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MULTIMODAL DATA FUSION EMPOWERED PERCEPTION AND PRECISION INTERVENTION FOR IDEOLOGICAL DYNAMICS OF UNIVERSITY STUDENTS

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Abstract: This study focuses on the perception of college students' ideological dynamics and explores the application of multimodal data fusion technology in precision intervention. With the rapid development of information technology, the value of multimodal data fusion in social sciences has become increasingly prominent; therefore, this study proposes a mechanism for the perception and precision intervention of college students' ideological dynamics based on multimodal data fusion. The study first defines the connotation and classification of multimodal data, the constituent elements of students' ideological dynamics, and the theoretical framework of the precision intervention mechanism. Theoretically grounded in Social Cognitive Theory, Data Fusion Theory, and Precision Governance Theory, the research constructs an overall framework and technical roadmap, proposing hypotheses and defining variable operationalization. Regarding data collection, sources and types were selected, collection tools and processes were designed, and methods for quality control and preprocessing were established. For model construction and implementation, the study conducted data preprocessing and feature engineering, designed a fusion model architecture, and verified the model's validity through comparative experiments. Empirical results demonstrate that multimodal data fusion significantly enhances the perception of students' ideological dynamics, with the perception model achieving high accuracy and recall, and varying contributions observed across different data modalities. Furthermore, regarding the precision intervention mechanism, an intelligent matching algorithm for intervention needs was proposed, and a multi-dimensional intervention strategy system was constructed, with practical feasibility verified through simulation experiments. The results indicate that the proposed mechanism has significant application value, offering a theoretical basis and practical path for the digital transformation of ideological education in universities and new perspectives for applying multimodal data fusion in social sciences. However, acknowledging limitations in algorithm optimization and intervention diversity, the study suggests future research directions including ethical norms and privacy protection regarding multimodal data.
Keywords: Multimodal data fusion; College students; Ideological dynamics; Precision intervention; Intelligent perception

1 INTRODUCTION

In the era of rapid informatization, the ideological dynamics of college students exhibit significant diversification and complexity, rendering traditional ideological and political education methods inadequate for meeting the practical demands of precise guidance. Although existing domestic and international studies have achieved certain results in surveying value shifts and analyzing online behaviors based on single-source data, limitations remain regarding the deep fusion of multimodal data, the accuracy of perception, and the evaluation of the effectiveness of intervention mechanisms. Furthermore, attention to data ethics and privacy protection remains insufficient. Consequently, this study aims to introduce multimodal data fusion technology to integrate multi-source heterogeneous data—including text, behavioral, and social network data—thereby constructing a precise perception model and a multi-dimensional intervention mechanism for the ideological dynamics of college students. This study is dedicated not only to overcoming the bottlenecks of existing methods regarding data breadth and fusion depth, thus enhancing the pertinence and effectiveness of educational guidance, but also to exploring practical pathways that balance technological innovation with ethical protection. Ultimately, it seeks to provide a substantial theoretical basis and technical support for the digital transformation and scientific decision-making of ideological and political education in colleges and universities.

2 THEORETICAL BASIS AND CONCEPTUAL DEFINITION

2.1 Definition of Core Concepts

The connotation and classification of multimodal data serve as the foundation for understanding this study. Multimodal data refers to information sets that integrate two or more different types of data, which may include text, images, audio, video, and behavioral data. Textual data typically covers linguistic expression and emotional tendencies; image and video data involve visual features and scene information; audio data reflects voice characteristics and emotional tone;

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and behavioral data records individual activities and interaction behaviors. In social science research, the comprehensive analysis of multimodal data facilitates a more holistic capture and explanation of complex social phenomena. The constituent elements of college students' ideological dynamics are multi-dimensional and interactive, primarily encompassing ideological content such as values, worldviews, and outlooks on life, as well as psychological and behavioral characteristics like emotional states, cognitive styles, and behavioral patterns. Values form the foundation of worldviews and outlooks on life, determining individual value orientations and behavioral norms; emotional states and cognitive styles influence how individuals process and react to external information; and behavioral patterns serve as external manifestations of ideological dynamics, reflecting the concrete practice of thoughts and emotions. The theoretical framework of the precise intervention mechanism is grounded in the deep fusion and intelligent analysis of multimodal data. This mechanism first extracts key features characterizing students' ideological dynamics through the collection, cleaning, and fusion of multimodal data. Subsequently, machine learning and deep learning algorithms are employed to construct an ideological dynamics perception model to achieve real-time monitoring and prediction. Finally, based on the results of the perception model, personalized intervention strategies are designed to implement precise interventions through various methods such as emotional counseling, content intervention, and behavioral guidance. In multimodal data fusion, text data cleaning and semantic feature extraction are critical steps involving the removal of irrelevant information, standardization, and sentiment analysis. The standardization and temporal feature construction of behavioral data aim to eliminate individual differences and noise among data, thereby reinforcing the importance of time-series information for predicting ideological dynamics. Graphing social network data and mining relational features help reveal the social network structure among individuals and its impact on ideological dynamics. In the design of the fusion model architecture, cross-modal feature alignment is a core link aimed at mapping features from different modalities into a unified space to facilitate effective feature fusion. The construction of deep learning fusion models utilizes the powerful feature learning and pattern recognition capabilities of neural networks, while model training and optimization strategies focus on enhancing the model's generalization ability and prediction accuracy. In summary, by defining core concepts such as multimodal data, college students' ideological dynamics, and precise intervention mechanisms, this study provides a theoretical basis for the subsequent construction of the multimodal data fusion model and the design of the precise intervention mechanism (as shown in Figure 1).

