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Multi-objective optimization of cross-disciplinary composite talent cultivation in higher vocational colleges under the backdrop of quality improvement and excellence promotion

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Abstract The increasingly severe employment situation requires higher vocational colleges to optimize the means of talent cultivation. This paper collects enterprise recruitment data through web crawler technology as the research data base of cross-border compound music talent skill cultivation. Using the word frequency-inverse document frequency (TF-IDF) and Word2Vec word embedding model, the recruitment data are processed to retain the job keywords. Mining association rules between job recruitment data and skill requirements. According to the results of association rule mining, the optimization scheme of cross-border composite music talent cultivation in higher vocational colleges is proposed. The study shows that the 6 job categories that provide the most positions for cross-border composite talents require talents to master 2 or more skills. The 6 strong association rules for each of the 3 types of cities show that the probability of different recruiting positions requiring composite talents to master a certain type of skill ranges from 80% to 100%, which is a mandatory requirement and requires more attention from institutions and job seekers.

Index Terms TF-IDF, Word2Vec word embedding, association rule mining, composite music talent cultivation

I. Introduction

With the increasing volume of China's economy, the bottleneck of growth rate is becoming more and more prominent, transformation and upgrading has become a strategic choice for China's social and economic development, and an inevitable choice to promote China's social and economic development, which inevitably puts forward higher requirements for talent cultivation of China's higher vocational colleges and universities [1]-[4]. Cross-border composite talent cultivation is an important trend in the current education reform and talent cultivation innovation in higher vocational colleges and universities, and is also an important guarantee for education to serve the social and economic development [5], [6].

Cross-border composite talents refer to the talents who have the basic knowledge and basic ability of two or more professions (or disciplines) and can engage in this discipline or the neighboring professions and marginal disciplines related to this discipline [7]-[9]. The cultivation of composite talents not only requires students to have solid professional skills, but also requires them to have cross-field knowledge, innovative thinking and comprehensive quality [10], [11]. At present, the education system and evaluation mechanism of many higher vocational colleges and universities still pay too much attention to the training of professional skills, ignoring the needs of students' diversified development [12], [13]. Students often lack the opportunity to learn interdisciplinary knowledge while receiving professional skills training, and there are not enough platforms to enhance their comprehensive qualities, such as leadership and teamwork skills [14]-[16]. In the context of globalization and informationization, the speed of knowledge and skill updating is accelerated, and a single vocational skills education can no longer meet the market's diversified demand for talents [17], [18]. The implementation of composite talent cultivation mode in higher vocational colleges can break the disciplinary barriers and enhance the flexibility and adaptability of education [19]-[21]. Through cross-border curriculum and comprehensive skills training, students can master a more comprehensive knowledge structure and improve their adaptability in different work environments [22], [23]. The composite talent cultivation model not only meets the needs of society, but also injects new vitality into the development of vocational education and provides vocational schools with a broader space for development [24]-[26].

This paper utilizes computers to conduct an analysis between job openings and occupational skills. Use Octopus Collector to crawl the enterprise recruitment text data. Combine the TF-IDF model to count the probability of keywords and other words appearing in the enterprise text data to extract the job keywords. Use Word2Vec word embedding model to extend the featured words with topic content. Mining the association rules between job recruitment needs and required skills in the processed text data, analyzing the skill requirements of high salary jobs, association rules between different cities, etc., to provide data support for the optimization of cross-border composite talent cultivation programs for higher vocational colleges and universities.

II. Technical support for computer-assisted job-skill correlation mining

This chapter systematically analyzes how to process the collected recruitment information and association rule mining, and the following is the specific process.

II. A. Recruitment data collection

The collection of recruitment information can be achieved through web crawler technology, due to the timeliness of the data source, the richer content, the large amount of data and other characteristics, it is necessary to first standardize the data crawling process.

Figure 1 shows the data collection rules. This paper chooses Lagou.com as the data source of the recruitment website, Lagou.com is a recruitment website specializing in providing job seekers with job opportunities, with a large number of users and covering more complete job information, which has a high degree of visibility in China, and its web site is specially equipped with a multi-type career recruitment column, which is a high degree of fit with the cross-border composite talent cultivation research of this paper. The authors launched recruitment data collection for first-tier, new first-tier and second-tier cities, totaling 10 cities.

Web crawling data steps: first select a specified URL as a sub-URL to build a URL queue, then crawl to the web page sequentially and interpret and analyze it, then crawl to the page as new sub-URLs are successively acquired to join the queue, and finally stop crawling to the sub-URLs when all the specific conditions will be crawled to the sub-URLs. Compared with manual data collection methods such as field research, web crawler technology realizes the collection of multiple types and large quantities of recruitment data, reducing the cost and difficulty of data collection. Currently, web crawlers can be realized by Java, C, Python, R and other programming languages, or data collection software can be used for collection.

In this paper, Octopus Collector is chosen to collect recruitment information, which can accurately locate each data path in the web page source code by simulating people's way of thinking and operating, so as to accurately collect the data needed for the research.

