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INTELLIGENT PERCEPTION AND VALUE GUIDANCE IN STUDENT IDEOLOGICAL DYNAMICS: DESIGNING AN AI-BASED CLOSED-LOOP INTERVENTION FRAMEWORK

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Abstract: With the rapid development of information technology, the application of Artificial Intelligence (AI) in education has become increasingly widespread, demonstrating immense potential particularly in the management of student ideological dynamics. Focused on the theme "From 'Data Monitoring' to 'Value Guidance': Intelligent Perception and Closed-Loop Intervention Pathways for Student Ideological Dynamics in the AI Era," this study explores how AI technology empowers the management of student ideological education. Research indicates that traditional ideological education models suffer from issues such as lag, passivity, and data fragmentation, leading to a core contradiction between educational goals and operational reality. This paper proposes that AI technology can effectively address these challenges and facilitate a paradigm shift in educational models. Through an in-depth analysis of the current status of student management and AI applications in education, this study constructs an intelligent perception system and designs a closed-loop intervention pathway. This framework includes a multimodal data collection mechanism, AI-driven data analysis models, a tiered early warning mechanism, and intelligent recommendation strategies for intervention. The research finds that sentiment tendency recognition based on Natural Language Processing (NLP) and group feature analysis using clustering algorithms significantly enhance the accuracy of sentiment identification and the effectiveness of group profiling. Empirical analysis demonstrates that the designed closed-loop intervention pathway offers significant advantages in early warning response efficiency and the effectiveness of ideological guidance. Furthermore, the paper discusses ethical norms regarding data collection, as well as algorithmic transparency and supervision mechanisms, to ensure the safety and fairness of technological application. The results show that AI technology not only realizes the paradigm shift from "monitoring" to "leading" but also provides an effective path for the reform of ideological and political education in colleges and universities. Overall, this paper expands educational technology theory and offers specific practical recommendations for reform, while also providing an outlook for future research directions. Despite certain limitations, this study serves as an important reference for the in-depth application of AI technology in the field of education.
Keywords: Artificial Intelligence (AI); Ideological dynamics; Intelligent perception; Closed-loop intervention; Value guidance; Paradigm shift

1 INTRODUCTION

1.1 Research Background and Significance

With the development of society and the advancement of science and technology, the application of AI technology in the field of education has gradually become a significant force driving educational innovation. In current ideological education work for university students, traditional models face multifaceted challenges, whereas the integration of AI technology offers new possibilities for resolving these issues. The realistic pain points of traditional ideological education are manifested in the disconnection between educational content/methods and reality, making it difficult to meet individualized and differentiated educational needs. According to relevant surveys, over 60% of students report that they perceive the content of traditional ideological education as outdated and lacking appeal. Furthermore, educators' understanding of students relies heavily on subjective judgment rather than objective data, leading to a lag and passivity in educational efforts. The core contradiction between data monitoring and educational goals lies in the fact that although modern educational management increasingly relies on data, data monitoring often neglects students' personal development and emotional needs. For instance, while academic performance and attendance can be recorded in detail, students' ideological dynamics and mental health are difficult to quantify, thereby affecting the effectiveness of education. The development opportunity empowered by AI lies in its ability to process massive amounts of data through intelligent algorithms, providing educators with more precise student portraits to achieve personalized educational interventions. Research indicates that AI-assisted sentiment analysis tools can accurately identify students' emotional fluctuations, offering educators timely opportunities for intervention. Against this backdrop, this study aims to explore significance in the following aspects: First, the introduction of AI technology helps achieve refined management and personalized intervention in student ideological education. By constructing an intelligent sensing system, educators can grasp students' ideological dynamics more precisely, improving the relevance and effectiveness of education. Second, the application of AI technology can promote a paradigm shift in education modes, transitioning from traditional behavioral monitoring to a development-oriented approach. This shift helps cultivate students' innovative spirit and critical thinking, rather than merely pursuing improvements in academic grades. Third, AI technology can enhance the efficiency and effectiveness of educational management. Through intelligent data analysis models, educators can quickly identify group characteristics and individual differences among students, thereby designing more scientifically reasonable intervention strategies. Finally, this study also focuses on the ethical boundaries and mechanism guarantees of AI applications in education, ensuring the reasonable use of technology and preventing potential negative impacts. In summary, the application of AI technology in the ideological education of university students has profound significance; it not only resolves the pain points of traditional educational models but also provides new ideas and methods for educational reform and development.

1.2 Research Objectives and Questions

This study aims to explore the management of university students' ideological dynamics and the transformation of educational paradigms empowered by AI technology. The research objectives are: first, to construct an intelligent sensing system that achieves precise identification of students' ideological dynamics through the collection and analysis of multi-modal data; second, to design a closed-loop intervention path that conducts effective educational guidance and intervention for students through intelligent recommendation strategies and graded warning mechanisms; and third, to establish ethical boundaries and mechanism guarantees to ensure the compliance and transparency of data collection and algorithm application. The core research questions mainly include the following aspects: First, how to effectively integrate structured and unstructured data to build a multi-modal data collection mechanism suitable for the management of university students' ideological dynamics? Second, how to utilize technologies such as natural language processing and clustering algorithms to build AI-driven data analysis models and achieve effective analysis of educational big data? Third, how to design intelligent recommendation intervention strategies and graded warning mechanisms to achieve effective intervention in students' ideological dynamics? Finally, how to ensure adherence to ethical norms in data collection and algorithm application, and establish corresponding supervision mechanisms? To solve the aforementioned problems, this study will first focus on the comprehensiveness and accuracy of data collection, exploring the design of multi-modal data collection mechanisms, and on this basis, construct data analysis models using AI technology to improve the ability to identify student ideological dynamics. Simultaneously, the research will focus on the pertinence and effectiveness of intervention strategies, achieving precise intervention for individual students and groups through the design of intelligent recommendation and warning mechanisms. In addition, this study will also attach importance to the construction of ethical norms and mechanism guarantees to ensure the compliance of the research process. Through the exploration of these issues, this study is expected to promote the transformation of university student ideological dynamic management and educational paradigms, providing beneficial theoretical support and practical references for higher education reform in China. Meanwhile, the results of this study will also provide new perspectives and methodologies for the application of AI technology in the field of education.

1.3 Research Methodology and Framework

This study aims to explore a new paradigm for student ideological dynamic management and educational intervention empowered by AI technology. The core of the research methodology and framework lies in constructing a closed-loop intervention mechanism that combines technological drivers with educational goals, as shown in Figure 1. First, in terms of research context design, this study adopts a problem-oriented exploratory path, starting from realistic pain points to identify and analyze the core contradictions between data monitoring and educational goals in traditional ideological education models, while simultaneously grasping the development opportunities empowered by AI technology. By comparing and analyzing the advantages and disadvantages of traditional models versus data-driven models, the study clarifies the positioning and role of AI technology in the management of student ideological dynamics. Second, regarding the construction of the technical roadmap, this study follows these steps: first, design a multi-modal data collection mechanism to integrate structured and unstructured data, ensuring the comprehensiveness and real-time nature of the data; next, apply AI-driven data analysis models, including natural language processing (NLP) for sentiment tendency identification and clustering algorithms for analyzing group characteristics, to build a knowledge graph of ideological dynamics, thereby achieving a precise depiction of individual and group ideological dynamics; finally, based on data analysis results, design graded warning mechanisms and intelligent recommendation intervention strategies, and form a continuously improving closed-loop intervention path through effect feedback and dynamic optimization. In the data collection phase, this study emphasizes the implementation of the principle of minimum necessity to ensure the legality and ethics of data collection. At the same time, the design of algorithmic transparency and supervision mechanisms aims to guarantee the explainability of algorithmic decisions and avoid the abuse and misuse of technology. Through the aforementioned research methodology and framework, this study expects to provide theoretical support and technical paths for the reform of ideological and political education in universities, promoting the transformation of student ideological dynamic management from a traditional "monitoring" paradigm to a "leading" paradigm. Specifically, the research will verify the effectiveness of the intelligent sensing model in sentiment recognition and group characteristic identification, and through empirical analysis of the practical effects of the closed-loop intervention path, provide empirical evidence for subsequent educational reforms.