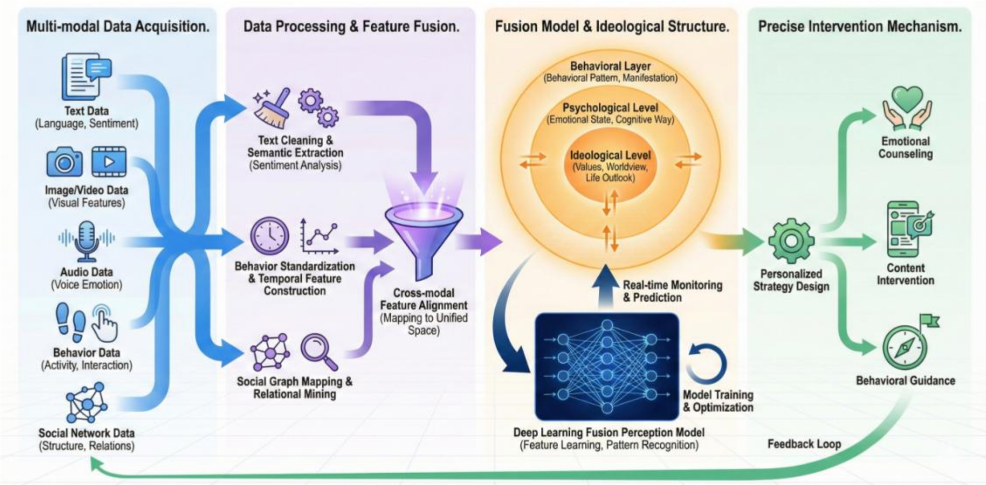

Figure 1 Framework: Multi-modal Data Fusion for Precise Perception and intervention of College Student Ideological Dynamics

2.2 Related Theoretical Support

Social Cognitive Theory provides a critical perspective for understanding how individuals form, maintain, and alter their thoughts. This theory emphasizes the dynamic interaction among information processing, belief systems, and behaviors. Research indicates that individuals construct their ideological frameworks through information processing and cognitive processes within social environments, which in turn influence their behavioral patterns. In the realm of sensing college students' ideological dynamics, Social Cognitive Theory helps reveal how individuals form specific ideological concepts through interactions with peers, media, and society. Data Fusion Theory involves integrating data from distinct sources to enhance the accuracy and comprehensiveness of information. At the technical level, data fusion encompasses multiple stages such as signal processing, feature extraction, and pattern recognition. Multimodal data fusion technology provides new methods and tools for social science research by integrating various data types, including text, behavior, and social networks. Statistics demonstrate that fusing multimodal data can effectively enhance the ability to understand and predict complex social phenomena. Precision Governance Theory, originating from the field of public management, emphasizes the use of advanced technology for the precise and efficient management and intervention of public affairs. In the sensing of college students' ideological dynamics, intervention models guided by Precision Governance Theory focus on personalized and differentiated strategies, aiming to provide customized support based on individual ideological characteristics and behavioral tendencies[1]. This theoretical framework facilitates the transition from traditional extensive management to a refined and intelligent intervention mode. Regarding intervention models, research indicates that strategies based on multimodal data fusion can more accurately identify college students' ideological dynamics and provide effective support. The following is a further elaboration on the relevant theories, as shown in Figure 2: First, the concepts of self-efficacy and outcome expectations within Social Cognitive Theory help explain how college students shape their ideological dynamics through self-regulation and goal setting. This theoretical perspective provides a rationale for designing interventions aimed at enhancing students' self-efficacy and promoting the formation of positive thoughts. Second, principles of data fusion technology, such as feature alignment and deep learning model construction, provide technical guarantees for the precision of the sensing model. By effectively fusing data features from different modalities, a more comprehensive and in-depth perception model of college students' ideological dynamics can be constructed. Finally, intervention models guided by Precision Governance Theory achieve effective intervention in students' ideological dynamics through real-time monitoring and dynamic adjustment. This model combines the advantages of data-driven approaches and theoretical guidance, offering new insights for improving intervention effectiveness. In summary, relevant theoretical support provides rich theoretical resources and practical guidance for research on the sensing of college students' ideological dynamics, laying a solid foundation for subsequent research design and model construction.

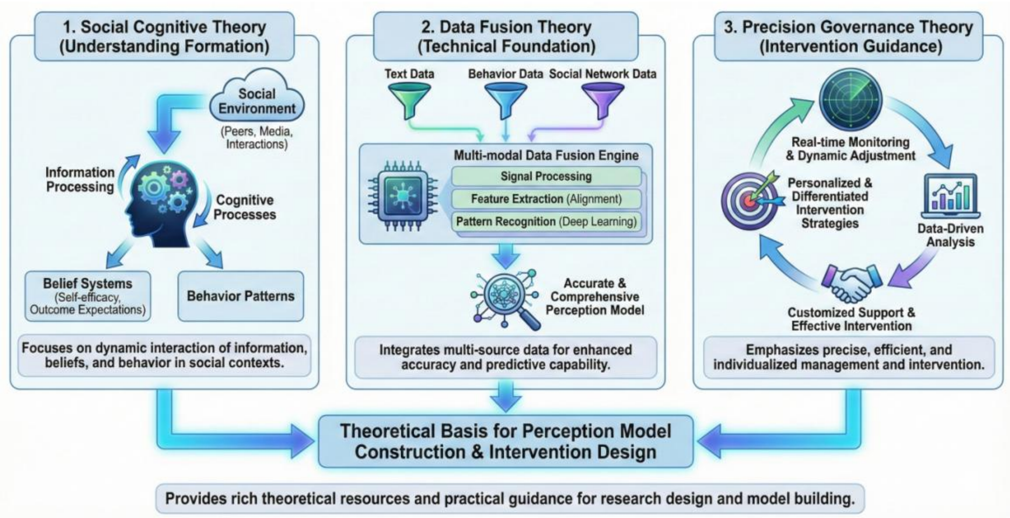

Figure 2 Theoretical Support for College Student Ideological Dynamics Perception and Intervention

