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Article

Research on Curriculum Design and Teaching Effect Enhancement Methods Based on Intelligent Technology in Innovation and Entrepreneurship Education System of Colleges and Universities

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Abstract: The future career prospects and required skills for the courses being studied are one of the key reference directions for the design of innovation and entrepreneurship courses. This paper proposes an innovation and entrepreneurship online course design process based on the Moodle platform, comprising three key components: pre-course preparation, learning unit design, and course management and evaluation. The association rule mining algorithm is selected as the analysis algorithm for mining the relationships between job positions, courses, and required skills. A sample of 230 third-year students from D University's innovation and entrepreneurship course was selected as the research subject to generate association rules linking innovation and entrepreneurship job positions, professional courses, and the skills required for job positions. Under the generated association rules, innovation and entrepreneurship course instruction was conducted, and the course received positive evaluations from over 140 students in terms of "likability" and "enhancing critical thinking skills."

Keywords: innovation and entrepreneurship; association rules; mining analysis; course design

1. Introduction

With the rapid development of information technology, intelligent education has garnered increasing attention due to its efficient, convenient, and engaging characteristics [1-3]. The design and implementation of intelligent courses can provide students with better and more challenging learning methods [4-5]. To effectively design intelligent courses, it is essential to thoroughly understand students' learning characteristics, learning objectives, and learning needs, while also considering their learning abilities and interests. The design of intelligent courses can be tailored to the actual teaching environment and incorporate diverse teaching methods [6-7]. Additionally, teaching objectives and course content should be tiered based on students' learning levels, offering activities of varying difficulty and formats. Intelligent education can also integrate advanced technologies such as machine learning and artificial intelligence to provide students with more personalized learning experiences [8-10]. For example, technologies like facial recognition and speech recognition can be used to intelligently assess students' learning progress and performance, identify their weaknesses, and provide targeted tutoring and practice. Additionally, intelligent technologies can be used to create customized course schedules and learning plans for students, offering personalized learning recommendations and guidance [11-12].

Course design based on intelligent technology can enhance student motivation. Literature [13] designed an intelligent course centered on intelligent vehicles using an intelligent vehicle teaching platform, including foundational courses, specialized courses, and practical courses. Application practice demonstrated that the teaching content of the intelligent course design stimulated students' learning enthusiasm and cultivated their leadership abilities. Intelligent education is one of the key directions for future education and holds significant importance for enhancing students' learning interest and learning outcomes [14-15]. For example, literature [16] indicates that the use of intelligent educational tools has facilitated the evaluation of student performance by the educational system. Compared with existing methods, students' learning efficiency has increased by 96.7% under intelligent education, and their academic performance has also significantly improved. Literature [17] combines relevant knowledge and, through a questionnaire survey, finds that the application of artificial intelligence technology in higher education can significantly influence students' self-efficacy perception and creativity, thereby affecting their learning performance. Literature [18] found that incorporating encouraging and warning feedback into intelligent learning environments enhances the appeal of the learning process, effectively improving students' emotional and cognitive engagement, thereby enhancing teaching effectiveness and students' learning interest. Literature [19] found that artificial intelligence education technology has made significant progress in auxiliary teaching, auxiliary exercises, auxiliary examinations, and auxiliary evaluations, exerting a significant positive influence on teaching effectiveness, with teachers' perceptions of teaching playing a mediating role. Literature [20] constructed an intelligent music teaching system centered on machine learning and SVM algorithms, and designed teaching experiments based on the intelligent music teaching system. The results showed that the intelligent music teaching system constructed in the literature performed well and could promote the teaching effectiveness of music learning. Literature [21] developed an intelligent English teaching system based on deep learning. The learning content designed by this system is more targeted, can meet students' personalized needs, and help students improve their English learning efficiency.

The following studies analyze how to use intelligent algorithms to analyze students' learning behaviors and states to improve teaching effectiveness. Literature [22] introduces a long short-term memory network to embed multi-feature models of students and courses, providing students with personalized course recommendations. Results showed that the recommendation algorithm achieved an accuracy rate of 91.46% and a recall rate of 87.71%, with personalized teaching resource recommendations enhancing students' learning motivation. Literature [23] developed a face detection algorithm based on an improved deep convolutional neural network and utilized a memory-enhanced neural network to track students' knowledge acquisition progress, experimentally demonstrating the practical value of intelligent algorithms in higher education. The efficient recurrent neural network (MO-ERNN) model proposed in [24] can accurately predict student grades, with accuracy, precision, recall, and F1 scores all ≥85%. Classroom observations showed that the experimental group's English grades were significantly higher than the control group's.