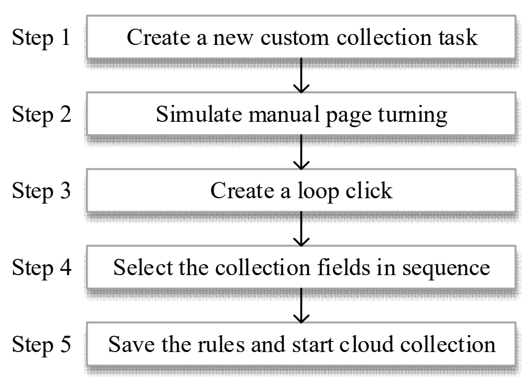

Figure 1: Data collection rules

II. B. Text message vectorization

II. B. 1) The TF-IDF model

TF-IDF model, Chinese translation for word frequency - inverse document frequency, this model assessment focuses on whether the words in the document is important, the higher the frequency of words in the document, the importance of the degree of elevation, the higher the frequency of words in more than one document, the importance of the degree of decline, formula (1) can be expressed as:

$$TFIDF_{i,j} = TF_{i,j} \times IDF_i \quad i = 1, \cdots, m \quad j = 1, \cdots, D. \tag{1}$$

TF calculates the frequency of occurrence of each word in the document, which is calculated by dividing the number of occurrences of the word by the number of all words in the document, equation (2):

$$TF_{i,j}=\frac{n_{i,j}}{\sum_{k}n_{k,j}} \tag{2}$$

IDF is the Inverse Document Frequency, when the word occurs only in fewer documents, then the word has a strong differentiation and can represent the document topic, the formula is the total number of documents divided by the logarithm of the number of documents in which the word occurs, the formula is (3):

$$IDF_i=\log\frac{|D|}{|\{j:t_i\in d_j\}|} \tag{3}$$

According to the above formula, the advantages of TF-IDF are firstly, some common but no practical role in the text of the words will be filtered, retaining the real keywords of the document, secondly, simple and fast, and finally easier to understand, but because it is still a discrete method, so there will still be a semantic identification of the problem, so in this paper, we will use the TF-IDF to extract keywords in the post, and then use the distributed approach to further analyze.

II. B. 2) Distributed Representation

Distributed representation approaches have a much wider range of application scenarios, centering on the representation of a word in terms of nearby words, with the precise semantic content connected by the vocabulary surrounding the word. This paper introduces the Word2Vec modeling approach.

Word2Vec is a word embedding model that embeds a high-dimensional space containing all feature words into a low-dimensional continuous vector space, the formula expression is $e_j=E\times W_j$, where W is the uniquely-hot representation, the embedding matrix is E, and e_j is a low-dimensional continuous vector space of much lower dimensionality than W_j. Word2Vec contains an input layer, a hidden layer, and an output layer, and currently there are two forms of network structure, CBOW and Skip-gram.The difference between CBOW and Skip-gram model is that CBOW outputs the current text with the input context, and Skip-gram outputs the output context with the input of the current text.

The middle word of CBOW is set to y, and other words are set to x. The hidden layer sums the input layer inputs, and after activating the function, the weights are trained, and the weight matrix is adjusted until the word generation probability is maximized. The structure is as follows:

The input $x_{n-2},x_{n-1},x_{n+1},x_{n+2}$ is predicted y,k as the sliding window size and the expression is (4):

$$p(y\mid x_{n-k},,x_{n-k+1},\cdots,x_{n+k-1},x_{n+k}) \tag{4}$$

The prediction equation is (5):

$$p(x\mid context(x))=\frac{\exp(e(x)^T z)}{\sum_{x\in V}\exp(e(x)^T z)} \tag{5}$$

$z=\sum_{i=1}^{n}e(x_i)$, $e(x_i)$ is the word vector of the word x_i.

The formula for the Skip-gram model is as follows:

Input y predicts $x_{n-2},x_{n-1},x_{n+1},x_{n+2}$, where $2k+1$ is the sliding window, expression (6):

$$p(x_{n-k},,x_{n-k+1},\cdots,x_{n+k-1},x_{n+k}\mid y) \tag{6}$$

The prediction formulas are (7) and (8), where y is the current word and u is the surrounding words:

$$p(context(y)\mid y)=\prod_{u\in content(y)}p(u\mid y) \tag{7}$$

$$p(u\mid y)=\frac{exp(e(u)^T e(y))}{\sum_{y\in V}exp(e(u)^T e(y))} \tag{8}$$

Overall comparing the two models, the Skip-gram model, although it will be more accurate and make the results more precise, but the training time is longer and will go through more predictions, so the computational cost is larger, and it needs to be combined with the actual choice.In this paper, because of fewer subject words obtained, the Skip-gram model is used to expand the subject content.

II. C.Analysis of association rules

II. C. 1) Basic concepts of association rules

In order to accurately describe the association rule mining problem and facilitate the discussion of the problem, a formal definition of the association rule mining problem needs to be given. The following is a definition of the association rule mining problem in terms of a transaction database.

