A Machine Learning-Based Intelligent Employment Management System by Extracting Relevant Features

Yiming Wang, Chi Che*
School of Economics and Management, Jilin Engineering Normal University, Changchun, 130000, China

***Abstract*—In recent years, there has been a significant increase in the number of students trying to broaden the work opportunities available to college graduates. This study presents an intelligent employment management system that may be used in educational institutions for students to gain a better understanding of their occupations and analyzing the sectors in which they will work. In this article, the fundamental concepts of information recommendation are discussed, as well as a customized recommendation system for entrepreneurship that is provided. The fundamental information and personal interest points of college students are represented by feature vectors. These feature vectors provide positive theoretical support for the career planning and employment and entrepreneurship information suggestions of college students. In conclusion, an analysis of the performance of the proposed model is performed to provide college students with a system that is both convenient and quick in terms of information recommendation. This will result in an indirect improvement in the employment rate of graduates and will provide solutions that correspond to the problem of difficult employment.**

Keywords*—Employment management system; recommendation system; feature index; accuracy and employment intention index

I. Introduction

The college job information that is available now has the characteristics of being diverse, very efficient, and quite extensive. As a consequence of the continuous advancement of information technology, this is one of the characteristics that has come into existence within the field [1]. There has been a significant amount of time that has passed since the conventional data statistics system was able to meet the actual requirements of data statistics [2]. The statistics of employment information in colleges and universities need to design a new model with intelligent technology to carry out technological innovation. This is in addition to the fact that they are responsible for conducting scientific data screening and doing a thorough job of data analysis. When there are a large number of collections, some of which include real data, there are also a significant number of collections that contain misleading information. Because of this, statisticians are necessary to design a data screening technique that is both scientific and efficient to carry out the real statistical process successfully. Two components make up this system: artificial screening and intelligent screening In the field of statistics, it is essential to make use of computers to provide a smooth operation process. This is important to guarantee a high level of efficiency in the collection of statistical data and in designing creative data statistics [3, 4].

It is essential to perform successfully while simultaneously developing new methods of data collection [5-8]. The establishment of a system for the collecting of data over an extended period is necessary in order to improve the rate at which high-quality data mining is performed. In and of itself, data mining is a kind of data deep processing that is focused on achieving certain goals. To accomplish this objective, active data users will be required to do statistical data deep processing for extended periods in real-world contexts [9, 10]. These are the most common types of operations that fall under the category of practical application. Effective management of cumulative data statistics and data analysis with a specific goal are examples of these types of operations.

Users of an intelligent data mining system are required to provide statistical data that is relevant to the information needs of the issue, taking into consideration the many real scenarios. This is necessary for the system to work properly. The source of the data and the method of computation must be able to satisfy the format criteria of the other units for the data statistics to be accurate when they are recorded and utilized in various other units. The capabilities of intelligent data mining technology have increased, and it is now able to better satisfy the requirements of complex data management [11].

Education that focuses on career planning helps to promote entrepreneurial education in higher education by increasing its effectiveness, affinity, and appeal. At the same time, it provides students with a more complete education. In conclusion, it discusses how this education may be used as a defence mechanism against the professional goals of college students [12, 13]. The demands of contemporary data processing technologies are too much for old recommendation systems to handle, especially considering the growing number of consumers. One application of data processing and collection in the context of remote learning is the utilization of virtual reality gesture recognition to provide recommendations for educational resources that may be used in the classroom environment [14]. The influence of user comments on their surroundings, the social platform itself, and content active filtering and recommendation are some of the fundamental user behaviours and social software services that are available on the platform [15]. Conceptual ideas, which are the user's perceptions of the items that are inferred from the usage of label data for free categorization, are utilized to achieve the selection of recommended things. This is performed via the utilization of conceptual concepts. Table I presents the comparison of proposed method with literature studies [16-19].

TABLE I. COMPARISON OF PROPOSED METHOD WITH LITERATURE STUDIES

Work focus	Key Findings	Relevant Literature
Machine Learning in HR	- ML algorithms effectively screen resumes, predict candidate suitability, and reduce bias in hiring. - Predictive models forecast employee performance, identify high-potential individuals, and provide targeted development plans. - ML algorithms predict attrition risks, enabling proactive retention strategies. - Personalized learning paths and skill development recommendations enhance employee growth.	Hong Zhu (2021) [16]
Feature Engineering for HR Analytics	- Feature selection and dimensionality reduction improve model performance and interpretability. - Domain expertise from HR professionals is crucial for effective feature engineering.	Ali Raza, et al., (2022) [17]
Ethical Considerations in HR Tech	- ML models can perpetuate existing biases, leading to unfair outcomes. - Addressing bias and ensuring fairness and transparency is crucial. - Data privacy and security measures are essential to protect employee data.	Andrieux, P., et al. (2024) [18]
Gaps in Existing Employment Management Systems	- Lack of personalization in recommendations. - Data silos and incompatibility across HR systems. - Limited predictive capabilities for future workforce needs and risks. - Potential for bias and unfair outcomes. - Complex and user-unfriendly interfaces.	Negt, P., et al., (2024) [19]
Proposed Solution: ML-Based Intelligent Employment Management System	- Personalized recommendations for career development and skill enhancement. - Data integration and analysis for a holistic view of the workforce. - Predictive analytics for proactive HR decision-making. - Mitigating bias and ensuring fair and equitable outcomes. - User-friendly interfaces for improved accessibility and engagement.	Proposed framework for an employment system

Additionally, the recommendation algorithm of the system creates a collection of synonymous labels in order to gather labels that are similar to one another to use them in definition classification, which is the foundation of label labelling [20]. The user-available resources were subjected to the cluster seepage methodology, which ultimately led to the creation of this selection [21]. There are a significant number of unfinished areas in the process of transferring learning that will be used in information recommendation systems [22, 23]. Before beginning the process of searching for information, it is required to first do an analysis of the information access history records of users, then extract their locations, then label them in accordance with semantic approaches, and finally search for individuals [24, 25].