Additionally, the application of intelligent algorithms in teaching evaluation has a significant auxiliary effect on teacher instruction. Literature [25] employs a random forest algorithm to construct a learning effectiveness evaluation model for multimedia-assisted teaching, combining teaching quality evaluation indicators to validate the model's effectiveness in auxiliary teaching, with user satisfaction reaching 72%. Despite advancements in artificial intelligence, challenges remain, including limitations in processing unstructured data and the need for more effective human-AI interaction. Nevertheless, the potential of AI to enhance educational quality and accessibility remains promising, and further research is needed to explore its full potential in the field of education [26].

This paper first combines the characteristics of innovation and entrepreneurship courses to provide a detailed explanation of the design process for innovation and entrepreneurship online courses based on the Moodle platform. It then uses a customer product detail record table as an example to illustrate the basic concepts and definitions of association rules. A sample of 230 third-year students from D University's innovation and entrepreneurship course was selected as the experimental group. Performance attribute values were set, and abnormal data was cleaned and processed to complete the preprocessing of the research data. The Apriori algorithm is then introduced to generate course data examples and analyze course relevance. The code for the core skills required for innovation and entrepreneurship positions, courses, and job roles is output, and association rules are generated through data mining and analysis. Finally, based on the generated association rules, student performance analysis and course satisfaction analysis are conducted.

2. Course Design and Analysis

2.1. Online Course Design Process Based on the Moodle Platform

The structure of a course follows objective laws. Course objectives, course content, course implementation methods, course evaluation, and course management are essential components of a course. Course design is a systematic process that applies the laws of course structure to build a course, as well as a process of determining the various elements of course structure and designing them into the various components of a system. Course design based on the Moodle platform should align with the general characteristics of online course design: the learning process should exhibit interactivity, sharing, openness, collaboration, and autonomy. It should fully consider the four key elements that promote knowledge construction in learners (context, collaboration, dialogue, and meaning construction), emphasize learner-centeredness, focus on personalized presentation of learning content, activity design during the learning process, and effective evaluation of learning outcomes. Based on the elements of course composition, combined with the principles of multiple intelligences and activity theory, and drawing on the experiences of teachers in designing Moodle courses across regions, it is proposed that online course design based on the Moodle platform should include the following stages. The process of online course design based on the Moodle platform is illustrated in Figure 1.

As shown in the course design process diagram below, online course design based on the Moodle platform comprises three parts: pre-design preparation, learning unit design, and course management and evaluation.