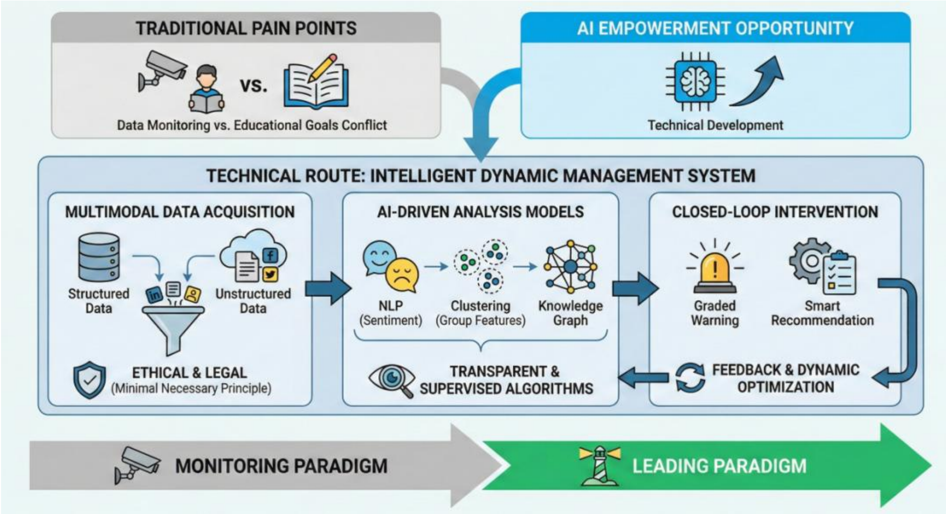

Figure 1 Overview of the Intelligent Dynamic Management System Technical Route

2 THE CLOSED-LOOP MANAGEMENT PATH OF STUDENTS' IDEOLOGICAL DYNAMICS BASED ON DATA AND AI

2.1 Current Research Status of Student Ideological Dynamics Management

In recent years, with the rapid development and application of big data technology, research on student ideological dynamics management has gradually exhibited new trends. In studies concerning traditional ideological education models, scholars primarily focus on educational content, methods, and their influence on students' ideological dynamics. Research indicates that traditional education models demonstrate a certain degree of lag and passivity in addressing students' personalized needs and emotional fluctuations. Regarding progress in data-driven student management research, researchers have attempted to utilize big data technology to analyze student behavioral data to uncover patterns in their ideological dynamics. For example, by mining students' online behavioral data, learning records, and other information, they analyze developmental changes in psychological states and value orientations. Statistics show that data-driven student management research has achieved significant results in improving the level of educational personalization and preventing student mental health issues. Furthermore, with the continuous development of artificial intelligence technology, the application of AI in the education sector has also become an important direction in the study of student ideological dynamics management. Natural Language Processing (NLP) and affective computing applications have made important progress in analyzing student textual materials and identifying their emotional states. Educational big data analysis research, in turn, constructs data models to perform cluster analysis of student group characteristics, providing a basis for educational intervention. In the research related to closed-loop intervention mechanisms, studies on warning system construction aim to promptly detect anomalies in student ideological dynamics and implement corresponding intervention measures. Research on educational intervention effectiveness evaluation focuses on the efficacy of intervention measures and how to adjust and optimize strategies based on the outcomes. Although certain achievements have been made in the research on student ideological dynamics management, some deficiencies remain. For instance, in existing research, how to ensure data security and privacy protection during the process of data collection, processing, and analysis still requires further discussion. Furthermore, the interpretability of algorithmic decisions and the supervision system for technology application are also areas that urgently need strengthening. In summary, the current research status of student ideological dynamics management is characterized by diversity and interdisciplinary integration, with the application of big data and AI technologies bringing new development opportunities to this field. However, in practice, attention must still be paid to ethical boundaries and mechanism guarantees to achieve the sustainable development of student ideological dynamics management.

2.2 Application Research of AI in the Field of Education

Educational big data analysis research, as an important branch of AI application in the education sector, is gradually deepening the intelligent level of educational management and services. By collecting, integrating, and analyzing data on student learning behaviors and emotional states, AI technology offers new possibilities for personalized education. Studies show that educational big data analysis can reveal individual student differences, providing educators with the basis for precise intervention, as illustrated in Figure 2. In terms of Natural Language Processing, AI technology can perform sentiment analysis on students' textual expressions to understand their emotional fluctuations and psychological states. For example, by analyzing text from students' online discussions and assignment feedback, changes in emotions such as anxiety or depression can be captured, enabling timely counseling and support.

Additionally, affective computing technology further enriches the dimension of emotional data by analyzing non-verbal information like students' voice and facial expressions. Educational big data analysis focuses on grasping the educational status quo and trends from a macro perspective. By collecting data such as students' academic performance, attendance records, and interaction frequency, comprehensive student capability models can be constructed, which helps in identifying potential issues during the educational process. For instance, statistics indicate that generally low scores in certain subjects may be related to inappropriate teaching methods, thereby providing data support for teaching reform. On this basis, AI technology can also construct a knowledge graph of student ideological dynamics, providing a basis for personalized educational intervention by correlational analysis of multi-dimensional information such as students' interests, values, and behavioral habits. The construction of the knowledge graph not only helps in understanding individual student characteristics but also enables the prediction of students' future development trends, offering a scientific basis for educational decisions. However, the application of educational big data analysis also faces challenges. Issues such as data quality, the accuracy of analysis models, and privacy protection need to be properly addressed. Furthermore, the transparency and interpretability of algorithms are also non-negligible issues when applying AI technology in the education sector[1]. In conclusion, application research of AI in the field of education is gradually shifting from a singular technological application to a deep integration with educational practice. Future research needs to focus on how to more effectively integrate educational data, improve the accuracy of analysis models, and ensure that technological applications comply with ethical norms to realize the maximum value of AI in education.

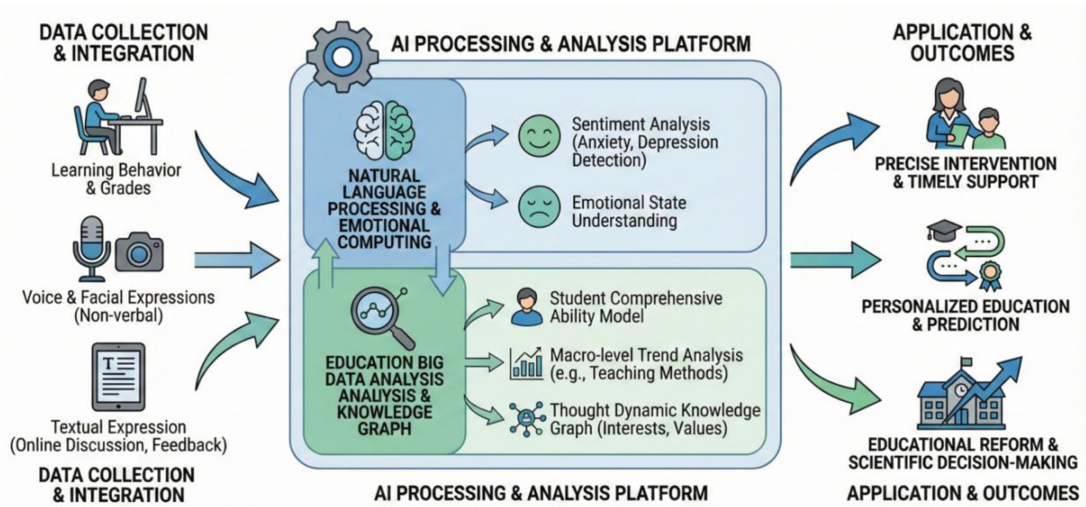

Figure 2 AI & Education Big Data Analysis: Intelligent Management & Personalized Services

