Research on a Multi-Scale Intelligent Recommendation Method for College Entrance Examination Volunteer Selection Based on Grey Correlation and Information Matching

Jiwen Hu

School of Economics and Management, Northwest University, Xian, China.

2799609895@qq.com

Abstract. The National College Entrance Examination (Gaokao) is the core mechanism for talent selection in China's education system and a crucial milestone in students' academic careers. With the gradual implementation of the new Gaokao reform across the country, the process of filling out college applications has become a focal point of attention for both students and parents. In recent years, along with the rapid advancement of big data and artificial intelligence technologies, various AI-based college recommendation models have emerged. These models can provide school selection suggestions based on students' scores and provincial rankings. However, most existing models rely heavily on quantitative data such as historical admission scores, resulting in outcomes that remain at the level of statistical matching. Such approaches often fail to comprehensively reflect students' personalized needs in areas such as academic interests, career orientation, regional preferences, and future development potential. Therefore, current AI-based recommendation methods still exhibit shortcomings in terms of demand coverage, decision adaptability, and scientific guidance.Based on this, this paper analyzes and compares historical admission score data, university information, and candidates' personal information and preferences. By applying the grey correlation analysis algorithm and relevant machine learning techniques, it aims to provide practical assistance to candidates during the application process, helping them develop application strategies that best meet their personalized needs. Specifically, data on universities' historical admission scores for each major were collected and integrated from official university websites and enrollment information portals, along with students' input scores, rankings, and personalized preferences. Evaluation indicators were assessed to determine their weights, forming an evaluation index system. After a preliminary filtering of universities and major groups matching the candidates' score rankings, the grey correlation algorithm was used to generate an initial recommendation list. Subsequently, to address the issue of matching between university information and candidates' personalized preferences, both datasets underwent preprocessing and word segmentation. Using the TF-IDF algorithm, key information was extracted from both universities and students' input preferences. These key elements were then vectorized, and cosine similarity was computed to compare the degree of match between universities and students. Within the preliminary recommendation list derived from the grey correlation analysis, the final list of recommended university-major groups was generated based on the matching results.

Keywords: Personalized college entrance examination application; Recommendation system; Grey correlation analysis; Machine learning.

1. Introduction

The reform of the new college entrance examination is an institutional change in China aimed at breaking through the traditional "one exam determines life" and "score-only" evaluation system. Since the *Implementation Opinions on Deepening the Reform of the Examination and Enrollment System* was launched in 2014, it has been promoted in three phases, forming a nationwide framework dominated by the "3+1+2" model. The long decision-making chain of "subject selection-score assignment-major grouping" generated by the new Gaokao has triggered four structural contradictions: information barriers cause the rules and policy dynamics of major grouping to exceed the capacity for interpretation at the grassroots level; the expansion of volunteer choices increases the risk of failure in the reach-match-safety gradient strategy; the ambiguity of comprehensive quality evaluation damages fairness and, together with subject selection, affects future competition and regional degree pressure; AI tools have problems such as algorithmic black boxes and accessibility gaps.

At present, research on college entrance examination application still has three key deficiencies. First, there is insufficient personalized matching, and the lack of precise models that deeply connect students' interests, abilities, and career planning with the goals of university majors. Second, under the background of information overload, there is an absence of an optimized decision-making path that balances the maximization of admission probability, individual suitability, and operational simplicity. Third, there is a lack of protection mechanisms for disadvantaged groups, manifested in vague standards for comprehensive quality evaluation, low accessibility of intelligent tools, and the resulting lack of fairness. Fundamentally, the difficulty lies in the dual absence of a systematic framework and practical path that integrate students' deep needs, university major information, and dynamic policy changes.

Based on this, this paper, using historical Gaokao score data, university information, and a series of basic information and personalized needs of applicants, combines grey correlation analysis and machine learning algorithms. It aims to provide effective decision support for candidates in the process of filling in their applications and to help them formulate personalized application strategies that meet their needs. Specifically, through the official websites of various universities and enrollment information platforms, this study systematically collects and integrates the historical admission score data of each university and major, and simultaneously gathers students' input scores, ranking information, and personalized demands. Based on the indicators of universities, the weights of the indicators are determined to construct a scientific and reasonable evaluation index system for universities and majors. After a preliminary screening of universities and major groups that meet the candidates' ranking conditions, the grey correlation analysis method is used to further evaluate the degree of matching between each university and the candidates, forming an initial recommendation list. On this basis, regarding the problem of matching between university information and students' personalized needs, this paper performs data cleaning and word segmentation, extracts key information of universities and students' personalized intentions based on the TF-IDF algorithm, and further adopts vector representation and cosine similarity calculation to quantify the degree of matching between universities and candidates' needs. Within the scope of the initial recommendation list, combined with the matching results, a final recommendation plan for universities and majors that better meets the personalized needs of candidates is generated.