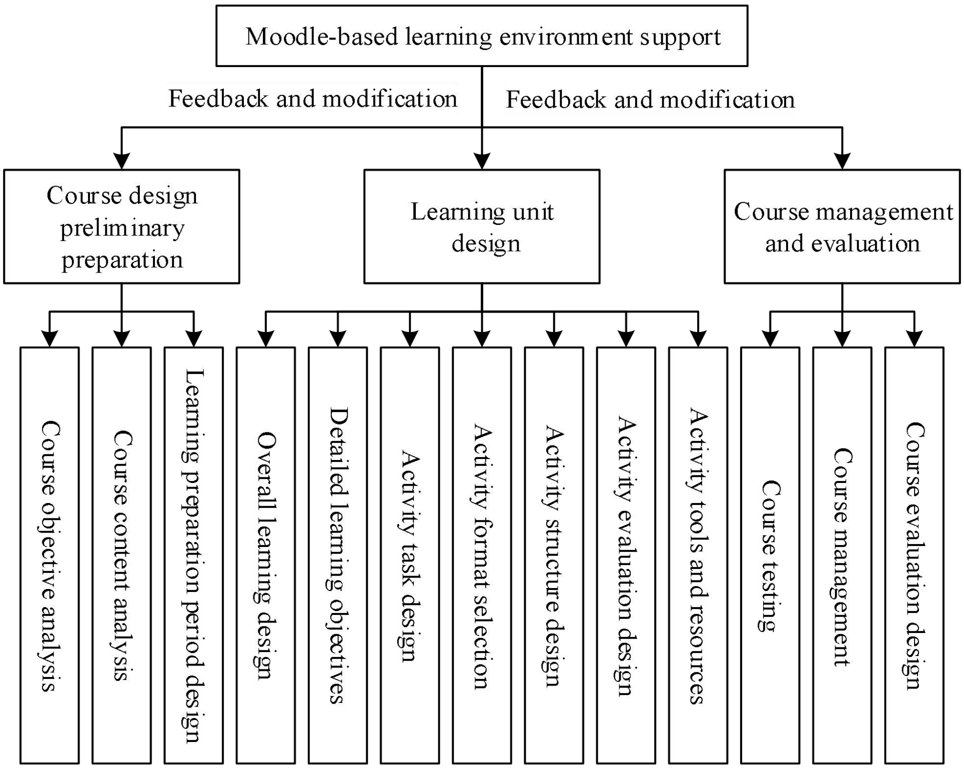

Figure 1. The process of online course design based on the Moodle platform.

2.2. Basic Concepts of Association Rules

Association rule mining is an unsupervised data mining technique. Its basic concepts mainly include: transactions, item sets, frequent item sets, support, confidence, lift, association rules, and strong association rules. To more clearly illustrate the meaning of these concepts and facilitate understanding, this article uses a customer product detail record table as an example to introduce the definitions of each concept.

Definition 1 Transaction: Let the entire data set for association rule mining be denoted as D, where $D=\{Z_1,Z_2,\cdots,Z_n\}$, and each $Z_k(k=1,2,\cdots,n)$ is referred to as a transaction. Each transaction is identified by a unique identifier TID. In this example, the detailed record of products held by a customer constitutes a single transaction.

Definition 2 Item and item set: Let $L=\{x_1,x_2,\cdots,x_m\}$ be a set, where $x_k(k=1,2,\cdots,m)$ is called an item, and L contains m items, which is called an m-item set. In this example, {fund, worry-free card, government bond} is referred to as a 3-item set.

Definition 3 Support: If there exists an association rule $X \Rightarrow Y$, where X and Y are both item sets and $X \cap Y = \varnothing$, then the proportion of transactions containing X and Y in the overall transaction set is the support of X for Y. The specific formula for calculating support is given by Equation (1):

$$Support(XY) = P(XY) = \frac{number(XY)}{number(AllSamples)} \tag{1}$$

In this example, there are three customers who hold both Wealth Management and Worry-Free Cards, so the support degree of {Wealth Management, Worry-Free Card} is 0.6.

Definition 4: Confidence: If there exists an association rule $X \Rightarrow Y$, where X and Y are both item sets and $X \cap Y = \varnothing$, then the probability that a transaction containing X also contains Y is the confidence of X for Y, i.e., the conditional probability $P(X \mid Y)$, which represents the reliability of the rule. The specific formula for calculating confidence is given by Equation (2):

$$\begin{aligned} Confidence\left(X \Rightarrow Y\right) &= \frac{Support(XY)}{Support(X)} \\ &= P(X \mid Y) = \frac{P(XY)}{P(X)} \end{aligned} \tag{2}$$

In this example, the probability that a customer holding a Worry-Free Card also holds a Wealth Management Product is 0.75, so the confidence level of the rule “Worry-Free Card $\Rightarrow$ Wealth Management Product” is 0.75.

Definition 5 Lift: The lift of an association rule $X \Rightarrow Y$ can be expressed as the ratio of the confidence of the rule $X \Rightarrow Y$ to the support of the item set Y. Lift is a metric used to measure the usefulness of a rule, describing how much the use of the rule improves the situation compared to not using it. Useful rules have a lift greater than 1, as shown in Equation (3):

$$Lift(X \Rightarrow Y) = \frac{Confidence(X \Rightarrow Y)}{Support(Y)} = \frac{P(XY)}{P(X)P(Y)} \tag{3}$$

In this example, the lift of the rule “Worry-Free Card $\Rightarrow$ Wealth Management Product” is 1.25, indicating that there is a certain positive correlation between the Worry-Free Card and the Wealth Management Product.

Definition 6 Frequent Item Set: Let X be an item set. If $Support(X) \geq \min\sup$, where $\min\sup$ is the predefined minimum support degree, then X is called a frequent item set. In this example, if $\min\sup$ is set to 0.6, then the frequent item sets are {Wealth Management Treasure}, {Worry-Free Card}, {Fund}, and {Wealth Management Treasure, Worry-Free Card}.