Definition 1: The dataset of association rule mining is denoted as D (D is a transaction database), $D=\{t_1,t_2,\ldots,t_k,\ldots,t_n\}$, $t_k=\{i_1,i_2,...,i_j,...,i_p\}(k=1,2,...,n)$ is a transaction; the elements $i_j(j=1,2,...,p)$ is called Item.

Definition 2: Let $I=\{i_1,i_2,...i_m\}$ is the set consisting of all items in D, any subset X of I is called the itemset in D, and $|X|=k$ calls the set X the k itemset. Let t_k and X be a transaction and an itemset in D, respectively, and a transaction t_k is said to contain an itemset X if $X\subseteq t_k$.

Although both transactions and itemsets are collections of items, they have different meanings. A transaction is a constituent element of a database D (analogous to a record or tuple in a relational database), whereas an item is simply a combination of items specified for the purpose of extracting association rules (analogous to a field in a relational database). The containment relationship between a transaction and an item set indicates that the items in this item set are interrelated for that transaction.

Definition 3: The number of transactions in the dataset D that contain the itemset X is called the support number of the itemset X and is denoted as σ_x. The support of the itemset X is denoted as $support(X)$, i.e., probability $P(X)$.

$$support(X)=\frac{\sigma_x}{|D|}\times 100\% \tag{9}$$

where: $|D|$ is the number of transactions in the data set D. If $support(X)$ is not less than the user-specified minimum support (denoted as: minsupport), then X is said to be a frequent itemset (or a large itemset), otherwise it is said to be an infrequent itemset (or a small itemset).

Definition 4: Let X,Y be an itemset in the dataset D.

(1) If $X\subseteq Y$, then

$$support(X)\geq support(Y) \tag{10}$$

(2) If $X\subseteq Y$, if X is a non-frequent itemset, then Y is also a non-frequent itemset

(3) If $X\subseteq Y$, if Y is a frequent itemset, then X is also a frequent itemset

Definition 5: If X,Y is an itemset and $X\cap Y=\Phi$, the implication $X\Rightarrow Y$ is called an association rule, and X,Y is called the premise and conclusion of the association rule $X\Rightarrow Y$, respectively. The support of the itemset $X\cup Y$ is called the support of the association rule $X\Rightarrow Y$, and is the percentage of transactions in D that contain $X\cup Y$, i.e., the probability $P(X\cup Y)$, denoted as: $support(X\Rightarrow Y)$.

$$support(X\Rightarrow Y)=support(X\cup Y)=P(X\cup Y) \tag{11}$$

The confidence level of the association rule $X\Rightarrow Y$ is the percentage of transactions in D that contain things in X that also contain things in Y, i.e., the conditional probability $P(Y|X)$, notated as: $confidence(X\Rightarrow Y)$.

$$confidence(X\Rightarrow Y)=\frac{support}{(X\cup Y)}support(X)\times 100\%=P(Y|X) \tag{12}$$

Usually, the minimum confidence level specified by the user according to the extraction needs is denoted as minconfidence.

Support and confidence are two important concepts for describing association rules, the former is used to measure the statistical importance of an association rule in the whole dataset, and the latter is used to measure the degree of confidence of an association rule. Generally speaking, only association rules with high support and confidence are likely to be interesting and useful to users.

Usually, users specify the minimum support (denoted as minsupport) and the minimum confidence (denoted as minconfidence) according to the extraction needs. The former describes the minimum importance of an association rule, and the latter specifies the minimum reliability that an association rule must meet.

Definition 6: An association rule $X \Rightarrow Y$ is said to be strong if $support(X \Rightarrow Y) \geq minsupport$ and $confidence(X \Rightarrow Y) \geq minconfidence$, otherwise an association rule $X \Rightarrow Y$ is a weak rule.

The association rule mining problem is to solve all association rules in D whose support and confidence exceed minsupport and minconfidence respectively, i.e., the solution is required to satisfy $support(X \Rightarrow Y) \geq minsupport$ and $confidence(X \Rightarrow Y) \geq minconfidence$ of the rule $X \Rightarrow Y$.

II. C. 2) Decomposition of the association rule problem

Given a database D, association rule mining is to find out all the strong association rules that exist in the database D. Therefore, the whole association rule mining process can be decomposed into the following two steps:

(1) Find all frequent itemsets: i.e., all itemsets whose support is not lower than the minimum support given by the user.

(2) Generate strong association rules from the frequent itemsets: i.e., mine the rules whose confidence level is not less than the minimum confidence level specified by the user from the frequent itemsets obtained from (1).

Where (1) is the core of the association rule mining algorithm, the overall performance of mining association rules is determined by the first step. Solving the first subproblem often requires multiple scans of the database D, which means that a lot of time will be spent on database scans and I/0 operations. Therefore, how to find out all the frequent itemsets quickly and efficiently is the main problem that various association rule mining algorithms need to solve, and it is also the standard to measure each association rule mining algorithm.