A. Contribution

The study proposes a novel ML-based employment management system architecture or approach. A unique mix of algorithms, data sources, or feature extraction methods may be used. A suggested system may have benefits over current systems [16-19]. Relevant characteristics may improve employee recruiting, performance assessment, and retention forecasts and classifications. The system may handle massive datasets quicker due to computational efficiency. HR specialists may find the system easier to utilize. The study identifies and extracts key employee data elements for certain activities. This may reveal employee performance, satisfaction, and retention variables. The report might boost industrial use of ML technologies by showing how they solve real-world HR problems.

II. PROPOSED RECOMMENDATION SYSTEM: METHODOLOGY

The proposed model collects and filters the information that the user provides, originating from a variety of sources [26], and then converts the information content into text information. This is the process that is referred to as the content suggestion process. Fig. 1 presents the block diagram of the proposed recommendation model.

Step 1: Remodel the content. The assumption is made that the text information after the content conversion is transformed into vector points of various dimensions of the space vector. Each feature point (i) of the content is therefore turned into vector points (x_i) is content feature point, and y_i is weight. The expression for information content $I(i)$ is

$$I(i) = \{x_1 : y_1; x_2 : y_2; \dots ; x_i : y_i\}$$

The feature points of the information are represented by vectors:

$$I(i) = \{y_1, y_2, y_3, \dots y_i\}$$

Step 2. An analysis is performed to determine the feature index (F_i) as well as the similarity connection between the content feature points. The many users each have their own unique preference models, and the statement may be stated as,

$$S(i) = \frac{\sum_i F_i I(i)}{F_i}$$

Step 3: Determine the degree of resemblance between each of the content's three points of similarity is written as,

$$\sin(S, I) = \cos(\vec{S}, \vec{I}) = \frac{\vec{S}, \vec{I}}{|\vec{S}| \times |\vec{I}|}$$

The three points of similarity is often computed for features like, Job Satisfaction, Job Security (Both the Employment Intention Index (EII) and the proposed Employment Management System emphasize the importance of job satisfaction in predicting employee retention), Career Advancement Opportunities (Both EII and proposed system recognize the significance of career advancement opportunities in influencing employee retention and job satisfaction) and Work-Life Balance (Both EII and proposed system) acknowledge the impact of work-life balance on employee retention, job satisfaction, and overall well-being.

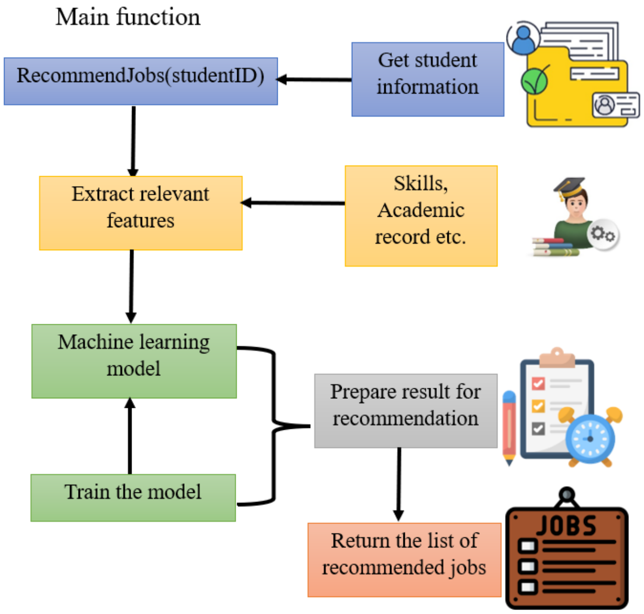

Fig. 1. Block diagram of the proposed recommendation model.

Step 4: The outcomes of the information suggestion should be generated. Users are provided with recommendations based on the information that is integrated and has the greatest similarity. The construction of the information distribution model is done in order to accomplish the mission of providing college students with information recommendations for career planning, employment, and entrepreneurial endeavors. Personal information should be collected from educational institutions, and data sequences of information characteristics should be produced such that

$$x = \{x_1, x_2, x_3, \dots, x_i\}$$

Step 5: Integrate the characteristic points of the personal information of the students, which is to say, the expression of the characteristic quantity of the learning model is written as

$$C(i) = \frac{x_i}{\sum_i F_i y_i}$$

Step 6: Compute the sample model (M) of the characteristic points of the personal information of college students such that

$$M = \frac{kC(i)}{q \sum_i x_i y_i}$$

The index of employment intention is denoted by q in the information feature point sampling model, while the quantity of employment information is denoted by k.

Step 7: Calculate the final feature point value Students in higher education develop their own career goals based on their majors and the interests they have outside of school and then combine these aspects. In the context of college students' career planning and job information referral, the learning model (C) describes $C = Min\{\max(C_i)\}$.