Definition 7: Association rules and strong association rules: Association rules reflect the association between item sets. If there are two item sets X and Y, and $X \cap Y = \varnothing$, then the association rule of X for Y can be expressed as $X \overset{s.c}{\Rightarrow} Y$, where X is called the antecedent and Y is called the consequent. If $Confidence(X) \geq \min conf$, where $\min conf$ is the predefined minimum confidence level, then $X \Rightarrow Y$ is called a strong association rule. In this example, if $\min conf$ is set to 0.7, then the rule “Worry-Free Card $\Rightarrow$ Wealth Management” can be considered a strong association rule.

In summary, the association rule mining process can be roughly divided into three steps, as shown in Figure 2. First, calculate the support of all item sets, screen out frequent item sets based on the minimum support, and generate association rules. Then, calculate the confidence of all association rules and screen out strong association rules based on the minimum confidence. Finally, valuable strong association rules are filtered out using the minimum support. Identifying valuable strong association rules with academic performance as the consequent is one of the research objectives of this paper.

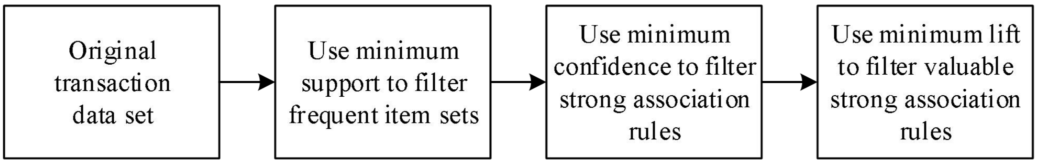

Figure 2. Association rule mining process.

2.3. Data Preparation Phase

Since its establishment, D University has recorded the grades of students enrolled in courses taught by faculty members into the academic affairs management system at the end of each semester. These grades include four components: regular grades, midterm grades, final grades, and overall grades. This study focuses on the grades of students enrolled in the innovation and entrepreneurship course for third-year students. Data extracted from the academic affairs management system indicates that there are 230 students enrolled in the innovation and entrepreneurship course, resulting in a total of 230 records.

(1) Focusing on required courses: According to the talent cultivation program, students must take required courses, general elective courses, and practical training courses based on the minimum credit requirements. Since required professional courses cover both foundational and specialized courses within a discipline, the performance in these courses can significantly reflect students' academic status. Therefore, a deeper analysis of required course grades can help identify the underlying factors influencing students' academic performance.

Additionally, while the various types of courses offered by the school are constantly being updated, the characteristics of required courses mean that they have the lowest rate of change. This implies that the grade data for required courses has the longest retention period and highest occurrence rate in the database, making them the most suitable subject for analysis.

(2) Courses classified as "grade levels" A,C are the subject of this study: This paper first discretizes the attribute values of the "kscj" field in the grade sheet, dividing the "kscj" attribute values into three levels A,B,C, corresponding to 100-85, 85-65, and 65-0 in the percentage-based grading system, respectively.

Given the complexity of grade analysis, to identify rules with higher typicality, this paper will analyze data from grades of A and C, i.e., courses with higher and lower grades, to identify the underlying factors influencing grades. Grades of B, which lack typicality, will be temporarily excluded.

During the score entry process, default scores such as absences or cheating may occur, and the scores displayed in the data table may vary widely. Therefore, some data cleaning and processing is required:

(1) Replace default scores with the average score of 75.

(2) For data tables of required courses with excellent scores, represent scores above 85 as 1 and all other scores as 0.

(3) For data tables with grades of passing or below, represent student grades below 65 as 1 and all other grades as 0.

(4) In the required professional course subject "kclb," A represents required foundation courses, and C represents required professional courses. Therefore, only subjects where "kclb" is A and C need to be filtered out.

3. Generation and Application of Association Rules for Innovation and Entrepreneurship Courses

3.1. Course Relevance Analysis

To better illustrate the execution process of the Apriori algorithm in course association analysis, we use 10 simple discrete data points as an example. The data examples are shown in Table 1, where TID is the identifier for each student's information, K1, K2, etc. are the course codes, 1 indicates a passing grade, and 0 indicates a failing grade.

Table 1. Data instance.

TID	K1	K2	K3	K4	K5
1	1	0	1	0	0
2	0	1	0	0	1
3	1	1	0	1	0
4	1	1	0	1	1
5	1	0	1	0	0
6	1	1	0	1	1
7	1	0	1	0	0
8	0	1	1	1	0
9	1	0	0	0	0
10	1	1	1	1	1

A simple correlation analysis was conducted on the grade data of seven innovation and entrepreneurship-related courses (K1-K7), as shown in Table 2. Overall, the correlation between the seven courses was ≥0.3, indicating a significant correlation.

