as possible.

2.1.2 Overview of Correlation Rules

Association rules are a hot topic in academia today. There are differences in academic understanding of the concept, but there is much that is well recognized [13].

Transaction: a collection of everything that happens to an object over a period of time. A transaction has its own database, which is expressed as $D = \{t_1, t_2, \cdots, t_n\}$. A concept that often appears in transactions is an item, which is a property field with a fixed range of values [14]. It is assumed that a transaction $I = \{I_1, I_2, \cdots, I_m\}$, then the item is represented as every element in the collection.

Support: in a transactional database, there are two meanings for rule $X \Longrightarrow Y$. One is the percentage of transactions containing both X and Y in the rule of all transactions, and the other is understood to be the probability that X and Y would occur simultaneously in the transaction [15]. Rule $X \Longrightarrow Y$ can also be expressed as $\mathrm{Support}(X \Longrightarrow Y)$, which is expressed by the Formula (6):

$$\mathrm{Support}(X \Longrightarrow Y) = \frac{\|\{T|(X \Longrightarrow Y) \subseteq T, T \subseteq D\}\|}{D} \tag{6}$$

Confidence: it is assumed that that transaction set D contains itemsets X and Y, and there is an association rule $X \Longrightarrow Y$, then the confidence level is expressed as the percentage of itemset X in D. Its specific can be expressed as $\mathrm{Confidence}(X \Longrightarrow Y)$, which can be represented by Formula (7):

$$\mathrm{Confidence}(X \Longrightarrow Y) = \frac{\mathrm{Support(XUY)}}{\mathrm{Support(X)}} = \frac{\|\{T|(X \cup Y) \subseteq T, T \subseteq D\}\|}{\|\{T|X \subseteq Y, T \subseteq D\}\|} \tag{7}$$

There are many influential algorithms in association rules, and the most famous is Apriori's algorithm [16]. The main method used in this article is also the Apriori algorithm.

(1) Improved algorithm based on hashing

This algorithm can effectively compress the size of the set $C_K(K \geq 2)$ of the candidate K itemset. Example: when scanning each transaction in the database, if the candidate 1 itemset in C_1 produces 1 itemset L_1 frequently, then all 2 itemsets can be generated for each transaction; in addition, it can be assigned to each bucket in the hash table and the corresponding bucket count added [17].

Improved algorithm based on partitioning (Apriori-P algorithm)

Two database scans can be used when mining frequent items, which is illustrated in Figure 1. At each step, the database is scanned only once, and the full local frequent itemset is available [18].

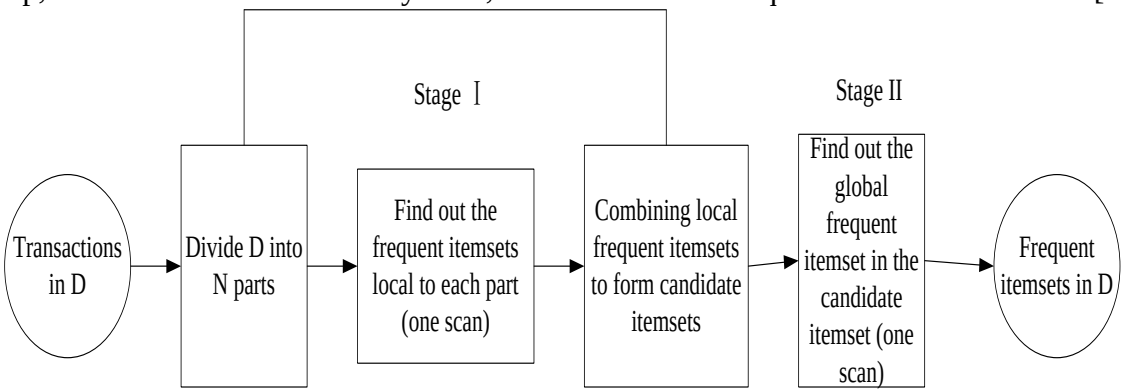

Figure 1: Mining by partitioning data

When applying the Apriori-P algorithm, the transaction library is first divided into N non-overlapping blocks, and then the algorithm is used to process each block to find all local frequent items. The local frequent terms in N blocks are then integrated into the global candidate set. In order to search for global frequent items, it is necessary to re-scan the database, and to evaluate the support level of every candidate. Since the Apriori-P algorithm only needs to perform two scan comparisons during the mining process, so comparing with Apriori algorithm, this method is simpler and has better performance.