The following is an example of the self-adaptive sampling model that divides the group size of college students into distinct professional sectors from one another such that

$$M = C[1 - C(i)]^{k-1}$$

To search the employment requirements and interest feature points of colleges, the deep learning approach is used, and the final feature point value $(\mathcal{M})$ is written as

$$\mathcal{M} = \sum_0^{\infty} \left[\frac{1 - C(i)}{M}\right]^k$$

B. *Pseudocode for the Proposed System*

Function: RecommendJobs(studentId)

// This function recommends jobs to a student based on their profile and machine learning model

Function RecommendJobs(studentId)

// Input: studentId *(unique identifier for a student)*

// Output: List of recommended jobs *(job IDs or descriptions)*

1. Get student data

studentData = GetStudentData(studentId)

// Call to StudentData class *(refer to previous explanation)*

2. Extract relevant features (e.g., skills, academic record)

skills = ExtractSkills(studentData)

experience = ExtractExperience(studentData)

majors = ExtractMajors(studentData)

3. Load pre-trained machine learning model

model = LoadModel("JobRecommendationModel.pkl")

// Replace with actual model loading method

4. Prepare data for prediction

preparedData = PrepareDataForModel(skills, experience, majors)

// Feature engineering

5. Make prediction using the model

predictedJobIDs = model.predict(preparedData)

6. Retrieve details of recommended jobs

recommendedJobs = GetJobDetails(predictedJobIDs)

// Call to EmploymentData class

7. Return the list of recommended jobs

return recommendedJobs

End Function

The above pseudocode is an example of a recommendation system that has been streamlined according to following steps:

1) The student ID serves as the foundation for the collection of information about the students.

2) The data on the students are taken into consideration, and from the information that is accessible, significant aspects such as the student's skills, experiences, and majors are extracted.

3) It loads a machine learning model that has previously been trained and is used for job recommendation.

4) The gathered attributes are then formatted for the model.

5) The student profile serves as the foundation upon which the model bases its ability to generate predictions for relevant job IDs.

6) This step involves retrieving information about the task from the database by using the required IDs.

7) As a last step, the function gives the learner a list of potential careers that are recommended for them to pursue.

C. Data Preparation

1) Collect pertinent information from a variety of human resource management (HRM) systems, such as learning management, performance management, and employee recruiting.

2) Inconsistencies, outliers (which may be eliminated or adjusted), and missing numbers (imputation) are all things that need to be addressed during the data cleaning process.

3) Scale numerical attributes to a common range, such as between 0 and 1, or with zero mean and unit variance, as part of the process of normalizing and standardizing the data. This is an example of a data transformation.

4) The dataset should be divided into three parts: one for training, one for validation, and one for training and testing. Listed below is the distribution of the available resources: 70% will be allocated for teaching, 15% will be used for validation, and 15% will be used for testing.

D. Feature Engineering

We performed a correlation research is to identify the characteristics that have a strong relationship with the variable that is being studied (for example, employee performance or turnover).

E. Training the Model

1) Make use of the chosen training data in order to train the model that was made selection.

2) Monitor how far along the training process you are: There are a number of measures that have to be monitored, including the accuracy, precision, F1-score, and feature index value.

F. Parameter Tuning

During the process of optimization, the learning rate is responsible for regulating the step size. Parameter tuning is the process of modifying the parameter. When it comes to machine learning networks, the design complexity of the neural network is determined by the number of hidden layers and neurons that constitute the network.

III. The Database Acquisition System: Capturing Student ID

The design of this system's network topology is comprised of three distinct services: the database service, the cluster management service, and the business management service. These services are not connected. The architecture must be broken down into these three different elements to function properly. Among the many examples of online firm management services, one example is website platforms that provide customers with a data collection system. This service may be used by commercial enterprises. The acquisition system can't perform its functions correctly if it does not gather the cluster management service, which is an essential component of the big data service. Assisting the data carrier that is included in the acquisition system is one of the functions that the database service is responsible for [18–20].

Since the platform provides services which are delivered via the external network, the platform needs to have a firewall in order to guarantee that users may access the system without risk. A multitude of subsystems that are quite similar to one another are what make up the business management service. Some examples of these subsystems are the portal, data gathering, task scheduling, visualization, and many more. To guarantee that data transfer between web servers is continuous, the creation of routing between subsystems is essential. For this reason, it is of the utmost importance to maintain continual connections between subsystems. Data collection from this vast data cluster and the maintenance of correct access among the machines that comprise the cluster are both obligations that fall within the purview of the acquisition system. It is the purpose of the acquisition system to ensure that this occurs. At this point, it is of the utmost importance that you provide the Web service access to the cluster for it to be able to get data that is stored inside the cluster.

Following the hierarchical architecture, the overall design of the system is composed of three levels: one level is dedicated to visual configuration, another level is dedicated to aggregation processing, and the third level is dedicated to storage. The acquisition and processing layer is the most important component of the system since it is the one that is responsible for actually gathering data in line with the acquisition technique that has been defined. Together, the term "storage" refers to both the end destination of the data as well as the initial method that was used to obtain it. In addition to that, it offers the capability of caching services. The visually configured layer, which is directly user-oriented, is responsible for carrying out all of the interactions that take place between the user and the acquisition system. On the browser side of the interface, the user can configure the components of the collection that are responsible for processing, terminal, and source. Additionally, the user can construct their collecting technique, which is an additional benefit.