Table 2. Results of correlation analysis.

		K1	K2	K3	K4	K5	K6	K7
K1	Pearson correlation	1	0.339	0.379	0.402 **	0.33 **	0.388	0.433 ***
	Significance (double tail)		0.115	0.124	0.042	0.025	0.105	0.009
	N	230	230	230	230	230	230	230
K2	Pearson correlation	0.339	1	0.485	0.341	0.384 **	0.409 *	0.305 **
	Significance (double tail)	0.115		0.15	0.126	0.039	0.073	0.045
	N	230	230	230	230	230	230	230
K3	Pearson correlation	0.379	0.485	1	0.332 **	0.391 *	0.45 *	0.326 **
	Significance (double tail)	0.124	0.15		0.031	0.07	0.077	0.017
	N	230	230	230	230	230	230	230
K4	Pearson correlation	0.402 **	0.341	0.332 **	1	0.398 **	0.46 *	0.36
	Significance (double tail)	0.042	0.126	0.031		0.014	0.054	0.133
	N	230	230	230	230	230	230	230
K5	Pearson correlation	0.33 **	0.384 **	0.391 *	0.398 **	1	0.377 *	0.357
	Significance (double tail)	0.025	0.039	0.07	0.014		0.09	0.106
	N	230	230	230	230	230	230	230
K6	Pearson correlation	0.388	0.409 *	0.45 *	0.46 *	0.377 *	1	0.355 **
	Significance (double tail)	0.105	0.073	0.077	0.054	0.09		0.039
	N	230	230	230	230	230	230	230
K7	Pearson correlation	0.433 ***	0.305 **	0.326 **	0.36	0.357	0.355 **	1
	Significance (double tail)	0.009	0.045	0.017	0.133	0.106	0.039	
	N	230	230	230	230	230	230	230

3.2. Generation and Analysis of Association Rules

After frequent item sets are generated, according to the association rule generation algorithm given in the previous section, for any frequent k-item set, find all possible proper subsets as the antecedents of association rules and calculate the corresponding rule confidence. When the confidence of a rule exceeds the specified minimum confidence, output the rule.

When searching for all proper subsets of a frequent k-item set, first identify k subsets containing only one item, then concatenate them to generate subsets containing two items, and continue this process until the final subset contains k-1 items. According to the association rule generation algorithm, the output code is shown in Table 3. The job positions include: entrepreneurship consultant, training instructor, product manager, business consultant, and marketing specialist. The core courses include: entrepreneurship strategy, product innovation and development, big data marketing, entrepreneurship awareness and action, and negotiation and communication. The skills required for these job positions include: design and creativity, leadership awareness, business knowledge, communication skills, market insight, and innovation.

Table 3. Code.

Attribute	Value	Code
Place of work	Entrepreneurship consultant	A1
	Training instructors	A2
	PM(product manager)	A3
	Business consultant	A4
	Marketing	A5
Course	Innovation and entrepreneurship strategy	A6
	Innovation and new product development	A7
	Big data marketing	A8
	Entrepreneurial awareness and actions	A9
	Negotiation and Communication	A10
Important skills in the job position	Creative and designing competence	A11
	Leadership	A12
	Business knowledge	A13
	Ability to communicate	A14
	Market insight ability	A15
	Innovation ability	A16

3.2.1. Data Mining

The minimum support thresholds were set at 5%, 15%, and 25%, respectively, and the minimum confidence thresholds were set at 15%, 50%, and 85%, respectively. The results of the data mining using the Apriori algorithm are shown in Table 4.

Table 4. The result of data mining using the Apriori algorithm.

	Association rules	Support degree	Confidence coefficient
Minsupp=5% Minconf=15%	$A1 \Rightarrow A6$	30%	17.4%
	$A1 \Rightarrow A9$	30%	50.7%
	$A1 \Rightarrow A15$	30%	54.3%
	$A2 \Rightarrow A10$	30%	55.4%
	$A2 \Rightarrow A14$	30%	18.9%
	$A3 \Rightarrow A12$	26%	55.1%
	$A3 \Rightarrow A7$	26%	11.9%
	$A3 \Rightarrow A11$	26%	55.9%
	$A3 \Rightarrow A8$	23%	12.4%
	$A4 \Rightarrow A6$	23%	55.4%
	$A4 \Rightarrow A13$	23%	55.0%
	$A4 \Rightarrow A15$	23%	16.7%
	$A5 \Rightarrow A8$	20%	51.7%

