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A Study on the Precision Implementation Path and Effectiveness Evaluation of Ideological and Political Education in Higher Education Based on Big Data

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ABSTRACT The integration of big data technologies provides new opportunities for improving the precision and effectiveness of higher education management. This study proposes a big-data-driven framework for the precise implementation and effectiveness evaluation of ideological and political education in universities. A three-layer architecture consisting of data acquisition, intelligent analysis, and decision support is established, while an evaluation system covering knowledge acquisition, value identification, and behavioral transformation is developed. Through a one-year empirical study involving multiple universities, learning behavior records, participation data, and practical activity outcomes are analyzed using association rule mining, clustering analysis, and propensity score matching. The results reveal distinct student profiles and demonstrate that personalized intervention strategies significantly improve educational effectiveness. The proposed framework contributes to data-driven educational governance and provides methodological references for behavior analysis, information processing, and intelligent decision-support systems.

INDEX TERMS big data analytics, educational effectiveness evaluation, behavior analysis, information processing, intelligent decision support

I. INTRODUCTION

THE advancement of big data technology is fundamentally restructuring the operational logic and decision-making paradigms across all sectors, driving a shift toward the automated precision and high-fidelity monitoring seen in digital textile manufacturing. This evolution enables a move from empirical estimation to the micro-level accuracy of material orientation and structural integrity analysis, ensuring that organizational strategies are as tightly structured and reliable as high-performance technical materials. The education sector, as the primary platform for the development of talents, is also undergoing a giant change from experience-driven to data-driven methodologies. Ideological and political education in universities as an important link in the execution of the fundamental task of fostering moral character and cultivating talent, from the beginning, mainly relies on the subjective experience and uniformized teaching model of educators, which involves a structural contradiction between "extensive supply" and "differentiated needs." On the one hand, the traditional models of education cannot do enough to accurately determine the individual differences of thinking, values, and habit of behaviors among students, and therefore allocate the educational resources ineffectively. On the other hand, in a period of mixed values, the heterogeneity of the ideologies of students is becoming more and more obvious, and it is not easy for the standardized educational content and methods to effectively solve the deep problems of various groups, resulting in the actual effect of ideology and political education not being enough to make it sink into the mind of students. The integration of big data technology to drive the revolution from a "broad-based" to a "precision-based" approach has become the central catalyst for innovative ideological and political education, mirroring the industry's shift toward the micro-level accuracy of smart production. By adopting these data-driven methodologies, universities can ensure educational delivery achieves the same consistent density and defect-free structural integrity found in high-precision technical materials. This paper makes three main contributions: First, we employ unsupervised machine learning to detect 4 typical characteristics of student groups, and design different paths of educational interventions for them, so as to solve the shortcomings in identifying student heterogeneity and designing differentiated strategies in existing researches. Second, it builds an evaluation index system of effectiveness with three dimensions - knowledge acquisition, value identified, and behaviors transformed. A difference in differences model is applied to quantitatively test the effectiveness of precision education provides the differences in benefits among various types of students and can provide empirical evidence for the optimal allocation of educational resources.

The structure of this paper is as follows: First, it reviews the relevant research progress on innovation in ideological and political education in colleges and universities, and clarifies the research positioning of this paper; second, it elaborates on data collection and preprocessing methods, student characteristic modeling and group identification technology, precise path design and matching strategies, and the construction and measurement methods of education effect evaluation indicators; third, it presents the results of student group cluster analysis, the implementation effect of precise education path and the empirical findings on the differences in effect among different types of students, and discusses them; fourth, it summarizes the research conclusions, points out the research limitations and future prospects.