The functions of managing processes such as data collection and the actual transactions that make use of it are the responsibility of the layer that is responsible for acquisition and processing. The collection may be carried out by the information on the workflow setup after the procedure of acquiring the data has been completed once and for all.

IV. Analysis of Results

The data set was selected from the time series categorization collection at UC Riverside [27]. Following the tagging of the time series included within each dataset, the datasets are then divided into training and test sets, each of which is characterized by a distinct scale. Table II summarizes the dataset description. A summary of the properties of the dataset may be seen in the table that I have provided below. This system intends to offer intelligent management by using the same workflow architecture that is used in automated offices. The use of data-gathering techniques contributes to the development of the employer's assessment system as well as the enhancement of the school's administrative capabilities. Therefore, students have the opportunity to make use of the findings of the assessment to get a more thorough knowledge of the company, which provides them with other references to choose the firm.

TABLE II. Dataset Description

Title	Description
Number of records	10,000
Number of attributes	15
Data Sources	Time Series Categorization Collection, UC Riverside [27]
Data Type	Time Series, Categorical, Numerical
Time Period	2010-2020
Sampling Frequency	Monthly
Missing Values	2%
Imbalanced Data	Yes (70% majority class, 30% minority class)
Relevant Features	Job Title, Industry, Location, Experience, Salary

For this investigation, we have used scientific approaches to classify, analyze, and evaluate the data that was gathered from a particular socioeconomic event. The investigation of the dependability and quality of this data is one of the methods that is considered to be of crucial importance. An evaluation of the dependability of the information must be carried out first.

A. *Correlation Analysis*

The correlation analysis method is used to investigate the structural validity of the scale. This is done to ensure that the scale is accurate. This indicates that the validity of the scale is evaluated based on the correlation that exists between the several components that comprise the scale, as well as the correlation that exists between each factor and the total score of the scale. The statistical indicators of the scale correspond with these results, which are congruent with them.

In the correlation results shown in Fig. 2-4, the relationship between employee intention index (q) and feature index (F_i) depends on the specific context of the feature being measured.

1) Positive correlation: If the feature index measures aspects that contribute to employee satisfaction, like work-life balance, compensation, or career development opportunities, then a higher FI might correlate with a higher Emplyment Intention Index (EII) (positive intention to stay). If the feature index measures the alignment between employee skills and job requirements, then a higher FI could indicate a better fit and potentially a higher EII (intention to stay and contribute).

2) Negative correlation: If the feature index measures factors that contribute to employee stress, like long working hours, heavy workload, or lack of resources, then a higher FI might correlate with a lower EII (intention to leave).

3) Neutral relationship: If the feature index measures aspects unrelated to employee retention, like office layout or color scheme, then there might not be a significant correlation with EII.

The specific interpretation of the relationship depends heavily on what the feature index represents. Statistical analysis of employee data with both EII and FI measurements would be necessary to determine the exact nature of the relationship (positive, negative, or neutral). Fig. 2-4 represents the positive, neutral and negative correlation graphs respectively.

Following the completion of the quality standards, we are now in a position to investigate how college students engage in entrepreneurship education. There is a link between the accuracy and feature point value in the subject matter of prediction of the recommendation, as seen in Fig. 5. When the facts are taken into consideration, it would seem that the current notion of entrepreneurship education has to be broadened significantly. A little less than ten per cent of the student population has a genuine interest in gaining knowledge about how to manage a business. In a different way of putting it, a sizeable proportion of students are enthralled by the idea of entrepreneurship education; they are just interested in it. There is a favorable correlation between the length of time that students spend receiving instruction on the subject of entrepreneurship and the level of excitement that they have for learning about entrepreneurship as shown in Fig. 6. At the same time, students who have a greater interest in completing degrees have been receiving more consistent instruction in the field of entrepreneurship. There is evidence to imply that educational institutions such as universities and colleges have not been successful in sufficiently promoting the concept of entrepreneurial education.

Table III presents accuracy results. The Employment Intention Index (EII) is strongly correlated with work happiness, employment stability, and career progression, according to correlation study. This reveals that contented, secure, and advancement-oriented individuals are more inclined to remain with their present employment. EII may be linked to work-life balance since balanced workers are more likely to have long-term career objectives. The feature correlation results are presented in Table IV-VI. The two variables are linked, although not as much as the other categories. This study might assist create an intelligent human resource management system that emphasizes employee retention-related traits.

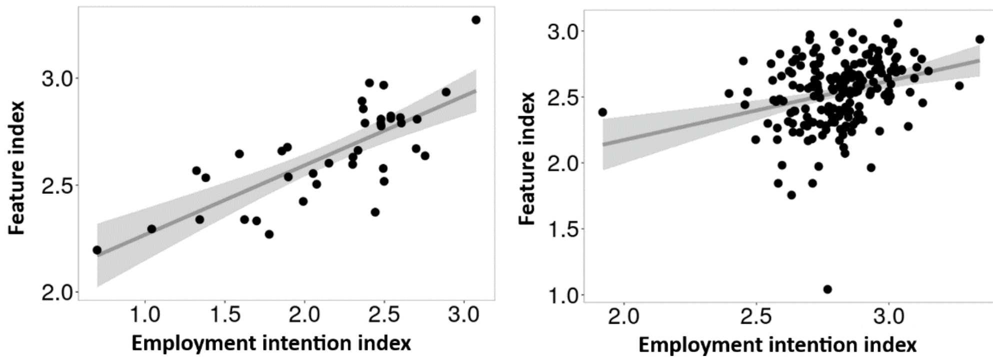

Fig. 2. Analysis with positive correlation: (a) Sample size 150. (b) Sample size 50.