	$A5 \Rightarrow A11$	20%	51.7%
	$A5 \Rightarrow A15$	20%	52.4%
Minsupp=5% Minconf=50%	$A1 \Rightarrow A9$	30%	53.6%
	$A2 \Rightarrow A6$	30%	57.6%
	$A3 \Rightarrow A7$	26%	53.1%
	$A4 \Rightarrow A13$	26%	14.6%
	$A5 \Rightarrow A8$	23%	14.7%

3.2.2. Data Analysis

Association rules convert the codes in the code table back into the form of "attribute=value." Here, we selected association rules with minsupp=5% and minconf=15% and 50% for analysis, as shown in Tables 5 and 6.

Table 5. Analysis of Association Rules(Minsupp=5%,Minconf=15%).

Association rules	Attribute = value	Support degree	Confidence coefficient	Effective ness
$A1 \Rightarrow A6$	Place of work=Entrepreneurship consultant$\Rightarrow$Course=Innovation and entrepreneurship strategy	30%	17.4%	Weak
$A1 \Rightarrow A9$	Place of work=Entrepreneurship consultant$\Rightarrow$Course=Entrepreneurial awareness and actions	30%	50.7%	Strong
$A1 \Rightarrow A15$	Place of work=Entrepreneurship consultant$\Rightarrow$Important skills in the job position=Market insight ability	30%	54.3%	Strong
$A2 \Rightarrow A10$	Place of work=Training instructors$\Rightarrow$Course=Negotiation and Communication	30%	55.4%	Strong
$A2 \Rightarrow A14$	Place of work=Training instructors$\Rightarrow$Important skills in the job position=Ability to communicate	30%	18.9%	Weak
$A3 \Rightarrow A12$	Place of work=PM(product manager)$\Rightarrow$Important skills in the job position=Leadership	26%	55.1%	Strong
$A3 \Rightarrow A7$	Place of work=PM(product manager)$\Rightarrow$Course=Innovation and new product development	26%	11.9%	Weak
$A3 \Rightarrow A11$	Place of work=PM(product manager)$\Rightarrow$Important skills in the job position=Creative and designing competence	26%	55.9%	Strong
$A3 \Rightarrow A8$	Place of work=PM(product manager)$\Rightarrow$Course=Big data marketing	23%	12.4%	Weak
$A4 \Rightarrow A6$	Place of work=Business consultant$\Rightarrow$Course=Innovation and entrepreneurship strategy	23%	55.4%	Strong
$A4 \Rightarrow A13$	Place of work=Business consultant$\Rightarrow$Important skills in the job position=Business knowledge	23%	55.0%	Strong
$A4 \Rightarrow A15$	Place of work=Business consultant$\Rightarrow$Important skills in the job position=Innovation ability	23%	16.7%	Weak
$A5 \Rightarrow A8$	Place of work=Marketing$\Rightarrow$Course=Big data marketing	20%	51.7%	Strong

$A5 \Rightarrow A11$	Place of work=Marketing ⇒ Important skills in the job position=Creative and designing competence	20%	51.7%	Strong
$A5 \Rightarrow A15$	Place of work=Marketing ⇒ Important skills in the job position=Innovation ability	20%	52.4%	Strong

Table 6. Analysis of Association Rules(Minsupp=5%,Minconf=50%).

Association rules	Attribute = value	Support degree	Confidence coefficient	Effective ness
$A1 \Rightarrow A9$	Place of work=Entrepreneurship consultant ⇒ Course=Entrepreneurial awareness and action	30%	53.6%	Strong
$A2 \Rightarrow A6$	Place of work=Training instructors ⇒ Course=Innovation and entrepreneurship strategy	30%	57.6%	Strong
$A3 \Rightarrow A7$	Place of work=PM(product manager) ⇒ Course=Innovation and new product development	26%	53.1%	Strong
$A4 \Rightarrow A13$	Place of work=Business consultant ⇒ Important skills in the job position=Business knowledge	26%	14.6%	Weak
$A5 \Rightarrow A8$	Place of work=Marketing ⇒ Course=Big data marketing	23%	14.7%	Weak

3.3. Analysis of Teaching Practice Results

This section is based on a questionnaire designed for innovation and entrepreneurship courses that incorporates two dimensions: knowledge integration and innovation and creativity. The questionnaire is divided into pre-test and post-test phases. It was distributed before and after learning under the association rules generated in this paper. A total of 230 questionnaires were distributed in both the pre-test and post-test phases, with 230 valid questionnaires returned, resulting in a 100% response rate.