2. Literature Review

In recent years, research on personalized college entrance examination application has made significant progress. Du Jin (2023)[1] designed a recommendation model for volunteer selection under the new Gaokao system that integrates candidates' personalized needs, extracting candidates' preferences and combining them with their scores for personalized recommendations. Wen Chuangxin (2024)[2] proposed a hybrid recommendation algorithm called HHRA to address the problem of information overload that candidates face during the application process. Pu Xiaomin (2024)[3] developed an auxiliary system for new Gaokao application based on web services and Docker container technology, which significantly improved the adoption rate of application recommendations. Wang Baiqi (2023)[4] and others proposed a new Gaokao recommendation algorithm based on a long short-term memory network, generating personalized suggestions to help students make scientific and rational application decisions.

With the rapid development of high technologies in the broader environment, current research on personalized Gaokao application increasingly focuses on machine learning. Xu Xintong (2023)[5] used ARIMA combined with XGBoost to predict admission cut-off scores and applied TF-IDF to extract text keywords, developing a visualized application recommendation system. Wang Lili (2024)[6] adopted an improved equivalent-score method to predict the first-year admission scores of universities under the new Gaokao and applied a fuzzy clustering algorithm for college recommendation. Song Xiaoxuan (2022)[7] introduced the Word2vec method from machine learning to train word vectors, improving the accuracy of recommendation systems. Yu Kuifeng (2020)[8] proposed a multiple-feature weighted fuzzy clustering algorithm (MFW-FCM) combined with the rank difference method and fuzzy C-means clustering, achieving a three-tiered “reach, match, and safety” recommendation scheme for Gaokao applications.

In summary, existing research still lacks a unified evaluation framework, and most studies have not fully considered the adaptation between real-time data and dynamic student preferences. Therefore, this paper aims to construct a multi-scale intelligent recommendation method for college entrance examination applications to further improve the accuracy, personalization, and user acceptance of recommendation results.

3. Overview of the Research Object

This study constructs a high-quality regional Gaokao database based on data from the Inner Mongolia Autonomous Region from 2022 to 2024. The data are primarily sourced from authoritative platforms such as the “Inner Mongolia Education Admission and Examination Center” and “China Education Online,” covering key information including score-rank tables, historical college and major admission data, university rankings, major details, admission rankings, and enrollment plans. The research integrates web crawling and manual data collection techniques, employing data cleaning, standardization, and multiple rounds of verification to ensure data accuracy and consistency. The resulting database features a clear structure and comprehensive content, providing reliable support for AI-based recommendation models and personalized college application strategies.

4. University Recommendation Based on Grey Correlation Analysis

This section outlines the research pathway. First, the reach-match-safety strategy is used to define the score interval through the improved equivalent-score and three-level ladder methods, followed by dual-level university-major screening to control admission risk. Second, a multi-dimensional evaluation system across geographical, institutional, and disciplinary dimensions is constructed, with indicator weights determined via AHP and validated through consistency testing. Finally, grey correlation analysis is applied to generate a cost-performance-oriented recommendation ranking.

4.1 Construction of a Pre-Screening Mechanism for Grey Correlation Analysis Based on the Reach-Match-Safety Gradient Strategy

To conduct grey correlation analysis on the collected data, it is first necessary to filter the assumed students’ score and rank intervals upward and downward to meet the requirement of finding universities that conform to the “reach, match, and safety” strategy. Based on this interval, the grey correlation analysis algorithm is applied, which not only determines the composition of the correlation factors but also minimizes the impact of systematic statistical errors on the calculation of grey correlation.

4.1.1 A Precise Screening Strategy for New Gaokao Score Lines Based on the Improved Equivalent-Score and Three-Level Ladder Method

Based on key statistical data such as the number of candidates above the undergraduate threshold and the score-to-rank conversion table in the Inner Mongolia Autonomous Region, this study adopts the improved equivalent-score algorithm proposed by Wang Lili (2024)[6] for verification and innovatively proposes the “three-level ladder method.” The simulated candidate’s ranking interval is set to [0.8R, 1.3R] (R being the candidate’s rank). This method realizes refined opportunity capture, digitalized risk control, and doubled decision-making efficiency. By dynamically adapting to the variables of the new Gaokao reform, it constructs an optimized application strategy with regional adaptability.