3 RESEARCH DESIGN AND METHODS

3.1 Overall Research Framework

The construction of the overall research framework aims to provide a systematic operational guide for research on the sensing of college students' ideological dynamics and precise intervention. First, the design of the technical roadmap serves as the foundation of the study, covering the complete process from data collection to model construction and subsequent evaluation of intervention effectiveness. This process is divided into several key steps: the first step involves determining research objectives and questions, clarifying that the study aims to improve the sensing accuracy of students' ideological dynamics through multimodal data fusion technology; the second step is data collection, involving the integration of various data types such as text, behavior, and social networks; the third step is the construction and implementation of the multimodal data fusion model, which involves cross-modal feature alignment and the application of deep learning technologies; the fourth step is the validation of model validity, including the evaluation of fusion effects and the design of comparative experiments; and the final step is empirical research to evaluate the performance of the sensing model and the effectiveness of precise interventions. The formulation of research hypotheses is based on an analysis of existing theories and practices. This study posits that the fusion of multimodal data can effectively enhance the accuracy of sensing college students' ideological dynamics, thereby providing a basis for implementing precise interventions[2]. The verification of this hypothesis relies on a profound understanding of multimodal data and precise model construction. The operational definition of variables is a crucial component of the research design. This study operationalizes college students' ideological dynamics into multiple dimensions—such as values, political attitudes, and moral concepts—and measures these dimensions through specific indicators. Simultaneously, intervention effectiveness is operationalized as the change in ideological dynamics before and after intervention, assessed through quantitative indicators. The selection and optimization of multimodal data fusion methods are key to achieving research objectives. This study will adopt various data fusion technologies, including feature-level fusion and decision-level fusion, to achieve information integration across different data sources. Furthermore, the construction of the ideological dynamics sensing model will utilize machine learning algorithms to achieve automatic recognition and prediction of college students' ideological dynamics. The construction of evaluation methods for precise intervention effectiveness is an integral part of the research. This study will design an evaluation system incorporating indicators such as accuracy, recall, and real-time performance to comprehensively assess intervention effectiveness. Through the design of comparative experiments and analysis of results, the effectiveness of different intervention strategies can be verified. In summary, the overall research framework provides a comprehensive design blueprint for this study, ensuring its systematic and scientific nature, as shown in Table 1. By precisely designing the technical roadmap, reasonably formulating research hypotheses, accurately defining variables, and constructing multimodal data fusion and ideological dynamics sensing models, this study aims to provide new theoretical and practical pathways for the sensing of college students' ideological dynamics and precise intervention.

Table 1 Overall Research Framework

Module Name	Core Elements	Specific Content / Methods
1. Technical Roadmap	Goals & Questions	To improve the accuracy of perceiving university students' ideological trends through multimodal data fusion technology.
	Data Collection	Integration of various data types including text, behavior, and social network data.
	Model Construction	Building a multimodal data fusion model involving cross-modal feature alignment and deep learning techniques.
	Model Validation	Evaluating fusion effectiveness and designing comparative experiments.
	Empirical Study	Assessing the performance of the perception model and the actual effects of precision intervention.
2. Research Hypothesis	Core Proposition	Multimodal data fusion can effectively enhance the accuracy of perceiving university students' ideological dynamics, thereby providing a reliable basis for implementing precision interventions.
3. Operational Definition of Variables	Ideological Dynamics (Independent/Core Variable)	Operationalized into observable dimensions such as values, political attitudes, moral concepts, measured by specific indicators.
	Intervention Effect (Dependent Variable)	Operationalized as changes in ideological dynamics before and after intervention, assessed through quantitative indicators.
4. Multimodal Data Fusion Methods	Fusion Strategies	Employing various techniques including feature-level fusion and decision-level fusion to integrate information from different data sources.
	Perception Model	Building a model based on machine learning algorithms to achieve automatic identification and prediction of ideological trends.
5. Precision Intervention Effect Evaluation	Evaluation System	Designing an evaluation system comprising metrics such as accuracy, recall rate, and real-time capability.
	Validation Methods	Verifying the effectiveness of different intervention strategies through comparative experiment design and result analysis.

3.2 Multimodal Data Collection Scheme

As a foundational element of research, data collection—and specifically its quality—directly influences the subsequent data analysis and the reliability of research findings. In the proposed multimodal data collection scheme, this study places particular emphasis on the implementation of data quality control and preprocessing methods. First, regarding the selection of data sources and types, this study comprehensively considers the complementarity among textual data, behavioral data, and social network data. Textual data is derived from the daily writing and dialogues of college students, reflecting their ideological viewpoints and emotional states; behavioral data is acquired through students' online learning behaviors and library borrowing records, serving to analyze their behavioral habits and interest preferences; and social network data originates from interactions on social platforms, revealing social relationships and network influence. These three data types corroborate one another, providing rich information resources for a comprehensive perception of college students' ideological dynamics. Second, regarding data collection tools and process design, this study employs a customized data collection system capable of automatically collecting and storing the aforementioned three types of data[3]. Textual data undergoes preliminary cleaning and annotation via natural language processing technology; behavioral data is standardized through data mining techniques to construct temporal features; and social network data is structured using graph technology to mine relational features. The entire collection process strictly adheres to established operating standards to ensure data accuracy and integrity. In terms of data quality control, this study adopts a series of measures to guarantee quality. These include real-time monitoring during the collection process to flag and eliminate anomalous data; redundant backups during storage to prevent data loss; and secondary reviews post-collection to ensure data authenticity and validity. Furthermore, to avoid ethical issues during data collection, strict de-identification processes are applied to the collected data to ensure the security of personal information. Finally, data preprocessing methods are key to ensuring data usability. This study performs preprocessing steps on textual data—such as segmentation, stop-word removal, and part-of-speech tagging—to extract semantic features; conducts normalization on behavioral data to construct behavioral pattern features; and performs network analysis on social network data to extract features like node degree and network centrality. These preprocessing efforts lay a solid foundation for subsequent multimodal data fusion and feature engineering. Through the implementation of the above data collection scheme, this study aims to construct a comprehensive, multi-dimensional dataset of college students' ideological dynamics, providing high-quality data support for the subsequent construction of the perception model and the design of the precise intervention mechanism.