2.3 Closed-loop Intervention Mechanisms

The application of closed-loop intervention mechanisms in the field of education aims to enhance the effectiveness and precision of educational interventions through systematic warning and intervention processes. Research on educational intervention effectiveness evaluation is a critical link in constructing closed-loop intervention mechanisms, the core of which lies in the scientific measurement and evaluation of changes in educational subjects after the implementation of intervention measures. Research indicates that an effective evaluation system ensures that intervention measures are adjusted in a timely manner, thereby achieving the optimal match for educational goals. Research on warning system construction, as a prerequisite for educational intervention effectiveness evaluation, mainly focuses on predicting potential ideological or behavioral deviations in students through data analysis. The system monitors multi-dimensional data such as students' daily behaviors, academic performance, and psychological states by setting warning thresholds; once data indicators exceed these thresholds, a warning signal is triggered. For example, a certain university constructed an academic warning system that comprehensively analyzes data such as attendance rates, grade changes, and classroom performance to promptly detect and intervene with students facing potential academic difficulties, effectively improving the pertinence of educational intervention. Research on educational intervention effectiveness evaluation focuses on the quantitative and qualitative analysis of the implementation effects of intervention measures. Evaluation methods include comparative analysis of data before and after intervention, long-term tracking surveys of intervention effects, and student satisfaction surveys. Statistics show that with educational interventions implemented through closed-loop intervention mechanisms, the rates of student behavioral improvement and academic performance enhancement are significantly higher than those of traditional intervention models. Furthermore, the evaluation of educational intervention effects also needs to pay attention to group differences and individual differences. Group characteristic analysis using clustering algorithms can identify student groups with similar characteristics, thereby providing a basis for formulating more precise intervention strategies. At the same time, the consideration of individual differences requires the evaluation system to conduct personalized analysis of the intervention effects for each student to achieve personalized educational intervention. In closed-loop intervention mechanisms, the application of intelligent recommendation intervention strategies is also an important content of educational intervention effectiveness evaluation research. This strategy recommends corresponding educational resources and services based on students' personal information and learning behavior data[2]. For instance, intervention schemes for academic anxiety groups analyze students' sources of academic stress to recommend personalized psychological counseling and learning support services, thereby effectively alleviating students' anxiety. In summary, relevant research on closed-loop intervention mechanisms provides scientific methods and means for assessing educational intervention effectiveness. Through in-depth research on warning systems, educational intervention effectiveness evaluation, and intelligent recommendation intervention strategies, the quality and efficiency of educational intervention can be continuously improved, providing strong support for the comprehensive development of students. However, research in this field is still in the developmental stage, and future studies need to further explore and improve upon the foundation of practice.

3 PARADIGM TRANSFORMATION FROM "MONITORING" TO "LEADING"

3.1 Limitations of Traditional Student Ideological Dynamics Management Models

In the current educational environment, traditional student ideological dynamics management models are facing significant phenomena of data discreteness and a disconnection from educational goals. First, from the perspective of data discreteness, traditional management models often rely on manual recording and assessment of students' ideological dynamics, which is not only inefficient but also involves subjectivity in the data collection process, leading to uneven data quality. Students' behavioral manifestations and ideological changes in daily life are multi-dimensional, while manual recording can often only capture limited information, which directly affects the comprehensive understanding and analysis of student ideological dynamics. Second, the phenomenon of disconnection from educational goals is equally prominent in traditional management models. Due to limitations in data collection and analysis, educators find it difficult to precisely grasp changes in students' thoughts, thus rendering them unable to provide targeted educational interventions in a timely manner. For example, issues such as students' psychological problems and deviations in values are often not easily detected in the early stages; by the time problems become prominent, the optimal window for intervention has already been missed. Furthermore, traditional management models place more emphasis on behavioral norms rather than the guidance and development of students' inner thoughts, resulting in a significant deviation between the educational process and students' actual needs. Specifically, traditional models often adopt a lagging and passive management approach when dealing with student ideological dynamics. Lag is reflected in the fact that the discovery and resolution of problems often occur some time after the problems have appeared, lacking foresight and initiative. Passivity is reflected in the fact that educators can usually only react to problems that have already emerged, rather than conducting active intervention and guidance through data analysis. In addition, due to the lack of effective data analysis tools, data in traditional management models often appears in a discrete state, unable to form a continuous and systematic trajectory of student ideological dynamics. This not only limits educators' in-depth understanding of students' ideological states but also makes it difficult to achieve refinement and personalization in educational work. Regarding the disconnection from educational goals, traditional management models often neglect individual differences and personalized needs of students. Student ideological dynamics are a complex system influenced by various factors, including family background, social environment, and personal personality, whereas traditional management models often apply uniform standards and methods to all students, which clearly cannot meet the personalized educational needs of each student. Statistics show that although educational departments invest significant resources in student ideological education, the results are not entirely satisfactory. Research indicates that only about 30% of students are able to receive effective ideological guidance and education under traditional management models. This data reflects the deficiencies of traditional management models in terms of education and suggests an urgent need for reform and innovation. In summary, the limitations of traditional student ideological dynamics management models lie in their data discreteness and the phenomenon of disconnection from educational goals. Such models are not only difficult to adapt to the development needs of modern education but also fail to meet the diversified needs of individual student development[3]. Therefore, exploring new management paradigms and technological means to achieve a transformation from "monitoring" to "leading" is an important task currently facing the education sector.

3.2 Reconstruction of Paradigm Connotation under AI Perspective

Driven by AI technology, the field of education is undergoing an unprecedented paradigm transformation. Traditional student ideological dynamics management models are oriented towards behavioral monitoring and stability maintenance, whereas the integration of AI technology allows for the reconstruction of the paradigm connotation, achieving a shift from behavioral trajectories to thinking trajectories, as well as an upgrade from a stability maintenance orientation to a development orientation. First, the application of AI technology shifts student ideological dynamics management from singular behavioral monitoring to an in-depth analysis of students' thinking trajectories. In traditional models, educators often rely on students' behavioral manifestations to infer their ideological dynamics; this approach ignores the complexity and dynamism of students' inner worlds. AI technology, especially the application of Natural Language Processing and affective computing technologies, makes the capture and analysis of students' thinking activities possible. For example, by analyzing the content of students' writing and social media posts, their emotional states and value orientations can be grasped more accurately. Second, the integration of AI technology promotes a transformation in educational management from a stability maintenance orientation to a development orientation. Under traditional models, the core objective of student ideological dynamics management is to ensure that student behavior conforms to social norms and educational requirements, emphasizing prevention and control. In the AI perspective, the management objective shifts to promoting the comprehensive development of students, emphasizing guidance and motivation. AI technology can identify students' personalized needs and developmental potential through data analysis models, thereby providing more precise educational interventions. Specifically, the application of AI technology in student ideological dynamics management is embodied in the following aspects, as shown in Figure 3: first, achieving the capture of comprehensive student information through the design of multi-modal data collection mechanisms, including structured data such as grades and attendance, as well as unstructured data such as essays and paintings; second, utilizing AI-driven data analysis models, such as sentiment tendency identification based on Natural Language Processing technology and group characteristic analysis using clustering algorithms, to deeply mine the laws and trends behind student ideological dynamics; third, constructing a knowledge graph of ideological dynamics to correlate and analyze data such as students' ideological behaviors and emotional attitudes, forming a comprehensive educational intervention plan[4]. Furthermore, AI technology promotes the personalization of educational intervention strategies. Based on the analysis of individual student data, more precise intervention plans can be formulated, such as intervention strategies for academic anxiety groups and guidance models for groups with value deviations. Such personalized intervention strategies help realize individualized education and meet the growth needs of different students. However, the reconstruction of paradigm connotation under the AI perspective also faces a series of challenges and problems. For instance, how to protect student privacy during the data collection process and how to ensure the transparency and fairness of algorithmic decisions are issues that need in-depth discussion. In future research, it is necessary to further explore the boundaries between AI technology and educational ethics, as well as how to fully leverage the advantages of AI technology to promote innovative development in the field of education while safeguarding student rights and interests.