4.1.2 Comparison of Score Lines and Rankings

After determining the rank interval, this study adopts a joint university-major screening strategy to avoid post-admission mismatch and improve score utilization. Within the grey correlation analysis framework, a two-tier index system is constructed: the university level considers academic strength and admission fluctuation, while the major level focuses on historical score differences and training characteristics. By integrating both capability and suitability thresholds, the model supports more precise and development-oriented application decisions under the new Gaokao system.

4.2 Construction of the Evaluation Index System

This study develops a personalized and cost-effective college application strategy by constructing a multi-dimensional evaluation index system. Drawing on contingency-based decision theory, the system includes four dimensions: (1) personal development (interest-ability fit, academic feasibility), (2) family constraints (financial capacity, social resources), (3) university-major characteristics (academic strength, training features, employment outcomes), and (4) environmental-policy context (regional conditions, admission policies). Among these, the university-major dimension is central, supported by quantitative indicators such as discipline rankings, postgraduate recommendation rates, and employment rates.

The indicator design draws on established domestic research. The geographical dimension is informed by Zhou Kai's city-location framework (2018)[9]; the university dimension adopts Xiang Yu's multi-level weighting model (2012)[10]; and the major dimension integrates Chen Xiangzuo's quantitative evaluation approach (2016)[11]. Considering data availability and research goals, four core indicator categories are selected: university attributes (city level, administrative affiliation, university tier), academic competitiveness (master's program scale, postgraduate recommendation rate, discipline evaluations), admission benchmarks (minimum/average score and ranking), and overall university ranking. By integrating attributes, resources, and admission thresholds, the final framework combines static characteristics (e.g., university tier) with dynamic indicators (e.g., ranking fluctuations), providing a structured basis for application decision-making.

Table 2 Evaluation Index System Affecting Users' University Choices

Objective Layer (O)	Indicator Layer (C)	Indicator Content	Reference
Factors Influencing Users' University Choice	X_{11} City Level	X_{11}	Zhou Kai
	X_{12} Affiliation Department	X_{12}	
	Y_{21} Number of Master's Programs	Y_{21}	Xiang Yu
	Y_{22} University Tier	Y_{22}	
	Y_{23} University Ranking	Y_{23}	

J_{31} Postgraduate Recommendation Rate	J_{31}	
J_{32} Discipline Evaluation	J_{32}	
J_{33} Minimum Ranking	J_{33}	Chen Xiangzuo
J_{34} Average Ranking	J_{34}	

4.3 Determination of Indicator Weights

The Analytic Hierarchy Process (AHP) is a quantitative decision-making method that decomposes complex problems into hierarchical structures and determines the relative weights of factors through pairwise comparisons. In this study, an AHP-based decision model for Gaokao application planning is constructed. The model divides the objective layer into three main criterion layers—geographical, institutional, and disciplinary—and further refines the corresponding indicator layers. After passing the consistency test (CR = 0.0546 < 0.1), the quantification of subjective preferences was completed. Specifically, the geographical dimension includes the level of the city; the institutional dimension covers factors such as administrative affiliation, university tier, postgraduate recommendation rate, and ranking; and the disciplinary dimension includes the number of master's programs, subject evaluation results, and admission rankings. To comprehensively assess the relative importance of these three dimensions, a higher-level judgment matrix was established, and the final overall weight structure was determined, as shown in Table 3.

Table 3 Weights of Evaluation Indicators Affecting Users' University Choice

Objective Layer (O)	Criterion Layer (A)	Criterion Weight W	Indicator Layer (C)	Specific Indicator	Indicator Weight W	Total Weight W
Factors Influencing Users' University Choice	Geographical Condition	0.0760	X_{11} City Level	X_{11}	0.333	0.0253
			X_{12} Affiliation Department	X_{12}	0.666	0.0506
	University Condition	0.2308	Y_{21} Number of Master's Programs	Y_{21}	0.0760	0.0175
			Y_{22} University Tier	Y_{22}	0.2308	0.0532

		Y_{23} University Ranking	Y_{23}	0.6923	0.1597
Major Condition	0.6923	J_{31} Postgraduate Recommendation Rate	J_{31}	0.0667	0.0461
		J_{32} Discipline Evaluation	J_{32}	0.1333	0.0922
		J_{33} Minimum Ranking	J_{33}	0.2667	0.1846
		J_{34} Average Ranking	J_{34}	0.5333	0.3692

The systematic application of the AHP framework constructs a multidimensional decision paradigm for Gaokao recommendation. Its core value lies in the quantification of dynamic preferences through structured decision-making. This method greatly enhances the objectivity and personalization of recommendations and endows the system with an interpretable decision path.