II. RELATED WORK

The innovative research on ideological and political education in colleges and universities is showing a multi-dimensional and in-depth development trend. Han [1] explored how to effectively combine theoretical teaching with practical links to become an innovative method of ideological and political education and enhance its pertinence and attractiveness. Liu et al . [2] combined the analysis of relevant policy documents and curriculum outlines to reveal the daily practice of ideological and political education from a micro level. Yu and Wang [3] explored how ideological and political education in colleges and universities dynamically affects the formation of students' political consciousness and further affects their civic participation behavior in reality and cyberspace, in order to respond to the question of the effectiveness of education in the era. Zhang et al. [4] showed that deep learning technology can effectively assist ideological and political education. By analyzing students' learning behavior data, teachers can be provided with accurate feedback on their learning situation, which can help teachers adjust their teaching strategies and achieve personalized teaching. Li [5] explored how students can transform from passive recipients of education to active participants and constructors, as well as the form, depth and influencing factors of participation.

Zixuan [6] reviewed and found that the application of intelligent media in ideological and political education has become a rapidly developing emerging research field. Liu and He [7] described the distribution and evolution of the research focus of ideological and political education in courses . Zheng [8] explored how to build a college ideological and political education system that adapts to the requirements of the new era in order to improve the accuracy, interactivity and attractiveness of education. Ren et al. [9] found that teaching quality directly affects students' learning satisfaction and also affects the quality of ideological and political education. Rui [10] analyzed the existing evaluation system of ideological and political education for college students and pointed out its defects . In the context of the deep integration of big data technology and ideological and political education, how to accurately identify individual differences among students, scientifically design differentiated implementation paths, and conduct multi-dimensional quantitative evaluation of educational effects are still key issues in existing research. This article aims to make up for the shortcomings of existing research in data-driven decision-making and empirical testing of effects, and provide theoretical basis and practical reference for the transformation of ideological and political education in the new era from experience-based extensive to scientific and precise.

III. METHODS

A. DATA ACQUISITION AND PREPROCESSING

This study has chosen three types of university as a research sample such as a comprehensive university, science and engineering, and normal universities. The research period was of a whole academic year from September 2023 to July 2024. On online learning behavior, classroom participation, after-class practice and campus, students were surveyed. Online learning data were retrieved from the school's online teaching platform, including time spent watching videos in the course, download of courseware, online test scores, and online forum post. Classroom participation data was gathered using the classroom interaction system: it comprised attendance, number of answered questions, and participation in group discussions. After-class practice data consisted of social practice report grades, volunteer service activity records, and attendance to themed class meetings. Campus life data comprised library borrowing records, cafeteria consumption records, and club activity participation records. Cafeteria consumption records were utilized solely as a proxy for identifying social interaction patterns and routine stability—indicators of campus integration—rather than as a direct measure of ideological belief. All such data collection was conducted under strict ethical oversight with informed consent regarding the use of behavioral metadata for institutional improvement. Data collection followed the principles of privacy protection, all data were anonymised, and students personal information was presented in coded form. A total of 43 data fields were acquired, which made up more than 126,000 raw data records. The raw data cleaning and pre-processing is done which encompass missing values, outliers, and data standardization etc. and finally a structured data set to be used for data analysis [11-12] .

B. STUDENT FEATURE MODELING AND GROUP IDENTIFICATION

This study employs unsupervised machine learning methods to model and categorize student groups. First, feature variables characterizing students' participation in ideological and political education are extracted from the raw data, including four dimensions: learning engagement, classroom activity, practical participation, and value orientation. Learning engagement is synthesized from three indicators: course video viewing time, courseware download frequency, and online test scores; classroom activity is synthesized from three indicators: attendance rate, number of questions answered, and frequency of group discussion participation; practical participation is synthesized from three indicators: social practice report scores, volunteer service activity duration, and number of themed class meetings participated in; and value orientation is synthesized from two indicators: forum posting sentiment and frequency of borrowing ideological and political books. All indicators are normalized to a value range of 0 to 1. Second, the K-means clustering algorithm is used to categorize students. The optimal number of clusters is determined using the elbow rule, and after calculating the sum of squared errors within clusters corresponding to different K values, K=4 is ultimately determined to be the optimal choice. Clustering analysis was performed in the Python environment using the Scikit-learn library. Euclidean distance was used for distance calculation, and the initial center point was selected using the K-means++ method to improve clustering stability. After clustering, the features of each category were analyzed to identify the typical characteristics of each type of student. Finally, the stability of the clustering results was tested. The Bootstrap method was used to repeatedly sample 100 times. The average Rand index of the clustering results was 0.87, indicating that the clustering has good stability [13] .