2.2 Entrepreneurship Education Management Evaluation System

The module's method of data mining on data sources is the Apriori-P improved algorithm. During the design process, the system user first specifies the data source and mining parameters, and then uses C Sharp (C#) to encapsulate the Apriori-P algorithm into components. Finally, the function call method is used to mine, and the results of the mining association rules are displayed.

3. Verification of the Evaluation System of Entrepreneurship Education Management

Firstly, the relevant information of teachers, students, and courses in the entrepreneurship education courses of several colleges and universities was collected. The collected information was then imported into the system with the relevant information of 100 teachers and the teaching evaluation information of 2260 students. After the information was imported, the system used the above algorithm to mine the evaluation data with association rules. Table 1 shows the imported teacher information data above (partial data).

Table 1: Basic data of teachers

number	gender	age	marriage or not	educational background	Professional title
1	man	57	yes	undergraduate	associate professor
2	woman	45	yes	undergraduate	associate professor
3	woman	39	no	master's degree	associate professor
4	woman	56	yes	undergraduate	lecturer
5	man	54	yes	master's degree	assistant lecturer
6	woman	48	yes	undergraduate	associate professor
7	man	47	yes	master's degree	lecturer
8	woman	50	yes	master's degree	assistant lecturer
9	woman	51	yes	master's degree	lecturer
10	woman	52	yes	undergraduate	associate professor
11	man	48	yes	undergraduate	lecturer
12	woman	40	no	master's degree	lecturer
13	man	38	no	undergraduate	lecturer
14	woman	45	yes	master's degree	assistant lecturer
15	woman	39	no	undergraduate	associate professor
16	woman	52	yes	undergraduate	lecturer
17	woman	35	no	master's degree	lecturer
18	man	49	yes	undergraduate	associate professor

Table 2 shows some of the evaluation data of teachers.

The data in Table 1 and Table 2 were discretized and analyzed and classified by age, gender, job title and other information. Finally, the field values were converted into transaction tables, which can be seen in Table 3.

Table 2: Part of the teaching quality evaluation data

number	teaching attitude	teaching content	teaching method	teaching effect	total score of evaluation	evaluation results
1	24	28	25	18	95	excellent
2	15	26	22	16	79	good
3	23	24	27	17	91	excellent
4	24	24	24	15	87	excellent
5	25	24	20	15	84	good
6	26	23	28	12	89	excellent
7	27	23	28	12	90	excellent
8	22	24	28	12	86	excellent
9	23	22	27	13	85	excellent
10	18	16	24	11	69	medium
11	29	24	26	14	93	excellent
12	27	23	26	11	87	excellent
13	28	22	26	13	93	excellent
14	25	22	25	14	86	excellent
15	26	20	27	12	85	excellent
16	25	22	26	15	88	excellent
17	28	23	28	12	92	excellent
18	24	23	26	16	89	excellent

Table 3: Association rule transaction table

field	field value	code
gender	man	S1
	woman	S2
age	22-30	A1
	31-35	A2
	36-49	A3
	50-60	A4
professional title	teaching assistants	J1
	lecturer	J2
	associate Professor	J3
	professor	J4
educational background	undergraduate	E1
	master's degree	E2
	doctor	E3
teaching attitude	25-30	T1
	20-25	T2
	10-20	T3
	0-10	T4
teaching content	20-25	C1
	15-20	C2
	10-15	C3
	0-10	C4
teaching method	25-30	M1
	20-25	M2
	10-20	M3
	0-10	M4
teaching effect	12-15	R1
	8-12	R2
	4-8	R3
	0-4	R4
total score of evaluation	below 60	D1
	60-70	D2
	70-85	D3
	85-100	D4

This system first enabled the system user to specify the data source and mining parameters, and finally used the function call method to mine. During the operation of the system, the database was

first screened, and then the support and confidence levels were set to 10% and 5% respectively. Finally, the Apriori-P improved algorithm was used to mine the frequent itemset of the entire database. The next step was to generate an association rule. After a frequent K itemset was generated, the candidate set can be applied to these association rules, and then the corresponding candidate set was determined based on this frequent K itemset. The corresponding confidence level was then calculated based on this candidate set. Some of the results obtained after data mining of related data are presented in Table 4.