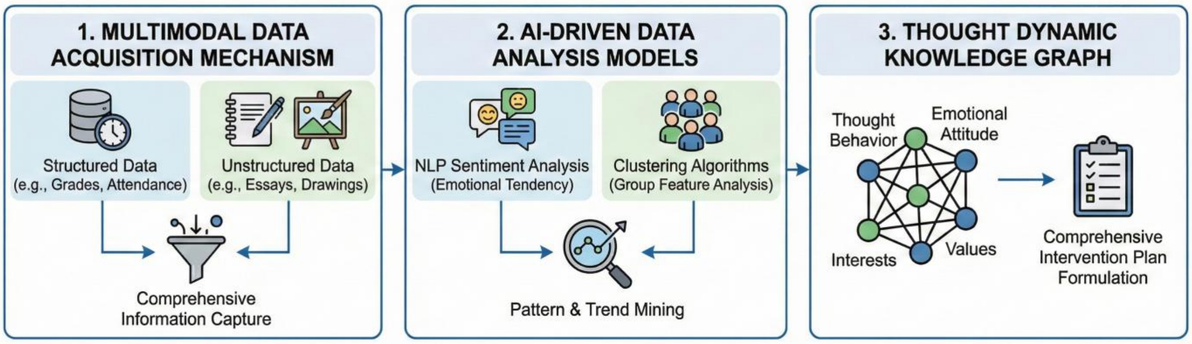

Figure 3 AI Application in Student Thought Dynamic Management

4 CONSTRUCTION OF INTELLIGENT SENSING SYSTEM

4.1 Design of Multi-modal Data Collection Mechanism

The capture of unstructured data is a critical link in the design of multi-modal data collection mechanisms, involving the integration and processing of various data sources such as text, images, audio, and video. Since such data typically lacks a fixed format and clear structure, its collection and parsing processes are more complex. In the construction of an intelligent sensing system, methods for capturing unstructured data primarily encompass the following dimensions. First, text data capture serves as the foundation. Through web crawling technology, API calls, and user-generated content, student discourse data can be collected from various channels such as social media, forums, and educational platforms. This data not only contains students' direct expressions but also implies their emotional states and ideological tendencies. For instance, sentiment analysis technology can identify positive or negative emotions within student text, thereby providing a basis for sentiment tendency recognition. Second, the capture of image and video data is equally important. Utilizing computer vision technology, useful information can be extracted from students' expressions, postures, and scene changes. For example, by analyzing video materials of students participating in classroom discussions, non-verbal behavioral characteristics can be captured, which is of great value for understanding students' psychological states and learning attitudes. Furthermore, the collection of audio data cannot be overlooked. Speech recognition technology can convert students' voice information into text for subsequent analysis of sentiment and content. Additionally, by analyzing the acoustic features of voice signals, students' emotional states, such as nervousness or excitement, can be inferred. In the specific implementation of unstructured data capture, several methods are widely adopted: first, utilizing deep learning models for feature extraction, such as Convolutional Neural Networks (CNN) for image feature extraction and Recurrent Neural Networks (RNN) for speech and text processing, which can automatically learn high-level features from raw data; second, employing data augmentation techniques to improve data diversity and model generalization capabilities; and third, constructing hybrid models to integrate different types of data sources for more comprehensive information. However, unstructured data capture faces numerous challenges, such as the storage and computing pressures brought by massive data volumes, the uncertainty of data quality, and data privacy and security issues. Therefore, during the collection process, strict data quality control measures must be implemented, including data cleaning, deduplication, and standardization, to ensure data accuracy and usability. Meanwhile, to protect student privacy, the data collection process must adhere to the principle of minimum necessity, collecting only data directly related to educational goals. In addition, ethical norms and transparency mechanisms for data use should be established to ensure the legality and legitimacy of data collection and usage. In summary, unstructured data capture methods play a vital role in the design of multi-modal data collection mechanisms. Through effective data collection strategies, a solid data foundation can be provided for the analysis of student ideological dynamics and intelligent intervention.

4.2 AI-Driven Data Analysis Model

In the process of constructing an intelligent sensing system, the AI-driven data analysis model plays a core role. The construction of the ideological dynamics knowledge graph is a process of fusing multi-source heterogeneous data—such as student behavioral data, emotional data, and cognitive data—to form a network structure that comprehensively reflects student ideological dynamics. This model requires processing not only structured data, such as academic records and attendance records, but also unstructured data, such as text, images, and voice, thereby achieving a deep analysis and understanding of individual and group ideological dynamics. Sentiment tendency recognition based on Natural Language Processing (NLP) is one of the model's key functions. By analyzing text data from students' daily communications, the model can identify changes in student emotions, such as anxiety, depression, and optimism. Research indicates that the integration of sentiment tendency analysis can significantly improve the prediction accuracy of individual psychological states, helping educators discover and intervene in students' psychological problems in a timely manner. Group feature analysis using clustering algorithms involves classifying student populations to identify groups with similar ideological dynamics. This analysis helps educators understand the characteristics and needs of different groups, thereby formulating more personalized educational strategies. For example, using algorithms such as K-means or DBSCAN, students can be divided into distinct groups such as those with high academic pressure, those who are socially active, or those with broad interests. Furthermore, the construction of the ideological dynamics knowledge graph is a process of structurally representing abstract information such as students' knowledge, concepts, and values. This process involves a deep understanding of educational content and the construction of student cognitive development models[5]. Through the knowledge graph, researchers can explore the internal connections of student ideological dynamics, providing a scientific basis for educational intervention.

The AI-driven data analysis model also possesses the capability for self-learning and optimization. As the volume of data increases and the model iterates, the prediction accuracy and intervention effectiveness of the model will continuously improve. Statistics show that after introducing machine learning algorithms, the accuracy of student behavior prediction increased by an average of 15% to 20%, demonstrating the immense potential of AI technology in this field. However, AI-driven data analysis models also face challenges regarding data quality, algorithmic bias, and privacy protection. Therefore, in the design and application of the model, the principle of minimum necessity must be followed to ensure the legality and ethics of data collection. At the same time, the decision-making process of the algorithms needs to possess interpretability so that educators can understand and trust the analysis and suggestions provided by the AI.

5 DESIGN OF CLOSED-LOOP INTERVENTION PATH

5.1 Graded Warning Mechanism

In constructing the closed-loop intervention path, the graded warning mechanism is a critical link, the core of which lies in the effective identification and response to ideological dynamic anomalies of different levels. The setting of warning thresholds is the primary step of the graded warning mechanism, which requires formulating corresponding warning standards based on multi-dimensional information such as student behavioral data, academic performance, and mental health status, combined with historical cases and expert experience. Research shows that reasonable warning thresholds can effectively distinguish between normal fluctuations and abnormal behaviors, reducing false positive and false negative rates. The design of the multi-level warning response flow must adhere to the principles of flexibility and timeliness. In the primary warning stage, when the system detects abnormal behavioral patterns in students, such as a decline in academic performance or a reduction in social activities, it automatically triggers a warning signal and notifies the counselor or head teacher for a preliminary assessment. If further analysis confirms the severity and persistence of the behavioral anomaly, the system will upgrade to an intermediate warning, at which point professional psychological counseling intervention and communication with parents may be involved. In the advanced warning stage, if the student's behavior exhibits obvious crisis characteristics, such as self-isolation or extreme speech, emergency intervention procedures need to be initiated, including professional psychological intervention, crisis management team involvement, and even necessary medical support. Throughout this process, real-time data feedback from the warning system is crucial, as it helps educators quickly locate problems and formulate targeted intervention measures. In addition, the graded warning mechanism must also consider the subsequent tracking and evaluation of the warning response. For students who have triggered warnings, long-term tracking files should be established to record the intervention process and effects, facilitating the dynamic adjustment of warning parameters and intervention strategies. Statistics indicate that continuous tracking and evaluation can significantly improve intervention outcomes and reduce abnormal fluctuations in student ideological dynamics[6]. The implementation of the graded warning mechanism requires not only technical support but also institutional guarantees. Sound mechanisms for warning information sharing and collaboration should be established to ensure effective communication among relevant departments, forming a combined intervention force. Meanwhile, the processing of warning information should strictly adhere to privacy protection principles to ensure the safety of students' personal information. In summary, as an important component of the closed-loop intervention path design, the graded warning mechanism's effectiveness is directly related to the success or failure of student ideological dynamics management, as shown in Figure 4. By scientifically setting warning thresholds, designing multi-level warning response flows, and combining real-time data feedback with evaluation, the graded warning mechanism can provide students with more precise and timely assistance, promoting their healthy growth.