C. PRECISE PATH DESIGN AND MATCHING

Based on the student group identification results, differentiated educational implementation paths were designed to address the differences in characteristics among different types of students. To ensure the scientific nature and operability of the path design, this study adopted the expert consultation method, utilizing a two-round Delphi process. We invited 8 front-line teachers and 4 educational technology experts to establish the initial framework, which was then cross-validated against a secondary survey of 30 senior pedagogical researchers to ensure the universality and scalability of the intervention strategies for the broader student population for various types of students in conjunction with the cluster analysis results. On this basis, a matching rule library for intervention paths and student characteristics was constructed. The 16 rules were derived through a 4x4 matrix mapping process, where the four identified student clusters (K=4) were cross-referenced against four distinct environmental intervention variables: pedagogical content, interaction frequency, platform accessibility, and assessment feedback. By defining specific logic gates for each clusterenvironment intersection, we ensured that the resulting 16 rules provide a granular and mathematically consistent framework for targeted education. In the specific implementation process, the propensity score matching method was used to control selection bias and ensure the comparability between the intervention group and the control group [14-15] . The propensity score was estimated using a logistic regression model, and the covariates included background variables such as gender, grade, major, and entrance examination scores, as well as the characteristic variables used in the cluster analysis. The nearest neighbor matching method was used for matching, with the caliper set to 0.05 and the matching ratio to 1:1. Finally, a matching sample of 632 students in each of the intervention group and the control group was formed. The students in the intervention group received a one-year period of precise educational intervention, while the students in the control group received regular ideological and political education.

D. CONSTRUCTION AND CALCULATION OF EDUCATIONAL EFFECTIVENESS EVALUATION INDICATORS

An evaluation index system was built with three dimensions of knowledge acquisition, value identification, and transformation of behaviour. The knowledge acquisition dimension was synthesized by 3 Indicators (final exam's scores in ideological and political education courses, average exam's score in the course's online tests and course paper's grade). A weighted summation method was applied to obtain the comprehensive score where the weights were calculated by using principal component analysis. The information on the value identification dimension was collected by a questionnaire survey. The questionnaire consisted of 4 sub-dimensions (political identification, national identification, cultural identification and institutional identification). Each sub-dimension contained five items with a five-point Likert-scale. Reliability analysis indicated good internal consistency with a Cronbach's Alpha coefficient of 0.89. The behavioral transformation dimension was synthesized out of four indicators: frequency of social practice participation, duration of volunteering service activities, participation on ideological and political educationed student organizations, and positive tendency in online discourse. Positive tendency in online discourse obtained through the sentiment analysis of the comments of students on the forums and social media platforms. Sentiment analysis was performed using a hybrid model combining the domain-specific sentiment dictionary with a pre-trained Transformer-based architecture (e.g., BERT-based-Chinese). This approach allowed the system to move beyond static keyword matching to capture semantic nuances, such as sarcasm and context-dependent ideological discourse. The deep learning component served to disambiguate complex sentences that traditional dictionary methods typically misclassify, ensuring a higher fidelity in measuring student value identification. A sentiment score was determined for each comment, and the semester average considered as the individual indicator value. All three dimensions of scores have been standardized to have a range of 0 to 100. The educational effectiveness was assessed by the difference-in-differences model, based on the differences of the changes of the intervention group and the control group before and after the intervention. To account for the inherent cultural and academic differences between comprehensive, science and engineering, and normal universities, 'institution type' was introduced as a primary categorical confounding variable. We employed a multi-level mixedeffects model to nest student-level data within institutional-level variances, thereby isolating the true effect of the precision intervention from environmental academic influences. To address potential multicollinearity between 'value identification' and 'behavioral transformation'—which are theoretically interdependent—we performed a variance inflation factor (VIF) analysis and applied a structural equation modeling (SEM) approach to isolate the unique variance of each dimension before calculating the net effects.