Table 4: Some results of data mining

rules	age	professional title	educational background	teaching attitude	teaching content	teaching method	teaching effect	degree of support	confidence
1	A1	---	---	---	---	---	---	33	18
2	A2	---	---	---	---	---	---	36	47
3	A3	---	---	---	---	---	---	13	32.6
4	A4	---	---	---	---	---	---	15	18.8
5	---	J3	---	---	---	---	---	66	82
6	---	J2	---	---	---	---	---	15	35
7	---	J1	---	---	---	---	---	17	11.9
8	---	---	E2	---	---	---	---	34	71.4
9	---	---	E1	---	---	---	---	59	28.8
10	---	---	---	T1	---	---	---	33	13.4
11	---	---	---	T2	---	---	---	24	17.2
12	---	---	---	T3	---	---	---	14.1	7
13	---	---	---	T4	---	---	---	26	36
14	---	---	---	---	C1	---	---	51	68
15	---	---	---	---	---	M1	---	47	33
16	---	---	---	---	---	M2	---	32.5	17
17	---	---	---	---	---	M3	---	45	53
18	---	---	---	---	---	M4	---	26	15
19	---	---	---	---	---	---	R1	33.4	26.2
20	---	---	---	---	---	---	R2	26.2	26

After sorting out the association rules mined above, Figure 2 can be obtained.

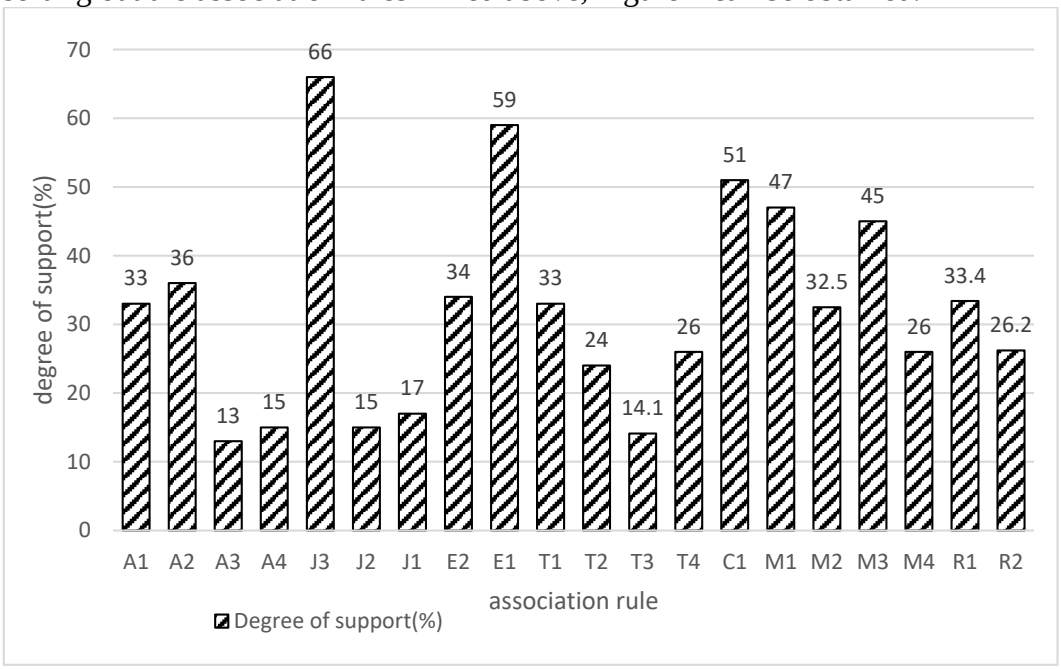

Figure 2: Support degree under different association rules

In terms of teaching content, 51% of teachers with a C1 rating of excellent results in the survey were surveyed. In terms of teaching methods, 47% of teachers with excellent evaluation results were M1, and 32.5% of teachers with excellent evaluation results were M2; the proportion of teachers who were M3 with excellent evaluation results was 45% in the survey, and the proportion of teachers who were M4 with excellent evaluation results was 26%. In terms of teachers' teaching effectiveness, the proportion of teachers with excellent evaluation results of R1 was 33.4% in the survey, and the proportion of teachers with excellent evaluation results of R2 was 26.2%.