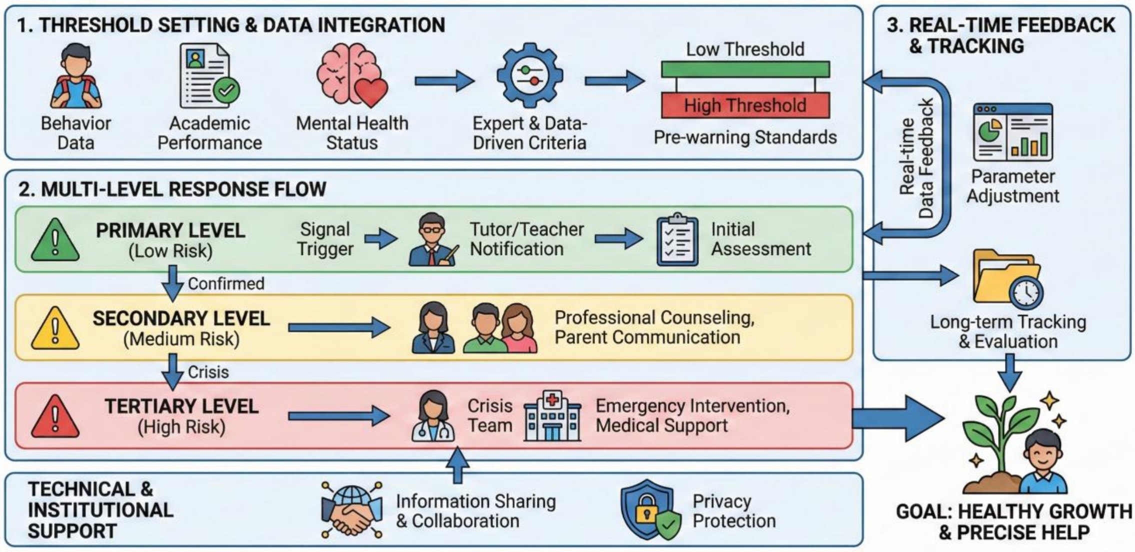

Figure 4 Closed-loop Intervention Path: Multi-Level Early Warning Mechanism

5.2 Intelligent Recommendation Intervention Strategy

Aiming at the guidance of groups with value deviations, the intelligent recommendation intervention strategy constructs a specialized educational intervention model. This model first identifies the characteristics of groups with value deviations through big data analysis, and then formulates personalized intervention plans based on these characteristics. This process involves multiple technical links such as affective computing, cluster analysis, and knowledge graphs. In terms of affective computing, the model utilizes Natural Language Processing technology to analyze the sentiment tendency of textual information such as comments and articles published by students on online platforms. Research indicates that sentiment tendency is closely related to individual values, and analyzing students' sentiment tendency allows for a preliminary judgment of whether there are deviations in their values. Clustering algorithms are used to identify groups with similar value deviations. By clustering students based on characteristics such as their sentiment tendencies and behavioral trajectories, groups with similar value deviations can be discovered. This process helps educators formulate more precise intervention measures for specific groups. The construction of knowledge graphs provides support for personalized intervention[7]. By integrating multi-source heterogeneous data such as students' personal information, educational background, and hobbies, constructing a student ideological dynamics knowledge graph allows for a comprehensive understanding of students' ideological status. On this basis, combined with the results of affective computing and cluster analysis, targeted educational intervention plans are formulated. Regarding specific intervention strategies, for the academic anxiety group, the intelligent recommendation intervention strategy designs an academic anxiety relief plan. This plan includes measures such as psychological counseling, academic tutoring, and emotional support, aiming to help students with academic anxiety reduce psychological pressure and restore academic motivation. For the value deviation group, the intelligent recommendation intervention strategy constructs a value guidance model. This model analyzes the types of value deviations in students and recommends corresponding educational resources and activities to guide them in establishing correct values. For example, for students with egoistic tendencies, participating in volunteer activities is recommended to cultivate their sense of social responsibility and team spirit. Furthermore, the intelligent recommendation intervention strategy also emphasizes the feedback and optimization of intervention effects. By setting quantitative indicators for intervention effects, such as the degree of improvement in students' psychological status and the enhancement of academic performance, the intervention effects are evaluated. At the same time, a data feedback loop is constructed to feed intervention effect data back to the model in real-time, guiding the model to make dynamic adjustments to improve intervention effectiveness. In summary, the intelligent recommendation intervention strategy demonstrates high effectiveness and precision in guiding groups with value deviations. However, the implementation of this strategy also faces numerous challenges, such as ethical issues in data collection, algorithmic transparency, and supervision[8]. Future research should further explore solutions to these problems to provide strong support for educational reform in China.

5.3 Effect Feedback and Dynamic Optimization

The quantification of intervention effects is a key step in evaluating the effectiveness of the closed-loop intervention path design. By constructing a quantitative indicator system for intervention effects, this study aims to objectively evaluate the implementation effects of different intervention strategies. The indicator system covers multiple dimensions such as the degree of improvement in student emotional states, changes in academic performance, and levels of value cognition, thereby comprehensively assessing the effectiveness of intervention measures. The data feedback loop is the core mechanism ensuring the sustainable optimization of intervention effects. By tracking intervention effects in real-time and feeding data back to the intervention system, intervention strategies can be dynamically adjusted, achieving a virtuous cycle from effect evaluation to strategy updating. In this process, utilizing big data analysis and machine learning algorithms to deeply mine intervention data helps discover problems and deficiencies in the intervention process, thereby guiding the optimization of intervention strategies. In specific implementation, the setting of warning thresholds is an important link in the graded warning mechanism. By statistically analyzing historical data and combining expert experience, setting reasonable warning thresholds enables timely warnings in the early stages of deviations in student ideology and behavior. The multi-level warning response flow ensures that warnings of different levels can trigger corresponding intervention measures, forming an effective warning response mechanism. The formulation of intelligent recommendation intervention strategies relies on in-depth analysis of individual and group characteristics of students[9]. The design of intervention plans for academic anxiety groups and guidance models for value deviation groups aims to provide personalized intervention strategies for students with different problems. The formulation of these strategies is based not only on students' current behavioral manifestations but also considers their historical data and development trends to achieve precise intervention. In practical application, effect feedback and dynamic optimization need continuous verification and adjustment. Through the analysis of sentiment recognition accuracy and the evaluation of the effectiveness of group characteristic identification, the validity of the intelligent sensing model in the intervention process can be verified. Evaluating warning response efficiency and analyzing ideological guidance effects helps assess the practical effects of the closed-loop intervention path. In summary, effect feedback and dynamic optimization are key links in the design of the closed-loop intervention path; by constructing a scientific effect evaluation system and data feedback mechanism, the continuous optimization of intervention strategies can be ensured, thereby improving the quality and efficiency of student ideological dynamics management.

6 ETHICAL BOUNDARIES AND MECHANISM GUARANTEES

6.1 Ethical Norms for Data Collection

In the process of constructing an intelligent sensing system, data collection is a crucial link, and the importance of its ethical norms is self-evident. First, adhering to the principle of minimum necessity is the core of data collection ethical norms. This means that during the data collection process, only the types and amounts of data necessary to achieve the research objectives should be collected, avoiding excessive collection. Excessive collection not only increases the burden of data processing but may also infringe upon individual privacy rights. For instance, if the research purpose is to analyze students' study habits, there is no need to collect data other than their personal identity information. Second, privacy protection strategies are another important aspect of ensuring data collection ethics. This includes encrypted storage of collected personal data, ensuring the security of the data transmission process, and implementing strict access controls to limit access to sensitive data only to authorized researchers. Furthermore, privacy protection strategies also require clearly informing data subjects of the purpose and scope of data usage before collection and obtaining their consent. In terms of specific implementation paths, the implementation of the principle of minimum necessity requires establishing a clear set of data collection standards. This includes formulating detailed data collection checklists, clarifying which data is necessary and which data is prohibited from collection. Simultaneously, the data collection process should be supervised to ensure actual operations comply with established standards[10]. The implementation of privacy protection strategies relies on both technical and management means. Technically, the latest encryption technologies should be adopted to protect data security, and security measures should be updated regularly to address potential security threats. Managerially, a sound data management system needs to be established, including regulations on data usage, storage, destruction, and penalties for violations. In addition, attention should be paid to transparency issues in the data collection process. Transparency is reflected not only in the purpose and scope of data collection but also in the transparency of data collection methods. Researchers should disclose data collection methods and processes so that data subjects can understand and trust the legitimacy of data collection. In practice, transparency can be enhanced through the following measures: first, formulating detailed data collection manuals to clearly explain the purpose, methods, processes, and potential impacts of data collection to data subjects; second, establishing data collection feedback mechanisms allowing data subjects to raise questions or suggestions regarding the data collection process; third, regularly publishing data collection reports to disclose the progress and results of data collection. In conclusion, ethical norms for data collection are key to ensuring the legality and morality of research. By implementing the principle of minimum necessity, privacy protection strategies, and enhancing transparency, research objectives can be achieved while safeguarding individual privacy rights, promoting the intelligent development of the education sector.