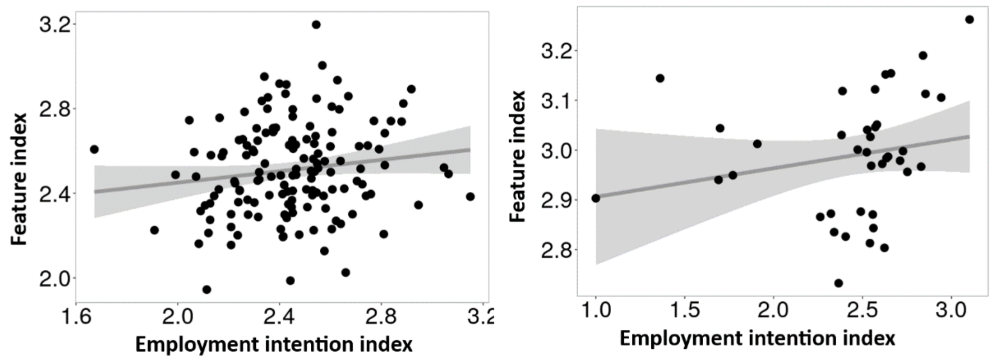

Fig. 3. Analysis with neutral correlation: (a) Sample size 150. (b) Sample size 50.

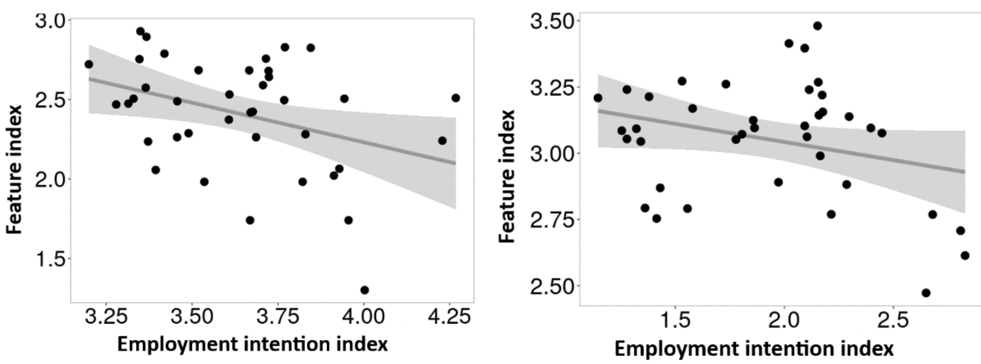

Fig. 4. Analysis with negative correlation: (a) Sample size 150. (b) Sample size 50.

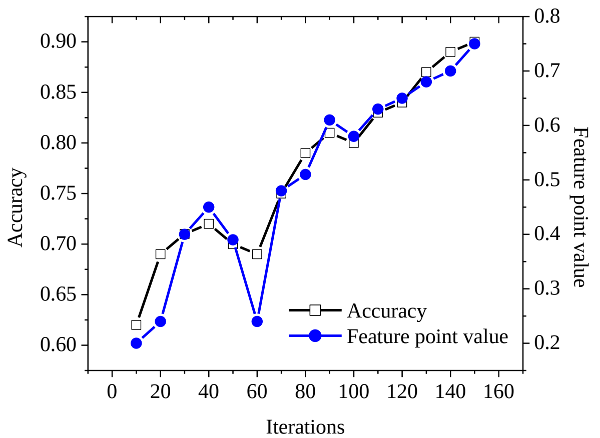

Fig. 5. Plot between accuracy (%) and feature point value for multiple iterations using the recommendation algorithm.

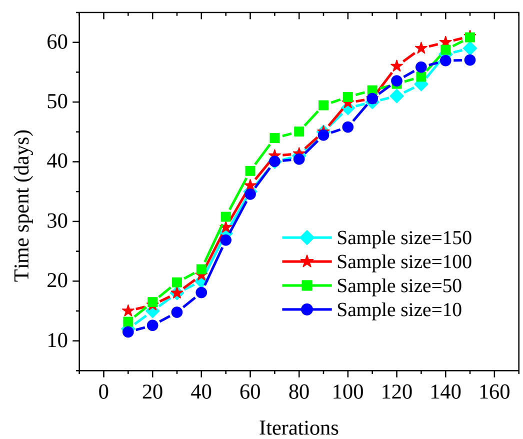

Fig. 6. Time spent for different sample sizes and iterations.