Once the frequent itemsets are found out by the transactions in database D, it is straightforward to generate strong association rules from them. The specific steps are as follows:

For each frequent itemset I, generate all non-empty subsets of I.

For each non-empty subset s of I, output the rule $s \Rightarrow (I - s)$ if $(support(I) / support(s)) > minconfidence$. where minconfidence is the minimum confidence threshold.

Generated from the set of frequent items in the stemmed rules, each rule automatically satisfies the minimum support. Frequent itemsets along with their support are pre-positioned in a hash table, making them quickly accessible.

III. Analysis of the correlation between job categories and skill needs

This chapter collects multi-city and multi-job recruitment data, mines the association between jobs and skills, and provides support for the optimization of cross-border composite music talent cultivation programs in higher vocational colleges and universities.

III. A. Analysis of collected data

III. A. 1) Distribution of job categories

Table 1 shows the results of recruitment data statistics. Statistics on the collected recruitment data of multiple categories reveal that in the music talent recruitment market of the studied cities, the 6 categories of jobs that provide the most positions for composite music talents (a total of 27,701 positions) belong to the product category, technology category, functional category, marketing category, operation category, and design category, respectively. Each of these jobs contains 1 or more types of positions, for example, the operations category contains 5 sub-categories of operations, customer service, editing, promotion, data positions, these positions are more demanding, requiring job seekers to have 2 or even more than 2 skills, with the potential to become all-rounded employees.

III. A. 2) Work experience and salary levels

Figure 2 shows the distribution of work experience and salary level of composite music talents. The size of the point represents the level of salary, the smallest point is 6k per month, and the largest point is 40k per month. The data shows that the distribution of work experience of composite music talents is mainly concentrated in the time period of 2-10 years, and the distribution of composite music talents with less than 2 years and more than 10 years of experience is very small. There is a clear positive correlation between work experience and its salary level, and the salary level of each stage of work experience is relatively balanced. 10k-20k is a relatively common salary level, and it is also a relatively normal salary level that talents with 2 or more composite skills can get after working for about 2-6 years. Of course, we can't rule out individuals with relatively little experience, but with rich skills and high salaries. But the general situation is that the longer the working time, with more work experience, the accumulation of more professional skills, the more favored by the enterprise, the salary is naturally higher.

Table 1: Statistics of Recruitment Position Categories

Position category	Specific position	Frequency	Position category	Specific position	Frequency
Product category	Product	1309	Marketing category	Marketing	5811
				Market	1752
Technical category	Development	5237	Operation-related	Operation	2813
	Test	1435		Customer service	2114
	Operation and maintenance	1727		Editor	1516
	Optimization	358		Promotion	821
				Data	315
Functional category	Administration	1314	Design category	Webpage	2875
	Finance	817		Vision	2060
	Human resources	158			
Total	27701				

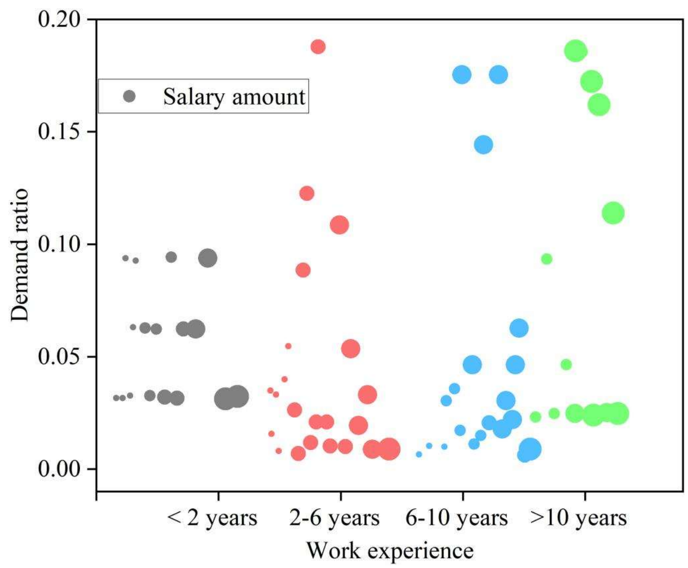

Figure 2: The distribution of work experience and salary levels

III. B. Analysis related to skill requirements

III. B. 1) Correlation analysis between job categories and first-level skill indicators

The correlation between job categories and first-level skill indicators is analyzed by TF-IDF. The basic analysis of skill requirements mainly focuses on the word frequency analysis of job categories and some skill keywords in the skill dictionary to get the proportion of skill categories in the text of job information. Although the word frequency analysis method can initially reflect the selected skill requirements, but if we want to carry out the demand analysis of each job category, we need to carry out the correlation analysis. Correlation analysis demonstrates the degree of correlation between job categories and selected skill indicators. The correlation value shows the ratio of the number of texts of a selected skill indicator appearing in a selected job posting information to the number of texts of the selected skill indicator appearing in all job posting information. If the correlation ratio is greater than 1, it means that there exists a uniqueness between the selected skill indicator and job posting, which needs to be further analyzed, and the greater the correlation ratio, the higher the uniqueness degree is. This uniqueness usually indicates a new skill association, which is a reflection of the skill needs of recruiting compound music talents and needs to be paid attention to.