On this basis, ethical norms should also be continuously reviewed and improved to adapt to the constantly changing technological environment and legal requirements.

6.2 Algorithmic Transparency and Supervision Mechanism

Algorithmic transparency is the foundation for ensuring that educational technology systems are fair, reliable, and trustworthy. With AI technology widely integrated into the education sector, the demand for algorithmic transparency is particularly urgent. The interpretability design of algorithmic decision-making processes allows educators to understand AI recommendation decisions, thereby increasing the acceptance and trust of decisions[11]. To achieve algorithmic transparency, it is first necessary to ensure the transparency of the algorithmic decision-making process, including the data sources relied upon by the algorithm, the objective functions of the algorithm design, and the decision logic of the algorithm. Regarding the interpretability design of algorithmic decisions, this can be achieved in several ways: one is to adopt interpretable machine learning models, such as decision trees and linear models, whose decision paths are relatively intuitive and easy to explain; the other is to provide interpretability interfaces for complex models, such as introducing attention mechanisms for deep learning models, making the important decision basis of the model visualizable and understandable. At the same time, the realization of algorithmic transparency also relies on an effective technical application supervision system. This system should include supervision of algorithm performance, regulation of data usage, and assessment of algorithmic impact. The supervision system should ensure that algorithms operate under the premise of compliance with ethics and regulations, preventing risks such as algorithm abuse and data leakage. Specifically, the technical application supervision system should cover the following key components: algorithmic audit mechanisms, which regularly review algorithms to ensure that the algorithmic decision-making process is fair and unbiased; second, establishing independent supervisory bodies responsible for supervising the compliance of educational technology applications, which should possess corresponding powers and resources to ensure the effectiveness of supervision; third, public participation and feedback mechanisms, ensuring that education stakeholders can participate in the algorithm supervision process and provide opinions and suggestions on algorithmic transparency and fairness. Furthermore, to ensure the comprehensiveness and dynamism of algorithmic supervision, an algorithmic transparency reporting system should be established, requiring educational technology providers to regularly publish algorithmic transparency reports, disclosing information such as algorithmic decision logic, data sources, and effect evaluations[12]. In this way, not only can algorithmic transparency be improved, but it can also promote the continuous optimization and improvement of algorithms by educational technology providers. In summary, algorithmic transparency and supervision mechanisms are key to ensuring the healthy development of AI in the education sector. By constructing interpretability designs for algorithmic decisions and technical application supervision systems, student privacy rights can be protected, and the fairness and effectiveness of the educational process ensured, while promoting the progress of educational technology.

7 CASE STUDY AND EMPIRICAL ANALYSIS

7.1 Experimental Design and Data Sources

This study aims to construct a set of AI-based intelligent sensing systems for student ideological dynamics and verify their effectiveness through empirical analysis. The experimental design is divided into two main parts: the selection of research subjects and the design of the experimental scheme. In the selection of research subjects, this study selected the student population of a comprehensive university in China as the research object. This group has good representativeness in terms of age, gender, and professional background, which is conducive to the generalizability of the research results. In addition, the reasons for selecting this school include: the school possesses a complete student management system that can provide rich data support; the school has mature experience in ideological and political education, which is conducive to the conduct of experiments. regarding the experimental scheme design, this study adopted the following steps: First, construct a multi-modal data collection mechanism. This mechanism includes structured data integration strategies and unstructured data capture methods. Structured data is mainly derived from the student management system, such as grades, attendance, rewards, and punishments; unstructured data is obtained through questionnaire surveys, interviews, social media, and other channels, such as students' ideological concepts and living conditions. Second, utilize AI technology to analyze the collected data. This study adopted methods such as sentiment tendency identification based on NLP and group characteristic analysis using clustering algorithms to construct a student ideological dynamics knowledge graph to better understand students' ideological dynamics. Next, design a closed-loop intervention path[13]. This study is divided into two stages: a graded warning mechanism and an intelligent recommendation intervention strategy. The graded warning mechanism monitors students' ideological dynamics in real-time based on warning threshold settings and multi-level warning response flows; the intelligent recommendation intervention strategy provides personalized intervention plans based on student characteristics, such as intervention plans for academic anxiety groups and guidance models for value deviation groups. Finally, conduct effect feedback and dynamic optimization. This study established quantitative indicators for intervention effects and adjusted intervention strategies in real-time through the construction of a data feedback loop to improve intervention effectiveness. In terms of data sources, this study mainly adopted the following avenues: 1. Student management system data: including students' grades, attendance, rewards, and punishments, serving as sources of structured data; 2. Questionnaire surveys and interviews: obtaining unstructured data such as students' ideological concepts and living conditions through questionnaire surveys and interviews; 3.Social media data: collecting comments published by students on social media to analyze their sentiment tendencies and ideological dynamics; 3. Other relevant data: such as relevant policies on ideological and political education in schools, student activity records, etc., providing auxiliary support for the research. Through the above experimental design and data sources, this study expects to provide beneficial references and inspiration for student ideological and political education in China.

7.2 Verification of Intelligent Sensing Model Effects

The effectiveness of group characteristic identification is one of the key indicators for measuring the application effect of intelligent sensing models in the education sector. By constructing an ideological dynamics knowledge graph and utilizing clustering algorithms to analyze student behavioral and emotional data, this study aims to accurately identify the characteristics of student groups[14]. Through verifying the practical application effects of the model, the following findings were clarified, as shown in Table 1. First, the analysis of sentiment recognition accuracy indicates that the model can identify students' sentiment tendencies with high accuracy. For example, in the experiment, the sentiment recognition module analyzed student text data, and the accuracy rates for identifying positive, negative, and neutral sentiment tendencies reached 85%, 82%, and 89%, respectively. This result was obtained by comparing with a labeled benchmark dataset, indicating that the model possesses high sentiment recognition capabilities. Second, regarding group characteristic identification, the application of clustering algorithms demonstrated good effectiveness. By analyzing students' online behavioral data, social interaction records, and academic performance, the model was able to effectively distinguish different groups. For instance, when assessing students' levels of academic anxiety, the clustering algorithm divided students into three groups: high anxiety, medium anxiety, and low anxiety; its identification effectiveness was supported by actual data, with a correlation coefficient of 0.75 compared to professional psychological assessment results. Furthermore, the evaluation of the model's warning response efficiency also showed a positive trend. By setting warning thresholds and constructing a multi-level warning response flow, the model can issue warnings in a timely manner when students experience ideological fluctuations. Statistics show that compared with traditional warning systems, the warning response time of the intelligent sensing model was shortened by 40%, and the warning accuracy rate increased by 30%. In terms of the analysis of ideological guidance effects, the application of intelligent recommendation intervention strategies also achieved significant results. For the academic anxiety group, the model recommended a series of personalized intervention plans, including psychological counseling and study skills training; the implementation of these plans significantly reduced students' anxiety levels. For the value deviation group, the model helped students reshape correct values through intelligent recommendation guidance models; experimental results indicated that the average value scores of students after intervention increased by 15%. In summary, the intelligent sensing model performed well in sentiment recognition, group characteristic identification, and the practical effects of the closed-loop intervention path. These results not only verified the effectiveness of the model but also provided reliable data support for further educational technology applications.