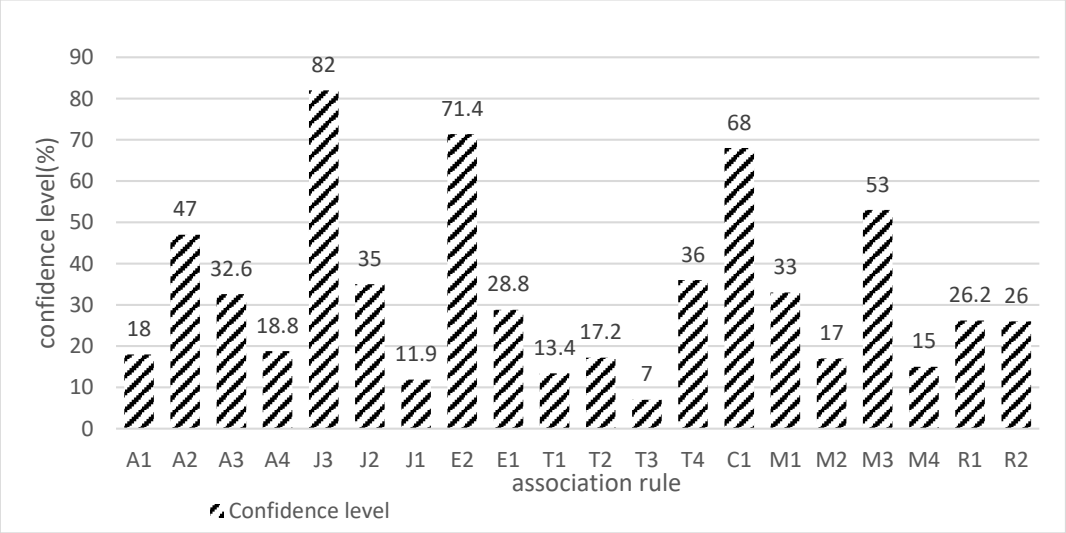

Figure 3: Confidence level under different association rules

From the perspective of teachers' teaching attitudes, the proportion of teachers with T2 attitudes in the evaluation of teaching quality was 17.2%; the proportion of teachers with T3 attitude in teaching quality assessment was 7%, and the proportion of teachers with T4 attitude in teaching quality assessment was 36%. In terms of teaching content, C1 teachers accounted for 68% of the excellent proportion in the evaluation of teaching quality. From the perspective of teachers' teaching methods, M1 teachers accounted for 33% of excellent teaching quality evaluation; M2 teachers accounted for 17% of excellent teaching quality evaluation, and M3 teachers accounted for 53% of excellent teaching quality evaluation. From the perspective of teachers' teaching effectiveness, the excellent proportion of teachers in R1 in teaching quality evaluation accounted for 26.2%, and the excellent proportion of teachers in R2 in teaching quality evaluation accounted for 26%.

On the whole, the important factors affecting the teaching quality of entrepreneurship education include teachers' academic qualifications, ages, professional titles, etc. It can be seen from Figure 2 and Figure 3 that the teachers with high evaluation scores, confidence and support are mostly young teachers aged 31~35, who have high education (most of them are master's degrees) and have strong teaching experience. Therefore, in order to set up a perfect management mode and evaluation system of entrepreneurial education, it is required to implement the talent strategy of vigorously introducing talents. By improving students' management decision-making ability, the problem of college students' difficulty in finding employment can be solved.

4. Conclusions

In this paper, the data mining technology is used to analyze and evaluate the teachers in the entrepreneurship education management model, so as to obtain what kind of teachers can promote the further improvement of the entrepreneurship education management model. As a result, it can improve the management decision-making skills of college students, which can further improve the

current situation of "college students are unemployed after graduation". However, this article only analyzed the faculty in the management model of college entrepreneurship education, which is not particularly complete. Therefore, in the future study and research, it is necessary to start from multiple dimensions and analyze and study the management mode and quality evaluation of entrepreneurship education in colleges and universities more comprehensively, so as to obtain more data and make the development of the entrepreneurship education management model more perfect.

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