3.3.1. Questionnaire Analysis

The specific analysis results of the pre- and post-tests of students' knowledge integration ability are shown in Figure 3. Among them: pre-test of knowledge integration ability (AK) and post-test of knowledge integration ability (BK). The average score of students' knowledge integration ability before the test was 3.022, and the average score after the test was 4.291. The Levene test Sig value was 0.066, indicating equal variance, and the T-test Sig value was 0.008, indicating a significant difference between the pre- and post-test data.

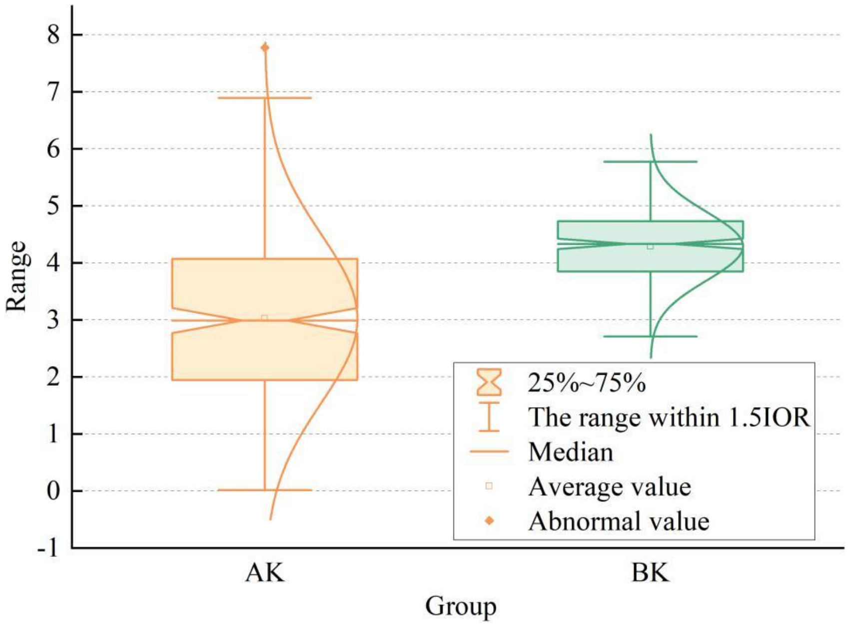

Figure 3. Analysis of students' knowledge integration ability.

The specific analysis results of the pre- and post-tests of students' innovation and creativity abilities are shown in Figure 4. Among them, the pre-test of innovation and creativity abilities (AC) and the post-test of innovation and creativity abilities (BC) are included. The average score of students' innovation and creativity abilities before the test was 3.077, and the average score after the test was 4.300. The Levene test Sig value was 0.068, indicating equal variance, and the T-test Sig value was 0.007, indicating a significant difference between the pre- and post-test data.

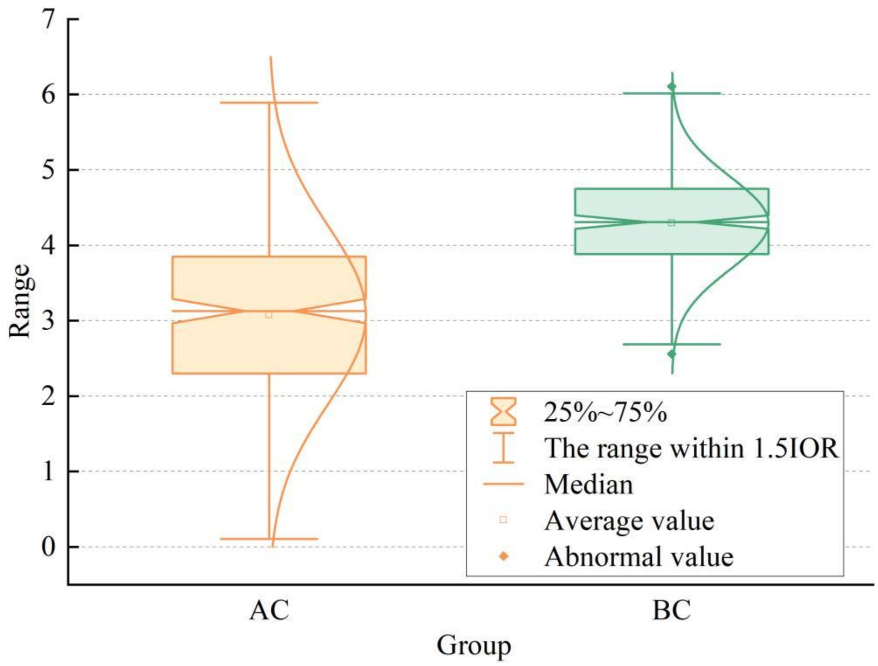

Figure 4. Analysis of students' creative ability.