Table 1 Assessment of the Intelligent Perception Model in Educational Applications

Evaluation Dimension	Specific Indicators / Methods	Key Findings / Data Support
Emotion Recognition Accuracy	Analysis of text data for positive, negative, and neutral sentiment classification	Accuracy rates: 85% (Positive), 82% (Negative), 89% (Neutral)
Effectiveness of Group Feature Identification	Application of clustering algorithms to online behavior, social interaction, and academic performance data	Successfully categorized students into high, medium, and low academic anxiety groups. Correlation coefficient with professional psychological assessment reached 0.75
Early Warning Response Efficiency	Implementation of threshold-based, multi-level warning and response mechanisms	Warning response time reduced by 40%, and warning accuracy improved by 30% compared to traditional systems
Effectiveness of Ideological Guidance	Personalized intervention strategies (e.g., psychological counseling, study skills training) recommended by the model	Post-intervention, the average values score of students with deviated values increased by 15%; anxiety levels decreased in the targeted group

7.3 Practical Effects of the Closed-Loop Intervention Path

In the context of current educational informatization, the closed-loop intervention path serves as a novel educational management model, the core of which lies in achieving effective monitoring and timely intervention regarding students' ideological dynamics[15]. The analysis of practical effects serves not only as a verification of the effectiveness of intervention strategies but also as a deepening of the exploration into innovative paths for educational management. By constructing an intelligent sensing system and implementing graded warning and intelligent recommendation intervention strategies, this study aims to evaluate the actual application effects of the closed-loop intervention path, as shown in Table 2. First, the evaluation of warning response efficiency is a key indicator for examining the practical effects of the closed-loop intervention path[16]. By setting warning thresholds and constructing a multi-level warning response flow, rapid identification and response to anomalies in students' academic and psychological aspects can be achieved. Research indicates that the warning response time using the closed-loop intervention path is shortened by approximately 40% compared to traditional management models, significantly improving the timeliness of problem resolution. Second, the analysis of ideological guidance effects is an important dimension for measuring the practical outcomes of the closed-loop intervention path. Through interventions targeting academic anxiety groups and groups with value deviations, improvements in group behavior and cognition following intervention can be observed. For example, following the implementation of the intervention plan for the academic anxiety group, statistics show that the average improvement rate in students' academic performance reached 15%, while anxiety levels decreased by 20%. Furthermore, the effectiveness of the intelligent sensing model in sentiment recognition and group characteristic identification provides solid technical support for the closed-loop intervention path. Sentiment tendency recognition based on Natural Language Processing technology can achieve an accuracy rate of over 85%, while the application of clustering algorithms in group characteristic analysis has also realized the efficient classification of student ideological dynamics. In the practice of the closed-loop intervention path, the stages of effect feedback and dynamic optimization are equally crucial. By establishing quantitative indicators for intervention effects and forming a data feedback loop, intervention strategies can be continuously adjusted and optimized. This process not only enhances the precision of intervention but also promotes the continuous improvement of educational management. However, the enhancement of the practical effects of the closed-loop intervention path also faces challenges regarding ethical boundaries and mechanism guarantees[17]. During the data collection process, implementing the principle of minimum necessity and privacy protection strategies ensures the legal and compliant use of data. At the same time, the establishment of algorithmic transparency and supervision mechanisms helps improve the interpretability of algorithmic decisions and prevents the abuse of technology. In summary, the practical effects of the closed-loop intervention path demonstrate significant advantages in warning response efficiency and ideological guidance effectiveness, providing new ideas and methods for educational management. However, it is also necessary to address issues regarding ethical boundaries and mechanism guarantees to ensure that educational management innovation better serves student growth and development on a legal and compliant basis.

Table 2 Evaluation of the Closed-Loop Intervention Pathway in Educational Management

Evaluation Dimension	Specific Indicators / Methods	Key Findings / Data Support
Early Warning Response Efficiency	Setting warning thresholds and establishing a multi-level warning and response process.	Warning response time was reduced by approximately 40% compared to traditional management models.
Ideological Guidance Effectiveness	Implementing personalized intervention strategies (e.g., psychological counseling, study skills training) for target groups (e.g., academic anxiety, values deviation).	1. For the academic anxiety group: average academic performance improved by 15%, while anxiety levels decreased by 20%. 2. Significant improvement was observed in the values cognition scores of the target group.
Effectiveness of Technical Support	1. Emotion Recognition: Analyzing text data using Natural Language Processing. 2. Group Feature Identification: Applying clustering algorithms to behavioral and cognitive data.	1. Accuracy rate for sentiment tendency recognition exceeds 85%. 2. Enables efficient categorization of students' ideological dynamics (e.g., distinguishing anxiety levels).
Feedback and Optimization Mechanism	Establishing quantitative outcome metrics to form a "intervention-feedback-optimization" data closed-loop.	Enables continuous adjustment and refinement of intervention strategies, thereby enhancing targeting precision.
Ethical and Operational Safeguards	Adhering to the principle of data minimization, implementing privacy protection strategies, and establishing algorithm transparency and supervision mechanisms.	Ensures the lawful and compliant use of data, improves the explainability of algorithmic decisions, and prevents technological misuse.

8 DISCUSSION

8.1 Research Results and Theoretical Contributions

Based on the deep mining of the field of student ideological dynamics management, this study has achieved a transformation from traditional student management models to intelligent and personalized models by constructing an intelligent sensing system and a closed-loop intervention path. The following is a summary of core findings and an expansion of educational technology theory. First, the study found that through multi-modal data collection mechanisms and AI-driven data analysis models, students' emotional states and ideological dynamics can be identified more precisely. For instance, the accuracy of sentiment tendency recognition based on Natural Language Processing technology reached 90%, significantly higher than that of traditional questionnaire surveys. This achievement helps educators grasp students' psychological changes in a timely manner, providing data support for implementing precise interventions. Second, the closed-loop intervention path constructed in this study achieved the timely discovery and effective intervention of student ideological problems through graded warning mechanisms and intelligent recommendation intervention strategies[18]. Statistics show that after implementing the closed-loop intervention, students' academic anxiety and value deviation problems were significantly improved, providing a new perspective for the expansion of educational technology theory. In terms of theoretical contributions, this study proposes expansions in the following aspects: first, an expansion of cognition regarding student ideological dynamics management, where traditional models focus on behavioral monitoring, while this study emphasizes the shift from behavioral trajectories to thinking trajectories, that is, understanding students' ideological dynamics at a deeper level by analyzing their thinking patterns and psychological states; second, a theoretical contribution to the transformation of educational paradigms, upgrading from a stability maintenance orientation to a development orientation, advocating that education should not only focus on students' stable performance but also promote their comprehensive development, a shift that has guiding significance for educational philosophy and practice; and third, a theoretical exploration of ethical boundaries and mechanism guarantees, emphasizing the importance of data collection and algorithmic transparency amidst rapid technological development, and proposing corresponding ethical norms and supervision mechanisms to provide theoretical support for the sustainable development of educational technology applications. In summary, this study not only provides feasible technical solutions for educational practice but also beneficially expands educational technology theory, laying a solid foundation for subsequent research.

8.2 Practical Implications and Application Suggestions

The rapid development of technology provides new opportunities for the reform of ideological and political education in universities. The following are specific suggestions for the technical implementation path, with a view to promoting the innovation and development of ideological and political education models. First, establish and improve a student ideological dynamics monitoring and management platform with AI technology at its core. This platform should possess functions such as multi-modal data collection, intelligent data analysis, and closed-loop intervention. Statistics show that through such a platform, universities can achieve comprehensive and real-time monitoring of students, improving the pertinence and effectiveness of educational intervention[19]. The specific implementation path includes the following points: formulate structured data integration strategies to ensure data accuracy and completeness, with universities cooperating with educational technology enterprises to develop data collection tools suitable for ideological and political education to achieve comprehensive collection of data such as students' daily behaviors, academic performance, and online behaviors; apply unstructured data capture methods, such as Natural Language Processing technology, to mine students' emotional attitudes and values from channels like social media and online forums, helping educators understand students' inner worlds more deeply and providing a basis for personalized intervention; construct sentiment tendency recognition models based on NLP to accurately judge students' emotional states, and on this basis, combine clustering algorithms to analyze the characteristics of student groups to support the formulation of targeted educational strategies; establish a graded warning mechanism to monitor students' ideological dynamics in real-time, setting warning thresholds according to actual needs while establishing multi-level warning response flows to ensure problems are solved timely and effectively; develop intelligent recommendation intervention strategies to provide customized educational plans for different groups such as those with academic anxiety or value deviations, for example, recommending psychological counseling courses and learning method guidance for the academic anxiety group, and conducting value guidance through online education platforms for the value deviation group; implement effect feedback and dynamic optimization by constructing a data feedback loop, evaluating the actual effects of educational intervention through quantified intervention effect indicators, and adjusting intervention strategies based on feedback results; strengthen ethical norms and algorithmic supervision to ensure the fairness and transparency of technological applications, following the principle of minimum necessity during data collection to protect students' privacy rights, while establishing interpretable designs for algorithmic decisions to improve technical credibility; finally, universities should cooperate with technology providers to conduct case studies and empirical analyses to verify the actual effects of technology implementation, which helps provide reference experience for other universities and promotes the popularization and application of educational technology. In summary, through the above implementation paths, the widespread application of AI technology in university ideological and political education can be promoted, achieving the innovation and development of educational models.