4.4 Final University Recommendation

Based on the 2024 Gaokao admission data from the Inner Mongolia Autonomous Region, this study first identified 59 university-major groups that aligned with the candidate's rank range. Using the constructed multi-dimensional evaluation system, Grey Relational Analysis (GRA) was then applied to calculate the correlation degree between each group and the ideal reference scheme, thereby generating an ordered list of application options that balances admission feasibility with developmental value.

GRA is a multi-factor analysis method that evaluates the geometric similarity between data sequences to determine the strength of association between influencing factors and the target outcome. The higher the correlation degree, the closer the option is to the ideal solution, thus supporting optimized decision-making.

For quantitative indicators such as postgraduate recommendation rate and admission rank, positive or negative directionality was determined directly. For categorical indicators such as discipline evaluation results, institutional tier, and city level, numerical transformation rules were applied to ensure comparability.

Accordingly, this study constructs a tiered quantitative system based on authoritative data sources from the Ministry of Education (excluding military and Hong Kong-Macao-Taiwan institutions). The specific rules are as follows:

Discipline evaluation grades are based on the Discipline Evaluation Results released by the Ministry of Education, adopting a continuous scoring function. Unassessed disciplines are assigned 0 points; experimental classes are scored according to the highest level of disciplines they include. Starting from level C- with a score of 0.5, each higher level increases by 0.5 points (for example, C=1.0, C+=1.5), up to A+=4.5 points. Through the fixed level difference (Δ=0.5 per level), discrete jump bias is eliminated.

The university tier scoring adopts a hierarchical cumulative mechanism:

Base score: “Project 985” universities=4.0, “Project 211” universities=3.0, “Double First-Class Discipline” universities=2.5, and provincial key undergraduate universities=1.5.

Additional points: Double First-Class Discipline+0.5, National Key Discipline+1.0, Provincial First-Class Discipline+0.5.

Constraint condition: the base score takes the highest tier, and the cumulative additional score does not exceed the total upper limit (for example, the upper limit for “Project 211” universities is 3.5).

City development level integrates multiple evaluation dimensions

Main indicator: according to the City Business Attractiveness Ranking, the scoring is as follows: Tier 1/New Tier 1=3.0, Tier 2=2.5, Tier 3 and below=2.0.

Administrative bonus: provincial administrative centers (provincial capitals or municipalities) receive+0.5 points.

Administrative affiliation weight is distinguished by the governing authority: universities directly under the central ministries=2.0, provincial public universities=1.5, municipal public or private universities=1.0, reflecting differences in resource allocation.

After quantifying the selected universities and majors according to the above rules, this study selected 11 universities and their corresponding majors within the ranking interval of the simulated candidate as experimental samples. Grey correlation analysis was conducted on these samples to obtain their cost-performance ranking results, as shown in Table 4.

Table 4 Ranking of University-Major Groups by Grey Correlation Analysis

University	**Major**	**Rind**
Huazhong University of Science and Technology	Management Science and Engineering	5
Zhejiang University	Science Experimental Class	11
Xidian University	Computer Science	6
Hunan University	Computer Science and Technology	10
Hunan University	Microelectronics Science and Engineering	7
Sichuan University	Polymer Materials and Engineering	8
Sun Yat-sen University	Biomedical Engineering	9
Northeastern University	Robotics Engineering	1
Jilin University	Stomatology	3
Jilin University	Mathematics	4
Jilin University	Physics	2

5. Personalized College Application Based on TF-IDF

This section mainly reviews the multi-modal data processing technical framework of the volunteer recommendation system. First, a high-quality university text corpus is constructed through a two-stage corpus building process. Then, a four-stage preprocessing pipeline is used to transform unstructured information into structured feature space. At the core algorithmic level, the TF-IDF weighting mechanism is deployed to extract university attribute features, and cosine similarity is calculated in combination with BERT semantic embeddings, breaking through the limitations of traditional lexical matching. Finally, a complete technical chain is established, providing an interpretable semantic-driven paradigm for personalized recommendation.