Table 2 shows the results of the correlation analysis between job categories and first-level skill indicators. After analyzing the correlation between job categories and skills of composite music talents, it can be found that there are significant differences in the skills needs of different jobs. For example, product jobs need to recruit talents with skills related to competitor analysis (1.8) and product selection (2.6), and there is also a greater demand for management and communication skills. While technical positions require higher skills in program development (2.2), network operation and maintenance (2.1), and code optimization (2.4). It is worth noting that no matter which job category, the skill of communication ability has relatively high requirements, which can be seen in the cultivation of cross-border compound music talents in higher vocational colleges and universities need to focus on cultivating their communication ability and improving their communication level.

Table 2: Analysis of Job Categories and First-level Skill Indicators

Skill indicators	Position category					
	Product category	Technical category	Functional category	Marketing category	Operation -related	Design category
Competitive product analysis	239	185	88	189	231	123
	1.8	1.5	0.4	1.5	1.7	1.1
Product selection ability	385	152	75	118	232	12
	2.6	1.1	0.3	1.0	1.7	0.0
Program development	36	336	28	10	12	10
	0.1	2.2	0.1	0.0	0.0	0.0
Network operation and maintenance	23	289	35	15	13	12
	0.1	2.1	0.2	0.0	0.0	0.0
Code optimization	49	297	81	17	15	10
	0.2	2.4	0.4	0.0	0	0.0
Administrative management	235	47	377	142	182	15
	1.4	0.4	2.8	1.3	1.2	0.0
Communication ability	345	189	345	173	193	298
	2.3	1.2	2.2	1.4	1.5	1.9
Hot spot capture	117	24	34	18	346	122
	1.0	0.1	0.2	0.0	2.4	1.1
Data analysis	122	142	31	14	179	48
	1.2	1.3	0.2	0.0	1.3	0.2
Web design	37	30	17	8	61	18
	0.3	0.2	0.0	0.0	0.3	0.0
Aesthetic consciousness	145	37	26	123	178	277
	1.3	0.2	0.1	1.1	1.4	1.9

III. B. 2) Cross-analysis of job categories and skill keywords

After correlation analysis of composite jobs and skills, more obvious skill associations were shown. In order to further reveal the specific skills required in composite employment positions, a correlation analysis between job and skill keywords is needed. Table 3 shows the correlation results of the cross analysis of job categories and skill keywords. There are some key skills that are highly correlated between different job categories. For example, in the product category, functional category, marketing category, operation category positions, all need key skills “copywriting”, in the operation category correlation even reached 2.6, indicating that the key skills are in different job categories to obtain a higher salary is an important factor. Equally important is the skill of “communication skills”, which has a high correlation in the functional (2.2), marketing (2.6), and design (2.1) job categories, and needs to be noted.

Table 3: Cross-analysis of job categories and skill keywords

Position category	Skill Keywords			
Product category	Bestseller 204,2.0	Planning 179,2.1	Copywriting 159,1.0	Execute 160,1.0
Technical category	Java 335,3.1	SQL 178,2.3	HTTP 162,2.1	HTML 155,1.9
Functional category	Management 232,2.5	Copywriting 227,2.3	Office 216,2.2	Communication 212,2.2
Marketing category	Photography 269,2.7	Content planning 246,2.5	Communication 259,2.6	Copywriting 228,2.3
Operation -related	Planning 277,2.8	Copywriting 256,2.6	Pressure resistance 265,2.7	Marketing 247,2.6
Design category	PS 232,2.5	PR 228,2.3	CDR 212,2.2	Communication 212,2.1

III. B. 3) Skill requirements for high-paying jobs

After the correlation analysis of job and skill dimensions and job and skill keywords, there has been a general understanding of the skills required for each job. In the future, higher vocational colleges and universities can combine the text frequency and relevance for cross-border course system design, and make targeted planning for the recruitment market demand. At the same time, students can also analyze their own strengths and weaknesses according to the specific skills required, and then target learning all kinds of skills. Next, the correlation between the high-paying positions of composite music talents and the skill keywords is analyzed to find out the unique skill needs of high-paying positions. Table 4 is the skill demand of high-tech positions. From Table 4, we can see that the highest salary and the most in-demand job skills is the ability to create pop-ups, with a monthly salary of more than 20k, appearing 2,901 times in the collection of recruitment text; followed by copywriting skills, with a monthly salary of the same more than 20k, and the demand for which reached 2,173.Focusing on the demand for the key skills of these high-paying jobs will help higher vocational colleges and universities to cultivate their students more in the direction of the relevant skills.