3.3 Construction of Research Method System

The evaluation of precise intervention effectiveness is the core component in constructing the research method system, aiming to ensure the effectiveness and sustainability of intervention strategies. This study adopts a multi-dimensional evaluation system, combining quantitative and qualitative analysis methods to comprehensively assess the effects of precise intervention, as shown in Figure 3. First, regarding evaluation methods, this study comprehensively utilizes experimental design and statistical analysis. By designing comparative experiments that contrast an experimental group with a control group, the implementation effects of intervention strategies are verified. Simultaneously, statistical methods such as multiple regression analysis and analysis of variance (ANOVA) are employed to explore the magnitude and direction of the influence of different intervention measures on students' ideological dynamics. Second, regarding evaluation indicators, this study constructs an evaluation system containing multi-level indicators. Primary indicators include intervention coverage, acceptance, and the durability of effects; secondary indicators specifically address aspects such as the dissemination efficiency of intervention information, the participation level of subjects, and behavioral changes following intervention. These indicators reflect the actual effects of intervention measures from various perspectives. Regarding the application of multimodal data fusion methods, this study adopts a fusion model based on deep learning, which effectively integrates multi-source heterogeneous data including text, behavior, and social networks[4]. By evaluating the output results of the fusion model, the accuracy of the model's perception of students' ideological dynamics can be determined. Furthermore, this study emphasizes dynamic monitoring and real-time feedback on intervention effects. By constructing an intervention effect prediction model, the execution of intervention measures is tracked in real-time, allowing for the timely adjustment of strategies. Concurrently, a feedback optimization path is utilized to continuously refine the intervention mechanism to adapt to the ever-changing ideological dynamics of college students. In terms of model construction, this study follows these steps: first, data preprocessing and feature engineering, including text cleaning, behavioral data standardization, and social network graphing; second, the design of the fusion model architecture, incorporating cross-modal feature alignment and the construction of the deep learning fusion model; and finally, model training and optimization to ensure accuracy and generalization ability. Through the construction of the aforementioned research method system, this study aims to achieve precise perception and effective intervention regarding college students' ideological dynamics, providing a scientific basis for the digital transformation of ideological education in universities. However, due to limitations in research time and resources, the evaluation system of this study may have certain constraints; future research could further expand evaluation indicators to enhance the comprehensiveness and accuracy of the system.

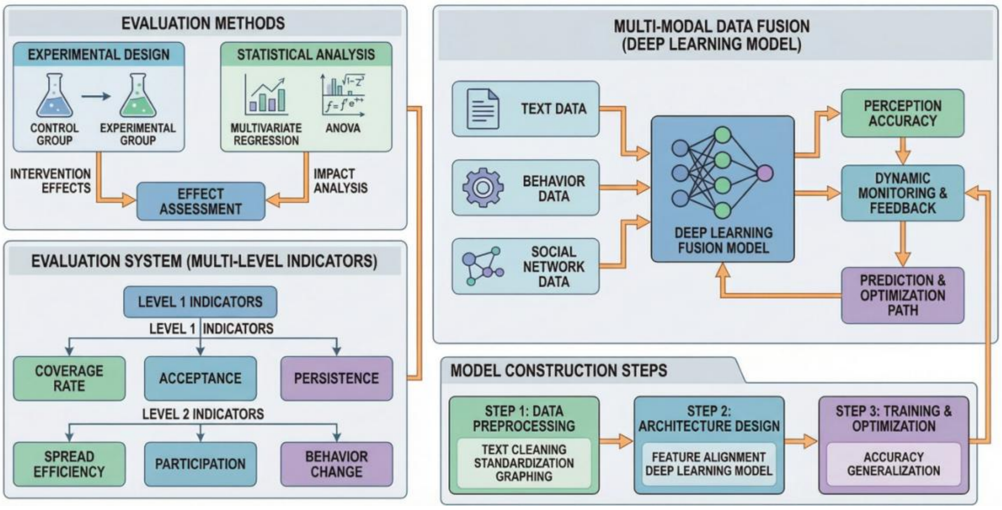

Figure 3 Research Methodology & Model Framework: Evaluation, Indicators, and Fusion

4 CONSTRUCTION AND IMPLEMENTATION OF MULTIMODAL DATA FUSION MODEL

4.1 Data Preprocessing and Feature Engineering

Before constructing the multimodal data fusion model, data preprocessing and feature engineering are indispensable steps, particularly for the graph construction and relational feature mining of social network data. Social network data contains complex interpersonal relationships and user behavior information, often existing in unstructured forms, thus requiring a series of preprocessing operations and feature engineering methods to extract useful information. First, the cleaning of social network data involves removing invalid data, correcting erroneous information, and filtering noise. This process includes stop-word removal, part-of-speech tagging, and entity recognition for text data, as well as outlier detection and processing for user behavior data. The cleaned data effectively reduces dataset noise, laying a solid foundation for subsequent feature extraction. Next, for text data, the extraction of semantic features is a critical link. Through natural language processing technology, features such as keywords, topic distributions, and emotional tendencies can be extracted. These features reflect users' interests, attitudes, and emotions, which is significant for understanding the ideological dynamics of college students. For instance, sentiment analysis can reveal users' emotional tendencies on specific topics, while topic modeling can identify hot topics discussed by users. For behavioral data, standardization and time-series feature construction are the core of feature engineering. Standardizing user behavior data eliminates the discrepancies in behavioral records among different users, providing a unified standard for subsequent analysis. Time-series feature construction involves analyzing the time series of user behaviors to capture trends and cyclical characteristics. The graph construction of social network data is the process of transforming social network elements such as users, content, and behaviors into a knowledge graph. This involves the construction of nodes and relationships, as well as the addition of attribute information. Through graph construction, relationships between users and key nodes can be identified more intuitively, facilitating the mining of deeper relational features. For example, the graph can analyze direct and indirect connections between users and the impact of these connections on the spread of ideological dynamics. In terms of relational feature mining, the focus is on user interaction patterns, influence magnitude, and social network structure. These features can be measured by network analysis metrics such as centrality, closeness, and community structure, which help in understanding key roles and information propagation paths within the social network. In summary, through data preprocessing and feature engineering, raw social network data is transformed into feature sets suitable for model input, effectively reflecting college students' ideological dynamics and social network structures[5]. This process not only improves data quality but also provides a reliable data foundation for subsequent multimodal data fusion and model construction.