IV. RESULTS AND DISCUSSION

A. RESULTS OF CLUSTER ANALYSIS OF STUDENT GROUP CHARACTERISTICS

Based on K-means clustering analysis, 2867 students were divided into four categories, with significant differences in scores across the four feature dimensions for each category. The clustering results are shown in Table 1.

TABLE 1. Student Group Type Characteristics Scoring Table

Student type	Sample size	Percentage (%)	Learning engagement	Classroom activity	Practical participation	Value orientation
Type 1: Fully Engaged	823	28.7	0.86	0.82	0.79	0.84
Type Two: Classroom-Focused	746	26.0	0.63	0.91	0.42	0.71
Type 3: Practice-oriented	589	20.6	0.45	0.38	0.88	0.65
Type 4: Passive Participation	709	24.7	0.32	0.28	0.35	0.41

As it is clear from Table 1, 28.7% of students are fully engaged and are excellent in all the four dimensions viz. learning engagement (0.86), classroom activity (0.82), practical participation (0.79) and value orientation (0.84). These students demonstrate the highest identification and enthusiasm to ideological and political education as the backbone of this field. 26.0% of students are focused in class in which they have the highest classroom activity score (0.91) out of the four categories. However, their practical participation score is 0.42, which is significantly lower than the former two categories, implying that although these students are good in terms of expressing self and extracurricular interaction within the class, their involvement in extracurricular practical activities is lower. 20.6% of students are practical education-oriented and they have a high practical participation score of 0.88. However, their learning engagement and classroom activity scores are fairly low, standing at 0.45 and 0.38 respectively. These students prefer to receive ideological and political education through practical and they have less interest in traditional classroom learning. Passive participation represented 24.7% of students with low scores in all 4 dimensions. It is important to note that while these students exhibit low digital and behavioral footprints, this category may include 'silent learners' who engage with the material through offline reflection rather than active digital interaction. Consequently, the intervention for this group focuses on providing diverse outlets for expression rather than assuming a total lack of engagement. These students presented a passive and perfunctory behavior towards ideological and political education, making them a group which needs to be seriously addressed and intervened in the targeted education. From the standpoint of student distribution, the proportions between the four types of student are relatively equal, with passive participants making up for almost one-quarter. This shows that the traditional ideology and political education model does indeed have blind spots, and which caused some students not to be effectively integrated into the educational process. The differences in scores in different dimensions between different types of students also confirm the heterogeneity of the student population, and provide empirical evidences to design precise educational path. Fully engaged students represented balanced and excellent overall performance in students; classroom focused students represented excellent performance in classroom activities; they were stumbling in practical activities; practical activities preference students represented the opposite; passively participating students need to improve in all aspects. These differences imply that a uniform educational model cannot meet the needs of different types of students, and educational paths should be differentiated based on the characteristics of students.

B. ANALYSIS OF THE IMPLEMENTATION EFFECT OF PRECISION EDUCATION APPROACH

Based on the group identification results, differentiated educational implementation paths were designed for four types of students. The "Extension and Deepening" path was adopted for fully engaged students, adding higher-level tasks such as theoretical study and research projects to the regular teaching, leveraging their exemplary role. The "Practice-Enhanced" path was adopted for students focused in class, maintaining the advantages of classroom learning while increasing practical requirements, guiding them to transform classroom learning into practical skills. The "Theory-Guided" path was adopted for students with a preference for practice, integrating theoretical teaching content through practical activities to enhance the depth and systematic nature of their theoretical learning. The “Basic Activation” path was adopted for passively participating students, starting with low-threshold, highly attractive activities to gradually increase their participation and sense of belonging.