Table 4: The skill requirements for high-tech positions

Monthly salary range	Skill Keywords			
6k-10k	Execute 1260	Office 1793	Pressure resistance 1921	PS 1011
10k-15k	HTTP 2071	HTML 1000	Marketing 1372	Content planning 1243
15k-20k	Planning 985	Java 1042	SQL 1335	PR 1205
>20k	Bestseller 2901	Copywriting 2173	Communication 2036	CDR 1020

Table 5: Strong association rules for skill themes in first-tier cities

Association rule sequence number	Previous item	Latter item	Support(%)	Confidence(%)	Improvement degree(%)
1	Educational course products 2-4 year	Product-related skills	7.04	100.00	4.81
2	Program development 20-30k	Technical skills	7.01	100.00	15.62
3	2-4 year Human resource services	Functional skills	6.59	91.02	4.26
4	Text media/publishing Private company	Marketing skills	6.23	87.67	4.06
5	We-Media 1-3 years	Operational skills	5.79	86.43	5.28
6	Internet/E-commerce 15k	Design-related skills	5.38	85.26	4.91

III. C. Analysis of association rule results

III. C. 1) Analysis of the results of the association rule for first-tier cities

Cities with different levels of economic development, industrial scale and characteristics have different skill demands for composite music talents, so it is necessary to carry out skill theme association rule mining analysis according to the city level. To analyze the association rules for the first-tier cities, the support degree is set to be greater than 1.2%, the confidence level is set to be greater than 65%, and a total of 60 association rules are obtained. Based on the data mining that the enhancement degree is greater than 4 is valuable, six strong association rules with the enhancement degree greater than 4 are finally filtered out as the generated strong association rules for the skill theme of the first-tier cities. Table 5 shows the results of analyzing the strong association rules of skill themes in first-tier cities. The features that have strong association relationships between job categories and skills in first-tier cities all have different probabilities. For example, the association rule 1 represents that the job seeker who is engaged in the education course product industry and requires 2-4 years of work experience in the related field has a 100% probability of requiring the job seeker to master the product skills, including competitive product analysis and product selection ability. From the five association rules of strong association, the probability of requiring job seekers to master certain types of skills are more than 85%, the probability is very high, indicating that these skills are necessary when applying for related positions in first-tier cities.

III. C. 2) Analysis of the results of the association rule for new first-tier cities

Association rule analysis of the new first-tier cities, set the support degree greater than 1.2%, confidence level set greater than 65%, a total of 40 association rules, according to the data mining that the degree of enhancement is greater than 4 is valuable, and ultimately filtered out the enhancement of more than 4 of the six strong association rules. Table 6 shows the generated strong association rules for the theme of skills in the new first-tier cities. The features that have a strong association relationship with the theme skill words within the new first-tier cities all have different probabilities. Compared with the first-tier cities, the probability of the requirement of related skills decreases in the new first-tier cities when recruiting for the same type of jobs, for example, the probability of the requirement of product skills in association rule 1 is 95.02%, which is smaller than the 100.00% in the first-tier cities. However, as a whole, the probability of the requirement for skills still remains above 80%, indicating that the requirement for skill learning cannot be relaxed because of the difference in the level of urban development.

Table 6: Strong association rules for skill themes in new first-tier cities

Association rule sequence number	Previous item	Latter item	Support(%)	Confidence(%)	Improvement degree(%)
1	Real estate products 6-8k	Product-related skills	2.01	95.02	4.10
2	Software operation and maintenance 3-4 year	Technical skills	2.17	90.37	4.61
3	1-2 year State-owned enterprise	Functional skills	2.56	86.23	4.13
4	News/Publishing 8-10k	Marketing skills	2.28	82.65	4.04
5	Anchor Private company	Operational skills	2.71	80.02	4.21
6	Poster design CDR	Design-related skills	2.34	80.00	4.01

Table 7: Strong association rules for skill themes in second-tier cities

Association rule sequence number	Previous item	Latter item	Support(%)	Confidence(%)	Improvement degree(%)
1	Culture/Sports/Entertainment 5-6k	Product-related skills	2.39	100.00	21.00
2	Web development 1-3 year	Technical skills	2.65	100.00	6.63
3	6-9k Librarian	Functional skills	2.73	96.24	7.13
4	Market promotion 1-3 year	Marketing skills	2.19	81.61	6.08
5	Game operation 4-5 year	Operational skills	2.30	100.00	7.25
6	Signboard design PS, PR	Design-related skills	2.26	100.00	5.74

III. C. 3) Analysis of the results of the association rules for second-tier cities

The association rules are analyzed for the second-tier cities, the support is set to be greater than 1.2%, the confidence level is set to be greater than 65%, and a total of 100 association rules are obtained, which are considered to be valuable if the enhancement degree is greater than 4 according to data mining, and 6 strong association rules with enhancement degree greater than 4 are finally filtered out. Table 7 shows the generated strong association rules for the theme of skills in second-tier cities. The probability of the features with strong association relationship with the theme skill words within the second-tier cities reaches 100% more than half, which proves that the probability of the demand for specific skills for some job features is extremely high. Meanwhile, the probability of skill requirements for the six strong association rules varies widely, with a maximum of 100.00% and a minimum of 81.61%, indicating that students' related skills should be targeted.