3.3.2. Course Satisfaction Analysis

To assess students' satisfaction with the course, a course satisfaction survey questionnaire was designed and administered to 230 students at the end of the semester. A total of 230 questionnaires were distributed, with 230 valid responses received, resulting in a 100% response rate. The satisfaction levels were categorized as follows: (S1) Disagree, (S2) Neutral, (S3) Agree, and (S4) Strongly Agree. The survey questionnaire included the following five questions:

(1) I have come to understand the importance of innovation and entrepreneurship for my future development.

(2) Practical activities based on innovation and entrepreneurship have allowed me to consider issues from different perspectives.

(3) I hope to continue participating in such teaching activities in the future.

(4) I can actively participate in all aspects of this type of teaching.

(5) I agree with and enjoy innovation and entrepreneurship activities based on intelligent technology.

Course satisfaction analysis is shown in Figure 5. It can be seen that, overall, students hold a positive attitude toward innovation and entrepreneurship courses, with satisfaction levels primarily concentrated at (S2) neutral and (S3) somewhat agree. Among these, the number of students who responded with (S3) somewhat agree for the second and fifth questions exceeded 140, indicating that innovation and entrepreneurship courses are popular among most students and can enhance their ability to think critically, improve their knowledge and skills, and strengthen their capacity to independently solve problems.

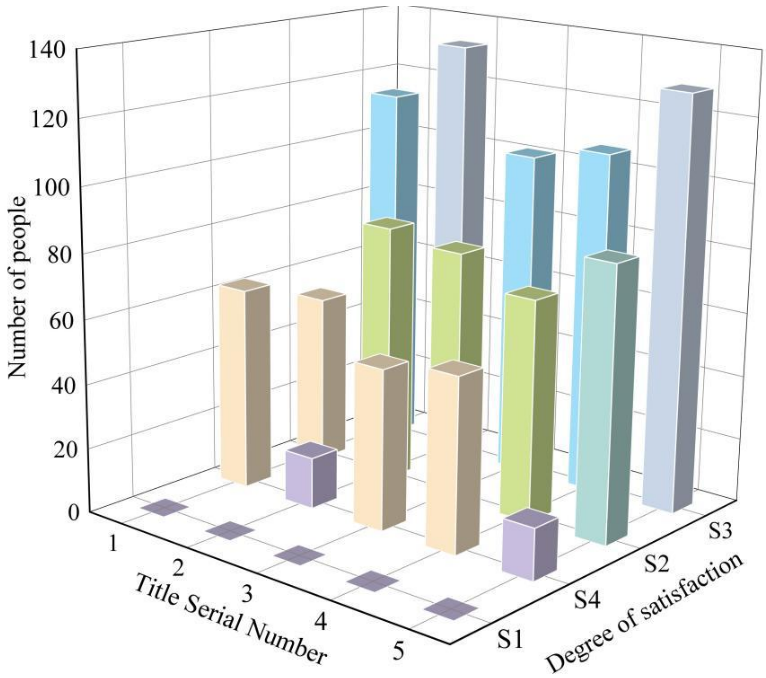

Figure 5. Course Satisfaction Analysis.

4. Conclusion

In the design of innovation and entrepreneurship courses, this paper proposes a step-by-step approach based on the Moodle platform, covering preliminary preparation, learning unit design, course management, and evaluation. To enhance teaching effectiveness, this paper introduces association rule mining algorithms to analyze and generate association rules between job positions, professional courses, and work skills. Under the guidance of the generated association rules, students' average scores for knowledge integration ability and innovation and entrepreneurship ability reached 4.291 and 4.300, respectively, and these scores showed statistically significant differences compared to pre-test scores. Additionally, the majority of students expressed positive attitudes toward the course, with over 140 students providing affirmative evaluations regarding their enjoyment of the course and its ability to enhance critical thinking skills. This indicates that intelligent technologies can effectively assist in the formulation of course directions and content design for innovation and entrepreneurship courses, thereby promoting improvements in teaching effectiveness.

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