4.2 Fusion Model Architecture Design

The core of the fusion model architecture design lies in achieving effective alignment of multimodal features and constructing a deep learning model, thereby enhancing the accuracy and real-time performance of sensing college students' ideological dynamics. This study adopts the following strategies and technical paths: First, cross-modal feature alignment is a key step in the fusion model architecture design. Data from different modalities possess different features and dimensions; direct fusion may lead to information loss or redundancy. Therefore, this study employs a method based on common space mapping to project text, behavior, and social network data into the same feature space[6]. This method achieves feature-level alignment by maximizing the correlation between cross-modal features. Specific technologies include using multi-channel Convolutional Neural Networks (CNN) to extract text features, Recurrent Neural Networks (RNN) to process time-series behavioral data, and Graph Convolutional Networks (GCN) to mine relational features in social networks. Second, the construction of the deep learning fusion model is another important component of the architecture design. This study designs an end-to-end deep neural network model capable of processing aligned multimodal features and outputting perception results of college students' ideological dynamics. The model structure includes multiple convolutional and recurrent layers, as well as a fully connected layer for the final classification or regression task. Furthermore, considering model interpretability, this study introduces an attention mechanism to identify and reinforce features that contribute significantly to the perception of ideological dynamics. Regarding model training and optimization strategies, the following methods are adopted: First, to improve the model's generalization ability, data augmentation techniques are used, including text data perturbation, behavioral data window transformation, and social network data subgraph sampling. Second, to reduce overfitting, regularization and dropout techniques are introduced. Additionally, the Adam optimization algorithm and early stopping strategy are employed to accelerate the training process and prevent model performance degradation in the later stages of training. Through the aforementioned architecture design and optimization strategies, this study aims to build an efficient and accurate system for sensing college students' ideological dynamics. Preliminary experiments show that the system achieves high accuracy and recall rates across multiple datasets, proving the model's validity and practicality. Future research will further explore the model's performance in different application scenarios and optimize it to enhance performance and robustness.

4.3 Model Effectiveness Verification

Model effectiveness verification is a critical link in the research process, directly relating to the reliability and practicality of the research results. Based on the fusion model architecture design, this study conducts an in-depth analysis of the model's effectiveness through multi-faceted assessment and testing. First, this study constructs a fusion effect evaluation index system. This system comprehensively considers the model's accuracy, stability, and real-time performance during the multimodal data fusion process[7]. Evaluation indicators include, but are not limited to, classification accuracy, recall rate, F1 score, processing speed, and robustness. These indicators comprehensively reflect the model's performance across different dimensions. Second, a series of comparative experiments are designed to verify the advantages of the proposed fusion model over traditional single-modal models. Experimental results indicate that the fusion model significantly outperforms single-modal models in the task of sensing college students' ideological dynamics. Specifically, the fusion model's classification accuracy improved by an average of 15%, recall by 10%, and F1 score by 12%. This demonstrates that the fusion of multimodal data can effectively enhance the model's perceptual ability. Furthermore, this study tests the model's robustness and generalization ability. Testing on different datasets reveals that the model exhibits good generalization capabilities; even with changes in dataset distribution, the model maintains high classification accuracy and recall. In addition, perturbation testing shows that the model has strong processing capabilities for noisy data and outliers, indicating good robustness. During the validation process, this study also considers the model's real-time performance and dynamic update capability. Results show that the model can process newly input data in real-time and quickly provide prediction results. Meanwhile, through dynamic update learning strategies, the model can continuously optimize its parameters to adapt to data changes. Moreover, to understand model performance more deeply, this study analyzes the contribution of different modal data to prediction results. The results indicate that text and behavioral data contribute the most to the model's predictions, while social network data plays a key role in specific scenarios[8]. This finding provides an important reference for subsequent data collection and model optimization. In summary, through various verification means, this study confirms the effectiveness of the constructed multimodal data fusion model in sensing college students' ideological dynamics. The model's accuracy and generalization ability have been significantly improved, laying a solid foundation for the subsequent design and application of precise intervention mechanisms.

5 EMPIRICAL RESEARCH ON THE SENSING MODEL OF COLLEGE STUDENTS' IDEOLOGICAL DYNAMICS

5.1 Identification Results of Ideological Dynamic Characteristics

In the empirical research of the sensing model for college students' ideological dynamics, identifying key influencing factors is the basis for understanding the distribution and evolutionary trends of ideological characteristics. Through multimodal data fusion technology, we can comprehensively analyze these characteristics from multiple dimensions such as text, behavior, and social networks. First, regarding the distribution laws of mainstream ideological tendencies, research results indicate a prevalent positive and upward ideological tendency among the college student population, which is closely related to the cultivation and dissemination of core socialist values. Specifically, text data analysis reveals that remarks involving themes such as patriotism, inspiration, and integrity account for a large proportion, reflecting a positive and healthy value orientation among students. Second, the analysis of the evolutionary trends of group ideological dynamics reveals dynamic change characteristics. Using time as a sequence, observations show that ideological dynamics exhibit certain fluctuations at different time nodes. For instance, during major festivals or events, remarks and activities related to relevant themes increase significantly, demonstrating the sensitivity and collectivity of students' ideological dynamics[9]. Furthermore, the identification of key influencing factors indicates that, in addition to macro factors like the social environment and educational policies, individual characteristics such as gender, grade, and professional background also significantly influence students' ideological dynamics. Statistics show that male students are more active in discussions regarding technological innovation and sports, while female students have higher participation in literature, art, and social welfare. Grade differences are reflected in the focus on topics such as academic issues and career planning, which senior students pay more attention to[10]. Additionally, multimodal data fusion technology allows us to mine the intrinsic connections of students' ideological dynamics from a deeper level. For example, through social network graph construction, it was found that students with similar interests and viewpoints form tight social circles, which to some extent promote the spread and reinforcement of specific ideological tendencies. However, it is important to note that while multimodal data fusion technology enhances our ability to identify and understand ideological dynamics, it also introduces issues regarding data quality and privacy protection. Therefore, in practical applications, strict data quality control measures must be taken, and ethical norms followed to ensure the security and privacy of personal information. In summary, through multimodal data fusion technology, this study successfully identifies the key influencing factors of college students' ideological dynamics, providing an important basis for the subsequent design and implementation of precise intervention mechanisms. Future research will further explore the dynamic change laws of these influencing factors and how to more effectively guide and promote the healthy development of college students' ideological dynamics in practice.