IV. Optimization Methods of Cultivating Cross-border Compound Music Talents in Higher Education Institutions

The employment results are good or bad, verifying the level of cross-border compound music talents training in higher vocational colleges and universities. And to improve the level of composite music talents and let more composite music talents be seen and favored by enterprises, it is necessary for managers of higher vocational colleges and universities to continuously optimize the cultivation program. Combined with the recruitment job data and skill association rules obtained by computer mining, the following optimization suggestions are put forward.

First, understand the overall skill demand of the recruitment environment, and make good connection with the cultivation of cross-border compound music talents. Through the analysis of network recruitment jobs and the categorization of employment skills theme words, the managers of higher vocational colleges and universities can see that there is a different probability of demand for cross-border composite music talents' skills in all levels of recruitment cities. This also reflects, to some extent, in which skills cross-border compound music talents are more favored by the market. In view of the overall skill demand of different levels of cities, cultivating higher vocational colleges and universities should pay more attention to the general needs of the recruitment market for cross-border composite music talents, and observe whether the development of the curriculum is reasonable based on the existing curriculum comparison. For most of the skills required for recruitment to formulate relevant courses to strengthen the resources set for the cross-border composite music talents have a high degree of matching and suitable for employment recruiters, training institutions can reach a school-enterprise alliance with recruiters, should be required by the recruiters, each year for the recruiters to enter a steady stream of cross-border composite music talents. On the other hand, the training institutions can be based on the comprehensive performance of cross-border composite music talents based on big data, the development of excellent talent recommendation big data platform, in the college side of the talent automatically selected by the entry of job-seeking related skills, in the recruiter side of the big data platform can be entered in the recruitment of skills for cross-border composite music talents to view or targeted learning of the required skills, time-saving and efficient.

Secondly, for the employment environment of cross-border composite music talents, higher vocational colleges and universities should assist students to plan a good job-seeking path as early as possible, and formulate skills training programs with reference to the status quo of the employment environment, so as to meet the skills required by recruiting units and their various needs. Cross-border composite music talents in the employment, can do a good job of career planning in advance, before graduation to the intention of post similar enterprises or industries for internships, in advance to obtain enterprise or industry-related experience, hands-on practice of the application of relevant skills. In the acquisition of professional skills, with reference to the skills required for the current positions, most positions for communication skills and copywriting skills have more demand, and in addition to the basic skills should be mastered, for the job search and the future of the work of all help. At the same time, cross-border composite talents for different employment environment selection should also pay close attention to recruitment statistics, first-tier cities in the statistics of cross-border composite music talents in greater demand, cross-border composite music talents in the delivery of resumes can be the first line of cities, new first-tier cities, enterprises for delivery, will get more job opportunities. Higher vocational colleges and universities should adapt to the needs of social development, and remind students in their daily teaching to seize the information time gap in time, understand the employment opportunities, and face the severe employment form can first learn vocational skills in advance to improve their personal working ability.

V. Conclusion

In this paper, with the help of computer-related technical support, we study the correlation between job recruitment needs and skill requirements, and improve the cultivation program for cross-border composite music talents in higher vocational colleges and universities. It is found that six types of positions, namely, product, technology, function, marketing, operation and design, provide the most employment opportunities for cross-border composite music talents, and at the same time, talents are required to have two or even more corresponding skills. The highest salary and the most demanded skill is the ability to create explosive models (monthly salary>20k, demand for more than 2,901 times), followed by copywriting skills. 3 types of cities with different levels of development in the recruitment demand for composite music talents with industry-related skills probability of more than 80%, especially in second-tier cities, the probability of the requirements of the majority of the probability of reaching 100%. According to the results of the association rule analysis, the relevant managers of higher vocational colleges and universities should target to integrate the skills courses that meet the employment market demand into the training program, and cultivate students' job-seeking advantages as early as possible.