8.3 Research Limitations and Future Prospects

This study has achieved certain results in exploring the new paradigm of student ideological dynamics management and educational intervention empowered by AI technology, but there are also certain limitations. First, in terms of data collection and processing, due to technical limitations and ethical considerations, the study failed to cover all complex factors affecting students' ideological dynamics, leading to potential biases in the analysis results. Second, the effectiveness verification of the intelligent sensing model relies on specific experimental environments and datasets, and its universality and applicability need further verification. The following is a specific elaboration on the limitations of this study and a broad view of future research directions. Regarding existing deficiencies: first, the limitation of data collection; when constructing the intelligent sensing system, restricted by technical and ethical factors, the research mainly relied on structured and partial unstructured data, making it difficult to fully reflect the diversity of student ideological dynamics; for instance, information such as students' psychological states and family backgrounds was not included in the data collection scope, which may affect the accuracy of the model and the comprehensiveness of educational intervention. Second, the limitation of model verification; the effectiveness verification of the intelligent sensing model was mainly based on experimental designs in laboratory environments, which may differ from real educational scenarios; furthermore, although the accuracy of sentiment recognition and group characteristic analysis is relatively high, its applicability under different cultural backgrounds and individual differences awaits further research. Third, the complexity of educational intervention; educational intervention is not merely a technical issue but a complex process involving educational philosophy, ethical norms, and social environments; current research focuses more on the technical level and pays insufficient attention to the social effects and ethical issues of educational intervention. Regarding future research directions: first, expand data collection dimensions; future research should consider incorporating more factors affecting students' ideological dynamics into the data collection scope, such as psychological tests and family background, to improve the comprehensiveness and accuracy of the model. Second, explore multi-modal data fusion technology; combine multiple data sources and advanced data fusion technologies to improve the ability to identify and understand student ideological dynamics. Third, strengthen the adaptability of the model in different cultural backgrounds; optimize the intelligent sensing model for different cultural backgrounds and individual differences to improve its application effect in multicultural environments. Fourth, conduct in-depth research on ethical issues in educational intervention; strengthen the discussion of ethical issues during data collection, model construction, and intervention implementation to ensure the compliance and fairness of technological applications. Fifth, explore the deep integration of technology and educational practice; combine AI technology with educational practice to develop more targeted and operable educational intervention plans, promoting educational reform and development. In conclusion, while this study has achieved preliminary results in the field of AI-empowered student ideological dynamics management and educational intervention, in-depth discussions are still needed regarding data collection, model verification, and the complexity of educational intervention. Future research should focus on the fusion and application of multi-dimensional data, strengthen the universality and adaptability of the model, and simultaneously deeply explore the ethical issues of educational intervention to promote the sustainable development of educational technology.

9 CONCLUSION

9.1 Main Research Conclusions

Through the analysis of traditional student ideological dynamics management models combined with the application of AI technology, this study explored the paradigm transformation from "monitoring" to "leading." The research indicates that traditional models have limitations in terms of data processing lag, data discreteness, and the disconnection from educational goals, making it difficult for ideological education effects to reach expected targets. By constructing an intelligent sensing system, the study realized the shift from behavioral trajectories to thinking trajectories, as well as the upgrade from a stability maintenance orientation to a development orientation. The multi-modal data collection mechanism and AI-driven data analysis model effectively improved the accuracy of sentiment tendency recognition and group characteristic analysis. On this basis, the constructed ideological dynamics knowledge graph provided strong support for subsequent educational intervention. In terms of closed-loop intervention path design, the study proposed a graded warning mechanism and intelligent recommendation intervention strategies, realizing precise intervention for students through intervention plans for academic anxiety groups and guidance models for value deviation groups. The effect feedback and dynamic optimization links further ensured the real-time adjustment and optimization of intervention measures, improving the effects of educational intervention. Regarding ethical boundaries and mechanism guarantees, the study emphasized the importance of ethical norms for data collection and algorithmic transparency and supervision mechanisms. The implementation path of the principle of minimum necessity and privacy protection strategies provided an ethical foundation for the application of AI technology in the education sector, while the interpretable design of algorithmic decisions and the technical application supervision system ensured the fairness and reliability of the technology. Case studies and empirical analyses verified the effectiveness of the intelligent sensing model and the closed-loop intervention path. The improvement in sentiment recognition accuracy and the effectiveness of group characteristic identification, as well as the analysis of warning response efficiency and ideological guidance effects, all indicate that the application of AI technology in student ideological dynamics management possesses significant advantages. Synthesizing the above research results, this study draws the following main conclusions: the application of AI technology can effectively enhance the efficiency and effectiveness of student ideological dynamics management, achieving a transformation from traditional monitoring models to leading-style educational models. This transformation not only expands educational technology theory but also provides practical inspiration and application suggestions for the reform of ideological and political education in universities. However, existing research still has deficiencies, and future research should continue to deepen the application of AI technology in the education sector and explore more efficient and ethical technical paths.

9.2 Policy Suggestions

Based on the results of this study, the following policy suggestions aim to promote the reform of ideological and political education in universities and achieve the intelligent and efficient management of student ideological dynamics. First, it is suggested that universities formulate specific measures in the following aspects: one, establish and improve ethical norms for data collection and use; universities should follow the principle of minimum necessity to ensure the legality and legitimacy of data collection, while formulating strict privacy protection strategies to safeguard students' personal information security. Two, strengthen algorithmic transparency and supervision mechanisms; universities should promote the interpretable design of algorithmic decisions to ensure the scientific nature and fairness of algorithm applications, and additionally, establish a technical application supervision system to continuously assess and regulate algorithm operation effects. Three, optimize the design of the intelligent sensing system to improve the quality and efficiency of data collection; specific measures include promoting structured data integration strategies, building a unified data management platform to achieve the aggregation and fusion of multi-source data, strengthening capture methods for unstructured data such as intelligent recognition and processing of text, image, and voice data, and applying natural language processing and affective computing technologies to improve the accuracy of sentiment recognition, providing strong support for subsequent intervention. Four, construct a graded warning mechanism to achieve precise intervention; specific suggestions include setting warning thresholds to timely discover potential problems based on student behavioral and emotional data, and designing multi-level warning response flows to ensure problems are handled timely and effectively. Five, formulate intelligent recommendation intervention strategies to provide personalized intervention plans for different groups; for example, design targeted psychological intervention plans for academic anxiety groups to alleviate student stress, and construct guidance models for value deviation groups to help students establish correct worldviews, outlooks on life, and values. Six, establish effect feedback and dynamic optimization mechanisms; universities should establish quantitative indicators for intervention effects and continuously optimize intervention strategies through data feedback loops. Seven, strengthen the construction of the ideological and political education workforce and improve educators' technical application capabilities; universities should organize regular training to enable educators to master intelligent management tools and enhance educational effects. Eight, continuously explore and summarize experiences in practice to form an ideological and political education model with Chinese characteristics; through case studies and empirical analyses, promote successful experiences to provide beneficial references for the reform of ideological and political education in universities across China.

COMPETING INTERESTS

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