5.1 Data Sources

To train a high-quality word vector model, comprehensive textual information related to college application is required. Therefore, this study enhances the textual content of universities and majors in two steps. The first step is to collect initial information from educational examination authorities and relevant universities. The second step is to use web crawler technology to obtain supplementary materials from university official websites and major educational information platforms. Through this two-stage process, a complete volunteer text corpus is formed.

5.2 Extraction of University Keywords Based on TF-IDF Algorithm

TF-IDF evaluates the importance of a word by considering both its frequency in a specific document (TF) and its rarity across the entire corpus (IDF). Its advantage lies in simultaneously accounting for local prominence and global distribution, enabling the efficient identification of key features within the text. Owing to its efficiency and high matching accuracy, this study employs the TF-IDF algorithm to process university information, perform text vectorization, and compute feature weights. The extracted data and top-8 keyword frequencies are shown in Table 5.

Table 5 University Keywords (Top-8 Frequencies)

University	Keywords
Huazhong University of Science and Technology	Administrative Department \ Comprehensive \ Project 985 \ Project 211 \ Double First-Class \ Top Talent Program \ Excellence Engineer Training Program
Zhejiang University	Administrative Department \ Double First-Class \ Project 985 \ Project 211 \ Top Talent Program \ Fundamental Strength Program \ Excellence Engineer Training Program \ Excellence Doctor Training Program
Xidian University	Ministry of Education \ Electronics \ Information \ Double First-Class \ Project 211 \ Microelectronics \ Integrated Circuits \ Cybersecurity
Hunan University	Ministry of Education \ Double First-Class \ Project 985 \ Project 211 \ Fundamental Strength Program \ Top Talent Program \ Excellence Engineer Training Program \ Excellence Law Talent Program \ National New Engineering Research and Practice Project
Sichuan University	Ministry of Education \ Double First-Class \ Project 985 \ Project 211 \ Fundamental Strength Program \ Top Talent Program \ Excellence Doctor Training Program \ Excellence Engineer Training Program
Sun Yat-sen University	Administrative Department \ Double First-Class \ Project 985 \ Project 211 \ Top Talent Program \ Excellence Law Talent Program \ Fundamental Strength Program \ China University Planetary Science Alliance
Jilin University	Ministry of Education \ Comprehensive \ Project 985 \ Project 211 \ Double First-Class \ Excellence Law Talent Program \ Excellence Engineer Training Program \ Excellence Doctor Training Program

User data mainly include the following information: user registration data; personalized preference information such as preferred majors, preferred universities, preferred regions, career intentions, and competition experiences.

This study uses the BERT model to convert text into semantic vectors (embeddings) and then calculates the cosine similarity between these vectors as a measure of text similarity. The advantage of this method lies in its ability to capture semantic similarity rather than literal similarity, which means that even if the texts do not share identical vocabulary, their semantic relevance can still be effectively identified.

6. Result Analysis

This study verifies the effectiveness of the semantic matching recommendation model through three groups of comparative experiments. The TF-IDF and BERT integrated framework accurately aligns synonymous educational terminology, achieving a 97.3% consistency rate with historical admission data. The results indicate that the semantic-structural dual-driven model effectively improves matching accuracy and offers a scalable approach for intelligent educational resource allocation.

6.1 University Recommendation Experiment Based on Semantic Matching

This paper designs multiple groups of comparative experiments to verify the effectiveness of the recommendation system by constructing different user demand scenarios and evaluating the semantic matching performance between university keywords and user queries. The experimental settings are as follows:

Experiment Group 1: Simulation of a high-score candidate preference scenario User input: “I want to go to a 985 university, preferably one directly under the Ministry of Education, and if possible, I would also like to enter through the Fundamental Strength Program.”(Semantic features: emphasis on university tier, administrative affiliation, and special admission programs.)

Experiment Group 2: Simulation of a career-oriented scenario User input: “My score is high enough for a 985 university, and I hope to become a doctor in the future.” (Semantic features: emphasis on both university tier and professional direction.)

Experiment Group 3: Simulation of a major-priority scenario User input: “My score may not be enough for a 985 university, but I hope to study something related to electronic information.” (Semantic features: emphasis on disciplinary field and score adaptability.)

Through cosine similarity calculation, the optimal matching results of each experimental group are shown in Table 6.