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References

[1] Wei, L., & Yanbin, C. (2021). China's Economic Growth and High-Quality Development: 2020-2035. China Economist, 16(1), 2-17.
[2] Fuzhan, X. (2019). China's economic development and development economics innovation. Social Sciences in China, 40(2), 100-110.
[3] Zhang, J., Fu, X., & Yan, S. (2016). Structural change, industrial upgrading and China's economic transformation. Journal of Chinese eConomiC and Business studies, 14(3), 211-213.
[4] Zhao, J., Li, Y., Zhang, S., Zhou, Y., & Guo, H. (2025). Analysing a Reform of The Training Model of Composite Talents with Multi-Co-Education Based on The ISM Model of Intelligent Manufacturing. Journal of Information & Knowledge Management, 2550006.
[5] Xin, W., Zhengying, Y., Sheng, W., & Lili, W. (2023). Training model of practical innovative talents in polytechnic colleges based on fuzzy set and its extended modeling. Learning and Motivation, 84, 101941.
[6] Guo, S. (2024). Exploration of the Cultivation Mode of Composite Talents in Coastal Sports Tourism from the Perspective of Cross-border Integration. International Journal of New Developments in Education. https://doi. org/10.25236/ijnde.
[7] Jia, S., Chen, X., & Yang, T. (2023). Research on the training model of financial technology talents based on interdisciplinary and multi-professional integration. International Journal of New Developments in Education, 5(2), 21-26.
[8] Liu, Y. (2024). Research on the Talent Cultivation Model of Interdisciplinary Integration in Art and Design. The Educational Review, USA, 8(4).
[9] Hu, X., Liu, F., & Yuan, Y. (2021). Research on talent training mode of interdisciplinary integration in colleges and universities. International Journal of Education and Humanities, 1(1), 28-35.
[10] Luo, J., Liu, J., Zuo, D., Luo, Q., & Ma, G. (2022). Research on the cultivation of innovative thinking and innovation ability based on IEC interdisciplinary talents. Transactions on Comparative Education, 4(3), 1-7.
[11] Cao, J., Liu, X., Jiang, G., Zheng, C., Liu, X., & Bao, X. (2021). Research on the Cultivation Model of Collaborative Innovative Talents for Interdisciplinary Engineering Training. In 2nd International Conference on Education and Educa-tional Development (EED 2021) (pp. 39-43).
[12] Zhou, D., & Niu, Y. (2025). Research on the Interdisciplinary and Interdisciplinary Training of High-Level Legal Talents in Jiangsu Universities under the Background of" Artificial Intelligence+". Journal of Educational Theory and Practice, 2(1).
[13] Li, Y., Guan, H., & Liu, K. (2024). Study on Cultivation Mechanism for Intelligent Navigation Talents Based on "Discipline Crossing, Interdisciplinary Integration". In Artificial Intelligence, Medical Engineering and Education (pp. 614-623). IOS Press.
[14] Yuan, R., Wang, S., & Qian, Y. (2024). Exploration and Practical Research on Cultivation of High-level Compound Talents of Master of Engineering Management (MEM) Based on the Concept of "Integration of Engineering and Literature". Journal of Industry and Engineering Management (ISSN: 2959-0612), 2(2), 9.
[15] Wang, L., Tian, S., Cheng, L., & Li, L. (2020). Research and Practice on Compound Talents Training Model of Safety Management—A Case Study from Xi'an University of Science and Technology. International Journal of Learning, 6(4), 236-240.
[16] Zhang, J., & Li, H. (2023). Research on the Cultivation of Interdisciplinary Translation Talents in the Energy Field---Take Colleges and Universities in Southwest China as Examples. Academic Journal of Humanities & Social Sciences, 6(4), 103-108.
[17] Xu, M. (2022). Exploration and practice of the teaching mode of innovative training of compound financial talents under the open business mode. International Journal of Educational Research and Development, 1(1), 33-33.
[18] Cao, H. (2019). Cultivation of Interdisciplinary Versatile Talents of Animal Wool Textile under the Vision of Innovation and Entrepreneurship. Revista Científica de la Facultad de Ciencias Veterinarias, 29(4), 881-889.
[19] Xing, H., Ye, X., Chen, Y., Li, H., Xing, X., & Zhao, X. (2024). Research on the Cultivating Mode of Interdisciplinary Innovative Talents in Bionic Robots. Journal of Intelligence and Knowledge Engineering (ISSN: 2959-0620), 2(2), 11.
[20] Han, X. (2025). Research on Multi-Objective Planning and Constraints of Cross-border Compound Music Talent Cultivation Mode in Higher Vocational Colleges Driven by Quality Improvement and Excellence Training. J. COMBIN. MATH. COMBIN. COMPUT, 127, 4949-4963.
[21] Li, Y. (2025). Development of Higher Vocational Education and Innovative Talent Cultivation Practices in a Selected University in Haikou City, China. Journal of Education, Humanities, and Social Research, 2(1), 74-80.
[22] Li, J. (2022). The Construction and Implementation of a Compound Foreign Language Talent Training Model. Journal of Contemporary Educational Research, 6(7), 99-106.
[23] Liu, H., Gao, F., & Wang, L. (2022). The Practice and Reflection on the Cultivation of New Technology Applied Entrepreneurial Talents in Higher Vocational Colleges. International Journal of Social Science and Education Research, 5(9), 307-314.
[24] Wu, Z., Liu, H. Y., & Deng, X. Y. (2024). Teaching Practices for the Cultivation of "AI+ X" Composite Talents in Higher Education: Challenges and Strategies. Education Science and Management, 2(3), 156-175.
[25] Yin, C., & Wen, D. (2024). Practice and Exploration of the Reform of the International Talent Cultivation Model in Higher Vocational Colleges from the Perspective of New Quality Productivity. Journal of Exploration of Vocational Education, 1(1).
[26] Chen, F., Zeng, Z., Liu, Y., Lin, X., & Bao, Z. (2023, September). Research on the Talent Cultivating Model of Integrated Vocational and Undergraduate Education. In 3rd International Conference on Internet, Education and Information Technology (IEIT 2023) (pp. 1148-1154). Atlantis Press.