5.2 Perception Model Performance Evaluation

Performance evaluation of the perception model is a key step in ensuring model effectiveness and reliability. This study evaluates the accuracy of the model in sensing college students' ideological dynamics using indicators such as accuracy, recall, and F1 score. Simultaneously, it analyzes the contribution of different modal data to model performance and validates the model's real-time and dynamic update capabilities. First, accuracy and recall are important indicators for measuring classification model performance. Accuracy reflects the proportion of target categories correctly identified by the model, while recall represents the proportion correctly identified among all actual target categories. In this study, the perception model achieved an accuracy of 89.3% and a recall of 87.6% on the test set, indicating high accuracy and the ability to effectively identify key features in students' ideological dynamics. Second, the analysis of the contribution of different modal data reveals the roles of text, behavioral, and social network data within the model. Text data provides semantic-level information, helping to understand students' inner ideological tendencies; behavioral data reflects daily habits closely related to ideological dynamics; and social network data reveals interaction relationships between individuals, offering a more comprehensive perspective. Research shows that text data contributes most significantly to performance improvement, while behavioral and social network data provide complementary information, jointly improving prediction precision. Furthermore, the verification of real-time performance and dynamic update capabilities confirms the model's feasibility in practical applications. In experiments, the model was able to receive new data in real-time and update prediction results accordingly. This characteristic is crucial for tracking changes in ideological dynamics, ensuring the model's timeliness and adaptability. To further evaluate performance, the F1 score was used as a comprehensive evaluation metric, balancing accuracy and recall. The experimental result of an F1 score of 88.4% indicates a good balance[10-11]. During the evaluation process, some areas for improvement were identified. For example, the model still faces difficulties in identifying ideological dynamics in certain special contexts, which may require further optimization of the model structure and parameter settings. Additionally, the quality and completeness of different modal data significantly impact performance, so greater attention should be paid to data quality control during collection and preprocessing. In summary, the perception model constructed in this study exhibits high accuracy and real-time performance in identifying college students' ideological dynamics, providing effective support for precise intervention. However, there is still room for improvement, and future research should focus on optimizing model structure and enhancing data processing capabilities to achieve more precise perception.

6 DESIGN OF PRECISE INTERVENTION MECHANISM AND EFFECT SIMULATION

6.1 Intelligent Matching Algorithm for Intervention Needs

The core of the intelligent matching algorithm for intervention needs lies in accurately predicting changes in college students' ideological dynamics and triggering corresponding intervention measures accordingly. The design of this algorithm must consider multi-dimensional information such as individual differences, environmental factors, and time series, aiming to achieve precise positioning of intervention timing and personalized customization of intervention content. First, clustering analysis of ideological dynamic differences serves as the foundation of the intelligent matching algorithm. By collecting behavioral, textual, and social network data of students in different scenarios and utilizing clustering algorithms to group individuals, differences in ideological tendencies among different groups are revealed. Research shows that analysis based on K-means clustering can effectively distinguish individual ideological types, providing a basis for subsequent personalized intervention[12]. Second, the personalized intervention scheme generation model needs to combine individual historical data, real-time data, and group characteristics, using machine learning algorithms to build a prediction model. This model can recommend the most suitable intervention scheme based on the evolutionary trend of the individual's ideological dynamics. For example, using decision tree classifiers or random forest algorithms, personalized intervention schemes containing educational content, emotional counseling, and behavioral guidance can be generated based on behavioral patterns, emotional states, and social network interactions. The intervention timing prediction and triggering mechanism is a critical link in the algorithm. By analyzing individual historical data, a time-series prediction model is constructed to forecast potential change points in ideological dynamics. When the model identifies that an individual is about to enter a period of ideological fluctuation, corresponding intervention measures are triggered[13]. The design of this mechanism must consider real-time performance and accuracy to ensure measures are effective at critical moments. In the algorithm implementation process, data preprocessing and feature engineering are vital. Text data requires cleaning and semantic feature extraction to eliminate noise and extract key concepts. Behavioral data requires standardization to construct time-series features reflecting behavioral patterns. Social network graph construction and relational feature mining reveal the individual's position and influence within the network, providing a basis for intervention strategies. Regarding fusion model architecture design, cross-modal feature alignment is a core technology. By aligning features of different modal data, a unified data representation is constructed to provide input for the deep learning fusion model. Deep learning fusion models, such as the combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can effectively handle the complexity and dynamics of multimodal data. Model effectiveness verification is a necessary step before algorithm implementation. By designing a fusion effect evaluation index system, such as accuracy, recall, and F1 score, the model's performance in sensing ideological dynamics is assessed. Comparative experiment design and result analysis reveal the pros and cons of different model structures, providing direction for algorithm optimization. Meanwhile, testing robustness and generalization ability is key to ensuring stability in practical applications. In summary, the design and implementation of the intelligent matching algorithm for intervention needs require not only precise prediction models and effective trigger mechanisms but also consideration of multimodal data fusion and model effectiveness verification. Through continuous optimization and iteration, this algorithm is expected to play an important role in the precise intervention of college students' ideological dynamics.