After a year of precise educational intervention, the changes in the effectiveness evaluation indicators between the intervention group and the control group are shown in Table 2.

TABLE 2. Comparison of Educational Effectiveness Evaluation Scores between the Intervention Group and the Control Group

Evaluation Dimensions	Group	Pre-test score	Post-test score	Change value	Net effect
Knowledge mastery	intervention group	72.6	81.3	8.7	3.2
Knowledge mastery	control group	73.1	78.6	5.5	
Value recognition	intervention group	68.4	79.5	11.1	4.8
Value recognition	control group	68.9	75.2	6.3	
Behavioral transformation	intervention group	63.2	74.8	11.6	5.1
Behavioral transformation	control group	63.8	70.3	6.5	

As seen in Table 2, the intervention group showed a higher level of scoring compared to the control group in all the three dimensions of assessment in the post-test with significant changes. In the knowledge mastery dimension of the performance, the performance of the intervention group was 81.3 and 8.7 points more than before the intervention and the performance in the control group was 78.6 and 5.5 points more than before, gaining a difference equal to 3.2 points. In terms of value identification dimension, the scores of intervention group were found to be 79.5, i.e. 11.1 points increase compared to pre-test score while control group had scores 75.2, i.e. 6.3 points increase compared to the pre-test score, thus the net gain was found to be 4.8 points for the intervention group. In terms of the behavior transformation dimension, the scores of the intervention group were 74.8, an increase of 11.6 points from the pre-test, while the scores were 70.3 for the control group, an increase of 6.5 points, resulting in an increase of 5.1 points for the intervention group.

From the perspective of net effect value, the precision education approach achieved the largest effect in terms of the behavioral transformation dimension with a score of 5.1 points, followed by the value identification dimension with a score at 4.8 points, and the net effect in the aspect of knowledge mastery dimension was not significant compared with the value of the other dimensions with a score at 3.2 points. This result suggested that there is a clear advantage of the big data-based precision education model in promoting knowledge internalization in students into value identification and externalization into practical actions. While improvement in the transmission of knowledge is also evident with precision education, the difference in comparison to the traditional model is relatively small. This might be because the ideological and political education has already formed a relatively mature system in the transmission of knowledge and the specific granularity of precision education is more effectively manifested in behavioral and value-based outcomes rather than purely pedagogical knowledge transfer. In terms of the magnitude of change, the intervention group experienced more than 11 points of improvement on both the value identification and behavioral transformation dimensions, suggesting that precision education can well address the shortcomings of the traditional model on these dimensions.

C. ANALYSIS OF DIFFERENCES IN EDUCATIONAL OUTCOMES AMONG DIFFERENT TYPES OF STUDENTS

To further explore the effects of precision education pathways on different student groups, a subgroup analysis of the intervention effects on four types of students was conducted, and the results are shown in Figure 1.