TABLE III. ACCURACY RESULTS

Feature	Accuracy	Precision	Recall	F1-Score	Feature index
Job Satisfaction	0.85	0.83	0.87	0.85	0.23
Job Security	0.82	0.81	0.83	0.82	0.21
Career Advancement	0.88	0.86	0.90	0.88	0.18
Work-Life Balance	0.85	0.84	0.86	0.85	0.15

TABLE IV. FEATURE CORRELATION RESULTS

Correlation results	Job Satisfaction	Job Security	Career Advancement	Work-Life Balance
Job Satisfaction	1.00	0.85	0.78	0.69
Job Security	0.85	1.00	0.83	0.73
Career Advancement	0.78	0.83	1.00	0.81
Work-Life Balance	0.69	0.73	0.81	1.00

TABLE V. CORRELATION ANALYSIS RESULTS

Correlation results	Correlation coefficient	Standard error	t-value	p-value	Confidence Intervals
Job Satisfaction	0.43	0.08	5.38	<0.001	(0.28, 0.58)
Job Security	0.31	0.09	3.44	0.001	(0.14, 0.48)
Career Advancement	0.23	0.23	2.30	0.021	(0.04, 0.42)
Work-Life Balance	0.29	0.20	3.32	<0.001	(0.16, 0.51)

TABLE VI. FEATURE BASED CORRELATION ANALYSIS RESULTS WITH CONFIDENCE INTERVALS

Correlation results	Job Satisfaction	Job Security	Career Advancement	Work-Life Balance
Job Satisfaction	1	0.85(0.79,0.90)	0.78 (0.72, 0.84)	0.69 (0.63, 0.75)
Job Security	0.85 (0.79, 0.90)	1	0.83 (0.77, 0.88)	0.73 (0.67, 0.79)
Career Advancement	0.78 (0.72, 0.84)	0.83 (0.77, 0.88)	1	0.81 (0.75, 0.86)
Work-Life Balance	0.69 (0.63, 0.75)	0.73 (0.67, 0.79)	0.81 (0.75, 0.86)	1

B. *Computational Complexity and Time Complexity*

By considering the algorithmic factors and implementing appropriate strategies the computational complexity of the proposed ML-based employment management systems is presented in Table VII.

Table VIII presents the time complexity results. Fig. 6 illustrates the amount of time that was allotted for the various sample sizes and iterations. The temporal complexity of the method for machine learning is linear with respect to the number of iterations and the size of the sample. Based on this, it seems that the approach can be expanded to accommodate bigger datasets; however, it may need a substantial amount of processing resources when applied to really large datasets.

The lack of excitement that college students often exhibit when it comes to beginning their enterprises is only one of the numerous factors that contribute to this unfortunate circumstance.

TABLE VII. COMPUTATIONAL COMPLEXITY OF PROPOSED ML-BASED EMPLOYMENT MANAGEMENT SYSTEM

S. no	Computation	Complexity	Details
1.	Data Cleaning	$O(n)$	n is the number of documents (job descriptions)
2.	Data Transformation	$O(n)$	n is the number of documents (job descriptions)
3.	Feature Engineering	$O(n \times d)$	n is the number of documents (job descriptions) and d is the average document length.
4.	Feature Selection	$O(n \times d^2)$	We use, correlation analysis where, n is the number of documents (job descriptions) and d is the average document length.
5.	Model Training	$O(n \times d^2)$ *or* $O(d^3)$	This is for training complexity.
6.	Parameter tuning	O(n)	Most common metrics (accuracy, precision, recall, F1-score) have linear complexity

TABLE VIII. TIME COMPLEXITY RESULTS

Iterations	Time Spent	Training and testing time	Sample size complexity	Iteration complexity
50	0.05	The training time increases linearly with the sample size and number of iterations. The testing time is relatively constant, with a slight increase for larger sample sizes.	$O(n)$ The sample size complexity is O(n), where n is the sample size.	$O(n)$ The iteration complexity is O(n), where n is the number of iterations.
60	0.25			
70	0.50			
80	0.25			
90	1.25			
100	2.50			
110	0.50			
120	2.50			
130	5.00			
140	2.50			
150	12.50			
160	25.00			

In conclusion, the majority of college students do not need an education in entrepreneurship because they do not have a strong sense of purpose, they do not have a strong sense of self-awareness, and they do not believe that having a thorough understanding of one's work is sufficient to manage the problems that they would experience while doing it. For the reasons that were discussed before, they are excluded from the requirement that they get an education in entrepreneurship.

V. DISCUSSION

There is a lack of clarity on the ultimate purpose of incorporating entrepreneurship courses in colleges, which ultimately results in a curriculum that is not relevant to the lives of the students. To fulfil the ever-evolving requirements of students, college entrepreneurship programs had to modify their entrepreneurial curriculum. In addition, these programs must cultivate an entrepreneurial attitude, excitement, and the ability to solve challenges that are encountered in the real world. Because of this, students will be able to develop into well-rounded businesspeople who possess strong character attributes. Additionally, the education curriculum of college and university entrepreneurship programs has failed to address the present mental health of entrepreneurs and the entrepreneurial spirit among today's students. This is a problem since these programs are designed to teach students about entrepreneurship. According to the data, college students who are not yet prepared to deal with the challenges of entrepreneurship are afraid of failing terribly in entrepreneurial endeavors. Many people give up on their dreams of being entrepreneurs because they just do not have the financial means to deal with the challenges and failures that they are certain to encounter. This psychological condition affects the perspectives and attitudes that college students have about business, namely entrepreneurship.