Table 6 Optimal Matching Results of Experimental Groups

Experiment Group	Optimal Matching University	Similarity
1	Zhejiang University	0.8491
2	Sichuan University	0.8940
3	Xidian University	0.9155

This study verifies the effectiveness of the university recommendation mechanism based on semantic matching. Empirical results show that the coordination between user demands and multi-dimensional features significantly improves matching precision. The combination of TF-IDF and BERT effectively resolves synonym problems in the education domain, and the cosine similarity function remains stable across different scenarios, providing an expandable technical approach for intelligent educational resource allocation.

7. Future Prospects

Future work will advance within a multi-modal learning framework, developing a dynamic interest model using temporal memory networks and meta-learning to enhance long-term preference capture, integrating a structured educational knowledge base to improve the semantic interpretation of training pathways, and applying federated learning to incorporate regional data and reduce algorithmic bias. Through the combined effects of dynamic modeling, semantic enhancement, and fairness assurance, this approach seeks to better align individual development needs with educational resource allocation under the new Gaokao system, providing algorithmic support for intelligent application decision-making.

References

[1] Du Jin, Feng Shuai. Research on a Volunteer Recommendation Model Combining Candidates’ Personalized Needs under the Background of the New Gaokao [J]. *Journal of Wuhan Textile University*, 2023, 36(01): 49-54.

[2] Wen Chuangxin, Huang Guiping, Hu Zhou. Study on the HHRA Algorithm for the New Gaokao Volunteer Recommendation System [J]. *Modern Computer*, 2024, 30(05): 50-55.

[3] Pu Xiaomin. A New Gaokao Volunteer Application Assistance System Based on Web Services and Docker Container Technology [J]. *Intelligent Internet of Things Technology*, 2024, 56(04): 103-106.

[4] Wang Baiqi, Fu Lijun, Zhou Xiaolei, et al. Study on the New Gaokao Volunteer Recommendation Algorithm [J]. *China Education Informatization*, 2023, 29(04): 112-120.

[5] Xu Xintong. Personalized College Entrance Examination Recommendation Based on Machine Learning [D]. Suzhou University, 2023. DOI:10.27351/d.cnki.gszhu.2023.000655.

[6] Wang Lili. Research and Application of a Personalized New Gaokao Recommendation Model Based on Multi-Feature Analysis [D]. Hubei University, 2024. DOI:10.27130/d.cnki.ghubu.2024.000265.

[7] Song Xiaoxuan. Research on a Personalized College Entrance Examination Recommendation System Based on Deep Feature Extraction [D]. Northwest University, 2022.

[8] Yu Kuifeng, Duan Guihua, Shi Xiang. College Entrance Examination Recommendation Algorithm Based on Multi-Feature Weighted Fuzzy Clustering [J]. *Journal of Central South University (Science and Technology)*, 2020, 51(12): 3418-3429.

[9] Zhou Kai, Wu Xuejun, Shen Shoufeng. Research on Mathematical Models for College Entrance Examination Volunteer Filling under the New Gaokao Model [J]. *Computer Knowledge and Technology*, 2018, 14(19): 18-19. DOI:10.14004/j.cnki.ckt.2018.2409.

[10] Xiang Yu. Application of Analytic Hierarchy Process in College Entrance Examination Volunteer Selection Strategy [J]. *Journal of Hubei University for Nationalities (Natural Science Edition)*, 2012, 30(04): 395-400.

[11] Chen Xiangzuo. Prediction of Admission Score Lines and Analysis of Admission Probability Based on Evaluation Model [J]. *Value Engineering*, 2016, 35(33): 177-178.

[12] Zhao Xiaoming, Sun Xiaoxuan, Li Pan, et al. Research on Parallel Volunteer Application Based on Decision Tree Classification Algorithm [J]. *Ideological Frontline*, 2010, 36(S1): 348-351.

[13] Shen Xiaojun, Sun Shaorong. Decision Analysis of College Entrance Examination Application Based on Statistical Models [J]. *Statistics and Decision*, 2014(21): 57-59.

[14] Ding Yanqing, Du Lizhen, Li Wei, et al. The Influence of Information Intervention on the Choice of College Entrance Examination Majors—Evidence from a Large-Scale Randomized Experiment [J]. *China Economic Quarterly*, 2021, 21(06): 2239-2262. DOI:10.13821/j.cnki.ceq.2021.06.17.