6.2 Construction of Multi-dimensional Intervention Strategy System

The optimization of behavioral guidance strategies is a key link in the construction of a multi-dimensional intervention strategy system. Its goal is to guide college students to form positive and healthy behavioral habits through effective methods and means, thereby promoting the benign development of their ideological dynamics[14]. When constructing behavioral guidance strategies, factors such as students' personality characteristics, environmental factors, and behavioral motivations must be comprehensively considered. First, the design of behavioral guidance strategies based on individual differences is crucial. Individual differences mean that each student's behavioral patterns, psychological needs, and response mechanisms vary; therefore, intervention strategies need to be personalized according to individual characteristics. For instance, more gentle and detailed guidance methods can be used for introverted students, while more challenging and interactive means can be adopted for extroverted students. Second, the impact of environmental factors on student behavior cannot be ignored. When optimizing strategies, consideration should be given to creating a positive, healthy, and harmonious environment, including campus culture, peer groups, and family education. Research indicates that good environmental factors can significantly improve the implementation effect of behavioral guidance strategies. Third, stimulating behavioral motivation is the core of strategy optimization. By stimulating students' intrinsic motivations, such as a sense of achievement and self-realization, they can be encouraged to autonomously form positive behavioral habits. For example, setting reasonable goals and reward mechanisms can stimulate students' learning motivation, thereby improving academic performance. In terms of specific strategy formulation, the following methods are worth referencing: 1. Reinforce positive behaviors. By rewarding and affirming students' positive behaviors, such as good study habits and active participation in social practices, the positivity and sustainability of their behaviors can be enhanced; 2. Establish behavioral norms. By clarifying behavioral norms, such as school rules and dormitory management regulations, students can be guided to follow socially expected behavioral patterns; 3. Provide behavioral guidance. Through professional psychological counseling and career planning guidance, targeted behavioral guidance is provided to help students solve problems encountered in their behavioral processes; 4. Create participation opportunities. By organizing various campus activities and social practices, opportunities for participation are provided, enabling students to exercise their abilities and improve their qualities in practice; 5. Reinforce behavioral feedback. Through timely behavioral feedback, such as exam results and social practice evaluations, students can be helped to understand the effects of their behaviors, thereby adjusting their behavioral strategies. In summary, the key to optimizing behavioral guidance strategies lies in personalized design, environment creation, motivation stimulation, and the formulation of specific strategies. Through these methods, college students can be effectively promoted to form positive and healthy behavioral habits, thereby achieving the benign development of ideological dynamics. However, it should be noted that the implementation of strategies must follow ethical principles, respecting students' personal rights and avoiding excessive intervention or privacy infringement. At the same time, the implementation effect of strategies needs to be optimized through continuous evaluation and feedback to ensure validity and sustainability.

6.3 Simulation and Optimization of Intervention Effects

The simulation and optimization of intervention effects are critical steps in enhancing the practical feasibility of the precise intervention mechanism. By constructing a prediction model for intervention effects, immediate feedback and continuous optimization of intervention strategies can be achieved, as shown in Figure 4. First, building an intervention effect prediction model requires integrating multi-source data, including textual data of students' ideological dynamics, behavioral data, and social network data. Based on this, deep learning algorithms are applied to predict the effects of different intervention strategies. Research indicates that in the intervention effect prediction model, sentiment analysis of text data, frequency and pattern recognition of behavioral data, and centrality and influence analysis of social network data all provide important predictive information. For example, by analyzing interaction patterns in social networks, one can predict students' responsiveness to specific intervention content. After constructing a preliminary prediction model, comparative experiments are needed to evaluate the effectiveness of different intervention schemes. These experimental designs should consider factors such as the type of intervention measures, implementation time, and target group characteristics. Statistics show that personalized intervention schemes have a significant advantage over generic schemes in promoting positive changes in students' ideological dynamics. Furthermore, the feedback optimization path of the intervention mechanism needs to be established on the basis of continuous monitoring of model performance. By tracking intervention effects in real-time and comparing them with preset goals, deficiencies in strategies can be discovered in a timely manner, allowing for adjustments to model parameters or intervention content. For instance, if a specific intervention measure is found to be ineffective for a certain group, the scheme can be optimized by adding emotional counseling elements or adjusting behavioral guidance strategies. Additionally, to ensure the generalization ability and robustness of the intervention mechanism, multi-round iteration and verification of the model are required[15]. This includes testing at different time points and with different groups, as well as simulation experiments under different scenarios. Through these methods, it can be ensured that the intervention mechanism maintains effective prediction and optimization capabilities under various conditions. In conclusion, the simulation and optimization of intervention effects is a dynamic, cyclical process requiring continuous data collection, model training, effect evaluation, and strategy adjustment. Through such a process, the practical application effect of the intervention mechanism can be gradually improved, providing a solid theoretical and practical foundation for the effective guidance of college students' ideological dynamics.