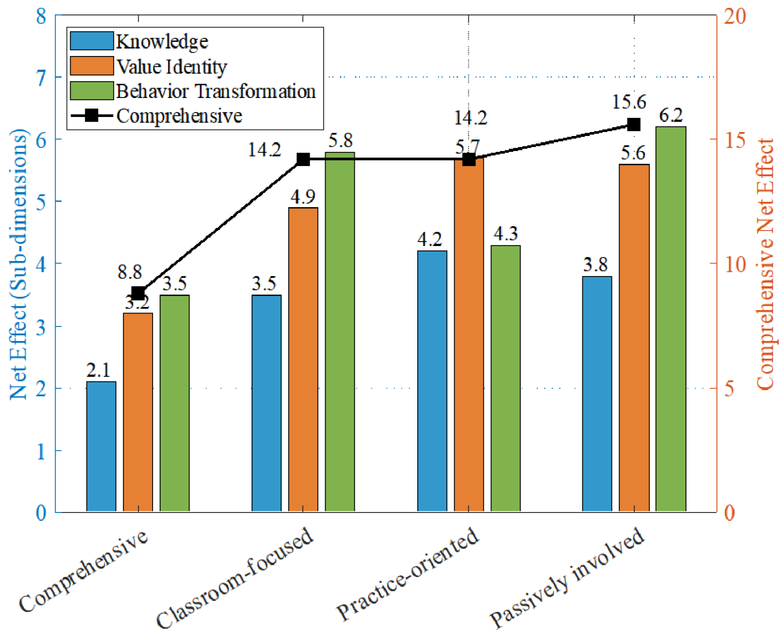

FIGURE 1. Comparison of net effects of interventions on different types of students

In the graph above shows that effects of the precision education approach are significant between the four types of students. In terms of the overall net effect the passively participating students had the biggest gain with a 15.6 points followed by those who focused in class and those that preferred the practical application, both scoring 14.2 points. Fully engaged students benefited not as much, scoring only 8.8 points. This result shows that precision education has a greater marginal effect on groups which have low participation and significant shortcomings under the traditional model, effectively mobilizing their enthusiasm for participation, and increases their sense of educational achievement.

From the view of net effects in multiple dimensions, the most positively impacted dimension in the behavioral transforming dimension were those actively participating students showed the net effects of 6.2 points, followed by value identification showed the net effects of 5.6 points, and knowledge mastery showed the net effects of 3.8 points. This means that the "basic activation" pathway created for these students was effective in boosting their level of participation and identification. Students with focused attention in class helped most in the behavioral transformation dimension with a net effect of 5.8 points on the scale; confirming the efficacy of the "practice reinforcement" pathway in addressing their defective practical. Students that have a preference for practice showed the strongest effect on the dimension of value identification with a net effect size of 5.7 points compared to the results for knowledge mastery (4.2 points), suggesting that the "theoryguided" pathway was effective in promoting the depth of their theoretical learning and the height of their value identification. Fully engaged students made improvement in all three dimensions, but the magnitude was relatively small, which is related to the fact that these students already had high pre-test scores and limited room for further improvement.

From the perspective of effect distribution characteristics, the precision education path effectively achieved the dual goals of "addressing weaknesses" and "leveraging strengths." For students with obvious weaknesses, such as those who are focused in class or have a preference for practical application, the path design specifically strengthened their weak areas, achieving balanced development. For passively participating students, the path design started with behavioral activation, gradually guiding their value identification and knowledge acquisition, forming a virtuous cycle. For fully engaged students, the path design provided space for expansion and deepening, maintaining their trend of continuous progress. These findings indicate that precision path design based on student characteristics has good targeting and effectiveness, and can meet the differentiated development needs of different types of students.

V. CONCLUSION

This study leverages big data technology to construct a technical framework and effectiveness evaluation system modeled after the automated quality control and structural consistency of high-precision processing, validating its practical impact through empirical research. By applying these rigorous metrics, the proposed system ensures university ideological education achieves the uniform tensile strength and microscopic flaw detection characteristic of advanced technical material engineering. This study has certain limitations: the data collection scope is limited to three universities, and the representativeness of the sample needs to be expanded; the research period is only one academic year, and the long-term sustainability of the educational effects needs to be tracked and verified; the dictionary method used for sentiment analysis has limited accuracy, and more advanced natural language processing technologies could be introduced in the future. Future research can be further expanded in terms of increasing the sample scope, extending the tracking period, and optimizing analysis techniques, to further promote theoretical innovation and practical deepening of big data-enabled ideological and political education in universities.

AUTHOR CONTRIBUTIONS

Na Zhou designed, collected and analyzed the data, and drafted the manuscript. Na Zhou conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Na Zhou participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

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