The current state of the labor market is so terrible that more than thirty-one per cent of students who are contemplating starting their own company are doing it as a last choice. Students who are motivated in this manner often strive to establish their firms as rapidly as they can in the expectation of achieving substantial financial gains. In the course of their entrepreneurial endeavors, people may find themselves in a state of confusion when they face obstacles and adverse conditions. Furthermore, according to the findings of a separate poll, more than eighty per cent of students are dissatisfied with the way lessons on entrepreneurship are currently being taught in schools. According to these students, the existing curriculum for entrepreneurship teaches students a great deal of theory but does not evaluate any actual business problems. In contrast, research conducted on student expectations about the growth of entrepreneurship education revealed that more than eighty percent of students had the desire that their school would provide a basis for entrepreneurial activity and provide them with a multitude of possibilities to put what they learn into practice. According to the findings, there is an immediate need to improve the practical teaching system of entrepreneurship education for students who are enrolled in college. In order to offer college students with advice and assistance throughout the process of establishing their own firms, the content of education that is included into entrepreneurship education should be correctly represented in real-world teaching situations [28].

The expansion of entrepreneurial education seems to have any impact on their ambitions for their future careers, according to their subjective perspective. This concept is the outcome of a mixture of many psychological factors that have come together. The education programs generally do not provide a sufficient amount of content and information about business. It is essential to do an analysis of this likelihood. Additionally, the two most common types of education when it comes to entrepreneurship are theoretical education and practical education. In order for students to have a significant influence on their future efforts in entrepreneurship, there must be a sufficient quantity of hands-on experiences [29-31]. This is necessary for entrepreneurship education to have a meaningful impact. The majority of students believe that education in entrepreneurship does not provide much in the way of development for their own personal growth.

Due to the fact that the education that is provided by educational institutions has not been able to successfully integrate theory and practice, and has not fully utilized the complementary role that entrepreneurship education plays, the majority of students have a negative view of entrepreneurship education. The development of these traits may be accomplished via the careful application of creative skill and imaginative thought. Two of these qualities include thinking that is inclusive and thinking with a focus on the broader picture. Within the realm of entrepreneurship education, there is no doubt that this is the path that will be taken in the future. To summarize, the realm of education should not be the only purview of classroom teaching; rather, theory and practice should collaborate in order to guarantee that this area is able to play the most important role possible.

VI. Conclusion

This paper aims to highlight need for entrepreneurial education to be integrated with education curricula. Up until now, very few people have looked at how entrepreneurial education has developed over time. When thinking about entrepreneurial education, it's important to take into account both internal and external factors. Afterwards, three nearby universities were surveyed for quality assurance purposes, and the findings showed that college students do not fully understand the entrepreneurial classes they take. Incorporating entrepreneurial education into students' thoughts requires drawing on the inclusive and thought-directing qualities of entrepreneurial education. But that isn't all. Some gaps remain. Inadequate theoretical comprehension raises the possibility that views may become somewhat biased. Consequently, it's likely that the study's results aren't comprehensive enough to gain broader recognition of the integration of entrepreneurial education for college students. What's more, there's a need for more research into potential methods to improve both ideological and political education and entrepreneurship education. This leads to an inadequate understanding of the current state of entrepreneurship education in higher education and an inadequate level of analysis. Eventually, more college students will embrace entrepreneurship education as a result of improvements in both content and delivery. The goal of this essay is to look at the practical significance of improving the entrepreneurial education system for college students. This will help produce more high-quality college graduates and increase their chances of finding work after graduation.

HR data may expose biases in hiring, promotions, and other HR decisions. If machine learning models are trained on biased data, they will undoubtedly perpetuate these prejudices. If previous data shows that males are promoted more than females, the model may unfairly favor men in future promotions. The figures may not represent the whole workforce, leading to biased conclusions. If the data is derived from high-performing people, the system may mispredict lower-performing personnel. Methodological flaws in data collection may cause bias. For example, reviewers' biases might influence subjective performance assessments.

Model training and maintenance may need a significant amount of processing resources for big datasets and considerable feature engineering. Deep neural networks may be difficult to grasp. This lack of transparency makes it difficult to explain model decisions and identify biases.

Real-time data streams may be integrated by combining learning platforms, communication tools (email and chat), and staff performance tracking systems. This helps to deliver up-to-date information and personalized guidance. Streaming algorithms examine real-time data and provide timely alerts or actions in order to build real-time prediction models. These models may identify employees who need assistance or who are at risk of leaving. Machine learning for evaluating candidate data, such as social media profiles and applications, has the potential to enhance recruitment technology by enhancing hiring, job suitability, and culture fit. Within the firm, this strategy may help you find mentors, partners, and knowledge networks. Internal employee contacts may be the focus of a future social network research.

Acknowledgments

1) Funding project: 2024 Scientific Research Planning Project of the Education Department of Jilin Province (JJKH20240212JY).

Project name: Research on the obstacles, systems and paths for college students in Jilin Province to stay for employment.

2) Funding project: Research Plan on Huang Yanpei's Vocational Education Thoughts (ZJS2024YB041).

Project name: Strategy Study on Enhancing College Students' Vocational Literacy from the Perspective of Huang Yanpei's Educating People Concept.

3) Funding project: 2024 Higher Education Research Project of Jilin Province (JGJX24C127).

Project name: Research on the integration of mental health education in vocational colleges (middle school, high school, and undergraduate) in Jilin Province.

References

[1] F.Y. Zhang. Thinking on The Information Construction and Standardized Management of University Construction Engineering Archives. Acta Informatica Malaysia. 2023; 7(2): 105-107.

[2] G.M. MD. N. Rabbani, A. Nath, M. H. Emon. Challenges and Opportunities in The Implementation of Big Data Analytics in Management Information Systems in Bangladesh. Acta Informatica Malaysia. 2023; 7(2): 122-130.