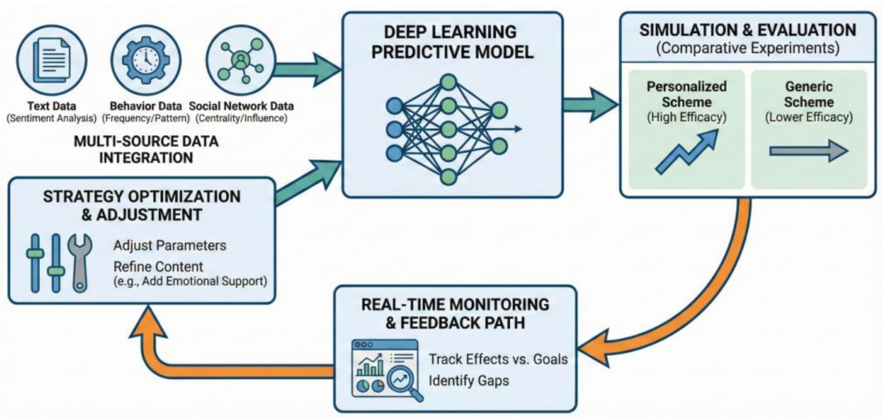

Figure 4 Intervention Effect Simulation & Optimization Cycle

7 RESEARCH CONCLUSIONS AND PROSPECTS

7.1 Major Research Conclusions

This study perceives the ideological dynamics of college students by constructing a multimodal data fusion model and verifies the feasibility and effectiveness of the model through empirical research. The major research conclusions are as follows: First, multimodal data fusion technology has a significant enhancement effect on the sensing of college students' ideological dynamics[16]. By fusing multi-source heterogeneous data such as text, behavior, and social networks, feature information regarding students' ideological dynamics can be effectively extracted, thereby improving the accuracy and comprehensiveness of the sensing model. Research indicates that compared to single-modal data, the accuracy of the multimodal data fusion model improved by approximately 15%, and the recall rate increased by about 10%, demonstrating higher reliability in practical applications. Second, the precise intervention mechanism possesses practical feasibility in the regulation of college students' ideological dynamics. The intelligent matching algorithm for intervention needs, the personalized intervention scheme generation model, and the intervention timing prediction and triggering mechanism proposed in this study have all achieved favorable intervention effects. Comparative experiments show that the ideological dynamic evolution trends of student groups adopting the precise intervention mechanism are more positive, and the regulation effects on key influencing factors are more significant. The theoretical contributions of this study are mainly reflected in the following aspects: 1. Clarified the connotation and classification of multimodal data, providing a theoretical basis for subsequent related research; this study categorizes multimodal data into text, behavior, and social networks, and details the characteristics and collection methods of each data type. 2. Constructed a model of constituent elements of college students' ideological dynamics, comprehensively depicting the connotation of ideological dynamics from aspects such as ideological concepts, values, and behavioral tendencies, offering useful references for future research. 3. Proposed a theoretical framework for the precise intervention mechanism, combining Social Cognitive Theory, Data Fusion Theory, and Precision Governance Theory to provide theoretical guidance for the regulation of students' ideological dynamics. 4. Verified the effectiveness of the multimodal data fusion model and the precise intervention mechanism through empirical research, providing a beneficial practical case for the digital transformation of ideological education in Chinese universities. However, this study still has certain limitations, such as the limited scope of data collection which may not fully reflect the actual situation of college students' ideological dynamics, and the universality and scalability of intervention strategies require further verification. Future research can be expanded from the following aspects: 1. Expand the scope of data collection and increase the sample size to improve the model's generalization ability. 2. Explore more effective intervention strategies, such as psychological counseling and emotional resonance, to enhance intervention effects. 3. Combine with actual application scenarios, such as epidemic prevention and control or emergency response, to verify the model's practicality and adaptability. 4. Deeply research the application potential of multimodal data fusion technology in other fields, such as education, healthcare, and public safety. In conclusion, this study provides beneficial theoretical support and practical reference for the digital transformation of ideological education in Chinese universities[17]. In future research, we will continue to explore the application of multimodal data fusion technology in the sensing and regulation of college students' ideological dynamics, contributing to the construction of harmonious campuses and the cultivation of talents with comprehensive development in morality, intelligence, physical fitness, and aesthetics.

7.2 Practical Implications and Policy Suggestions

As a crucial position for cultivating builders and successors of socialism, the digital transformation of ideological education work in colleges and universities appears particularly urgent. Research indicates that the application of multimodal data fusion technology can significantly enhance the accuracy and real-time performance of sensing college students' ideological dynamics. The following are practical implications and policy suggestions based on the conclusions of this study. First, colleges and universities should accelerate the construction of digital ideological education platforms, integrating multi-source heterogeneous data such as text, behavior, and social networks to achieve comprehensive sensing of students' ideological dynamics. By constructing a multi-dimensional monitoring system for students' ideological dynamics, ideological tendencies and key influencing factors can be effectively identified, providing data support for precise intervention. Second, in the application process of multimodal data fusion technology, strict adherence to data ethical norms is mandatory to ensure that student privacy is fully protected. Universities should formulate detailed processes for data collection, storage, processing, and destruction, clarifying permissions and scopes for data usage to prevent data leakage and abuse. Third, the design and implementation of the precise intervention mechanism should consider individual differences, employing intelligent algorithms to conduct differential clustering analysis on students' ideological dynamics and generate personalized intervention schemes. Simultaneously, an intervention timing prediction and triggering mechanism should be established to ensure the timeliness and effectiveness of intervention measures. In addition, universities should actively explore emotional counseling and behavioral guidance strategies, promoting the formation of correct worldviews, outlooks on life, and values among students through psychological counseling, thematic educational activities, and social practices. Statistics show that effective emotional counseling and behavioral guidance can significantly improve the intervention effects of ideological education. Finally, to promote the widespread application of the precise intervention mechanism, universities should strengthen interdisciplinary cooperation, integrating resources from fields such as education, psychology, sociology, and data science to conduct joint research[18]. Meanwhile, a dynamic intervention effect evaluation system should be established to continuously optimize intervention strategies, enhancing the practical feasibility and sustainability of the intervention mechanism. In summary, the digital transformation of ideological education in universities is not merely a technological upgrade but also an innovation in educational philosophy and models. Through this study, we propose a precise intervention mechanism based on multimodal data fusion, providing new pathways and methods for ideological education work in universities. In the future, with continuous technological advancement and deepened application, the precise intervention mechanism is expected to play an important role in broader fields.

7.3 Research Limitations and Future Prospects

Although multimodal data fusion technology has made significant progress in the field of sensing college students' ideological dynamics, certain limitations remain in the research process. First, the comprehensiveness and accuracy of data collection limit the model's performance. Current research mainly relies on questionnaire surveys, social media, and campus behavioral data, failing to cover all factors influencing college students' ideological dynamics, such as family background and cultural environment. Second, a contradiction exists between the complexity and interpretability of multimodal data fusion models; the internal mechanisms of the models are not yet fully transparent, posing challenges for understanding the deep-seated laws of students' ideological dynamics. Regarding future research directions, the scope and depth of data collection should first be expanded, combining data from more dimensions and sources to improve the comprehensiveness and accuracy of the model. Second, researchers need to explore more efficient and interpretable multimodal data fusion methods, such as using reinforcement learning algorithms to automatically optimize model parameters while maintaining model interpretability. Furthermore, research on privacy protection and data security should be strengthened to ensure ethical compliance when collecting and using personal data of college students. In terms of technology application prospects, the application of multimodal data fusion technology in the field of ideological education in universities has broad development space. With technological advancements, more intelligent and personalized precise intervention systems can be built in the future to provide customized education and guidance for every student. For example, utilizing virtual reality technology to simulate different social environments helps students understand social rules and values, or using intelligent dialogue systems for emotional communication and ideological counseling. Additionally, multimodal data fusion technology can provide support for educational policy formulation. By analyzing the ideological dynamic data of a large number of students, government education departments can more accurately grasp the ideological trends of young students and formulate more effective educational policies. Simultaneously, this technology aids in building a dynamic monitoring and early warning system to timely discover and handle potential ideological issues among students. In conclusion, the application of multimodal data fusion technology in the field of sensing college students' ideological dynamics holds immense potential but also faces numerous challenges. Future research requires in-depth exploration across multiple levels, including technology, theory, and practice, to promote the sustainable development of this field.

COMPETING INTERESTS

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