[3] F. Sheng. Design and implementation of internship management system based on Web. Journal of Hunan City University (NATURAL SCIENCE EDITION, 2016 (05).

[4] Yirui Song. Optimization of Quantitative Research Methods in Social Sciences in the Era of Big Data. Acta Informatica Malaysia. 2023; 7(2): 92-96. http//:doi.org/ 10.26480/aim.02.2023.92.96

[5] Hu Wenhong, sun Xinxin. Application of data mining technology based on time series in urban waterlogging disaster. Science and Technology Bulletin, 2016,32 (06): 229-231.

[6] Wang Shuxia, Xiong Zenggang. Research on dangerous web data mining technology under massive data interference. Microelectronics and computer, 2016 (02): 87-91.

[7] Xu Kun. Application and development of information management system. Digital communication world, 2018 (05).

[8] Li Yong, Zhang Min, Liu Hao, et al. Research on the current situation and trend of data mining and applied statistics -- academic summary of the 8th annual meeting of the International Association of Data Mining and Applied Statistics. Friends of accounting, 2016 (22): 24-26.

[9] Li Yong, Zhu Jianping, Yang Yunfeng. Theory and Application Research of excellent data sharing statistics: summary of the 8th International Conference on data mining and applied statistics. China Statistics, 2016 (08): 22-25.

[10] Tang Yongfeng. Research on the development of smart grid big data technology. Computer knowledge and technology: academic exchange, 2017, 013 (031): 242-243.

[11] Deng Song, Yue Dong, Zhu Lipeng, et al. Technical framework for intelligent and efficient analysis and mining of power big data. Journal of electronic measurement and instrument, 2016,30 (11): 1679-1686.

[12] Yang Lian Bao, Li Ping, Xu GUI Hong, et al. Research on railway safety management based on big data technology. Railway computer application, 2016 (9): 83-87.

[13] Hu Lijuan, Diao Yinglong, Liu Keji, et al. Reliability analysis of distribution network operation based on big data technology. Power grid technology, 2017 (01): 265-271.

[14] Ren Kai, Deng Wu, Yu Yan. Research on Weblog analysis system based on big data technology. Modern electronic technology, 2016, 39 (02): 39-41.

[15] Zhao Rui. Research on intelligent supply chain model of business big data technology in industry 4.0 era. Business Economics Research, 2018.

[16] Hong Zhu, Research on Human Resource Recommendation Algorithm Based on Machine Learning, Scientific Programming, 2021, https://doi.org/10.1155/2021/8387277.

[17] Ali Raza, et al., Predicting Employee Attrition Using Machine Learning Approaches, Appl. Sci. 2022, 12(13), 6424; https://doi.org/10.3390/app12136424.

[18] Andrieux, P., Johnson, R. D., Sarabadani, J., & Van Slyke, C. (2024). Ethical considerations of generative AI-enabled human resource management. Organizational Dynamics, 53(1), 101032.

[19] Negt, P., Haunschild, A. Exploring the gap between research and practice in human resource management (HRM): a scoping review and agenda for future research. Manag Rev Q (2024). https://doi.org/10.1007/s11301-023-00397-7

[20] Gao Xia, Wu Tao, Gao yueren. Filling and classification algorithm of e-government big data system in cloud computing environment. Electronic Design Engineering, 2020, V.28; no.445 (23): 79-85.

[21] Xiong Wen. Research on Key T echnologies of benchmark test and performance optimization of big data system. 2017.

[22] Xiong Jun, Xia yuan, Yang Yong, et al. Laser active avoidance flight object system based on CCD image intelligent analysis. Infrared and laser engineering, 2016, 45 (0z1): 65-70.

[23] Zeng Yitang, Zhang Yufeng. Research on the application platform of logistics information intelligent analysis based on cloud mining. China circulation economy, 2016, v.30; no.256 (01): 31-36.

[24] Zhang Yufeng, Zeng Yitang. Research on intelligent analysis method of logistics information based on cloud clustering mining. Information work, 2016, No.208 (01): 44-49.

[25] Ju Gengen, Sun Jieping, Chen Li, et al. Design framework of intelligent analysis platform for computer network virtual experiment under big data. Laboratory research and exploration, 2017, v.36; no.262 (12): 113-115.

[26] L. Liu, "Learning information recommendation based on text vector model and support vector machine," Journal of Intelligent and Fuzzy Systems, vol. 40, no. 2, pp. 2445–2455, 2021.

[27] https://www.cs.ucr.edu/~eamonn/time_series_data/

[28] P. Xu, "A probe into the construction of online and offline mixed courses of college students' career planning under the background of first-class curriculum construction," International Journal of Social Science and Education Research, vol. 4, no. 5, pp. 233–239, 2021.

[29] M. Lee and S. Oh, "An information recommendation technique based on influence and activeness of users in social networks," Applied Sciences, vol. 11, no. 6, p. 2530, 2021.

[30] M. Bartkowiak and A. Rutkowska, "Vague expert information/ recommendation in portfolio optimization-an empirical study," Axioms, vol. 9, no. 2, p. 38, 2020.

[31] C. Zhou, J. Shen, Y. Wang, and X. Guo, "Battlefield situation information recommendation based on recall-ranking," Intelligent Automation & Soft Computing, vol. 26, no. 4, pp. 1429–1440, 2020.