ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

Data Mining Analysis of the Formation Path of College Students' Integrity Cognition Guided by the Goal of Moral Education and Talent Cultivation

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SUMMARY: *It is against this background of the transformation of the system of higher education governance and the reinforcement of the value guidance in the new era that the mechanism of college students becoming integrity cognition have the features of multidimensional coupling and dynamic evolution. With the overarching aim of moral education and talent development, this paper combines insights based on pedagogy, cognitive science and data mining technology to conduct a review and critically examine the development trajectory of integrity cognition among college students. Through the introduction of techniques of multi-source data fusion, text mining, clustering analysis, and path modeling, an analytical paradigm of value input-cognitive processing-behavioral transformation is built, and the dynamics of change of the integrity cognition structure under various educational intervention models is outlined. The study concludes that integrity cognition does not lie in the accumulation of knowledge as a single entity and that it is a complex system that is collectively influenced by value internalization, situational experience and behavioral feedback. Data mining technology proves to be of great benefit in detecting differences in cognitions, forecasting development patterns, and streamlining learning paths. Moreover, this article presents a specific intervention model of integrity education based on the data, which should be a precise model, with theoretical justifications and practical examples to support ideological and political education in universities.*

KEYWORDS: *Moral education and talent cultivation; Integrity cognition; Data mining; Cognitive pathway; Higher education governance*

1 Introduction

The main task of higher education in the new era, moral education and talent cultivation, is at its core in accomplishing the unceasing construction and stable progression of the moral structure of students by systematic guidance of the values. In this overall goal paradigm, integrity cognition is not just a worthy aspect of ideological and political education, but also the primary aspect of gauging the success of talent development in higher education. Integrity cognition is not simply the learning of knowledge, or the memory of norms; it is a system of value judgment and choice of behavior that is gradually created by the interaction of various educational situations and social experiences, and its creation process is marked by high complexity and dynamism.According to the educational practice view, existing integrity education in universities predominantly depends on the methods of teaching the curriculum,

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https://doi.org/10.65102/is20261242 Published: 10 June, 2026

thematic tasks, and institutional policies. Despite some of the successes achieved in terms of knowledge transmission and normative restraints, the stages of cognitive internalization and behavioral change are still deficient in structure [1]. On the one hand, the concepts of integrity still seem to be on a surface level, with no deep identification of values in some students; on the other hand, the behavioral decisions of individuals in a complicated situation are still easy to be impacted by the environmental inducements and immediate interest and it is observed that there is a situational dependence. This indicates that traditional educational models still need further improvement in the systematic construction of cognitive generation mechanisms.At the same time, as the digital transformation of higher education is being constantly developed, the volume of multi-source heterogeneous data is increasing steadily in the context of education, such as the learning behavior trajectory, course assessment text, the log of real-life activities, and information about online interaction. These data offer a new line of research in the development of the integrity cognition of college students on the micro level. Through the implementation of data mining technology, complicated educational data can be thoroughly scrutinized to find out important variables that influence cognitive formation and the connection between various factors, thus, facilitating a systematic representation of the cognitive formation process [2]. The development of integrity cognition, at the theoretical level, consists of several processes, including value input, cognitive processing, and behavioral feedback and its nature is a part of a coupled system of processes of cognitive construction and socialization. The magnitude and interplay of various educational components in each stage are directly related to stability and sustainability of the cognitive structure [3]. Consequently, under the auspices of the objective of moral education and talent development, there is a need to develop a holistic analytical system incorporating pedagogy and data science, which will review and explored the formation of the integrity cognition formation systematically and with a deep analysis. In these terms, the integrity cognition of college students is considered the research object in this paper, and multi-source educational data and data mining techniques are integrated, followed by a review analysis based on the classification of the cognitive structure, factors influencing the integrity cognition, and path models. The purpose is to disclose the internal processes of the formation of integrity cognition and, based on it, present the data-driven educational optimization procedures, thus, offering theoretical foundation and practical ground of the accuracy and scientific elaboration of the ideological and political education in universities.

2 Theoretical Foundations and Analytical Framework

2.1 Structural Connotation of Integrity Cognition

Being one of the key elements of the value system of college students, the connotation of integrity cognition is not restricted to acquisition of one piece of knowledge, but it is a multi-dimensional system that consists of normative understanding, internalization of values, and orientation of behavior. Within the broad umbrella of the purpose of moral education and talent development, a structural analysis of the cognition of integrity assists in explaining the hierarchical processes and pathways of educational intervention [4].

2.1.1 Normative Cognition Level

This tier is primarily reflected in how people perceive and comprehend systems of integrity, disciplinary rules and limits of behavior. It considers explicit knowledge as its main vehicle and the beginning of the development of the integrity cognition. Its essence is to give people the basic guidelines of behavioral judgment.

2.1.2 Value Identification Level

This is the development of internal identification and emotional orientation towards the notion of integrity based on the comprehension of norms. It is a stage of the transition of outer limitations to internal ideation and is one of the major points in the evolution of cognition.

2.1.3 Behavioral Tendency Level

It is reflected in the decision-making orientation of people in particular circumstances and is the direct realization of the cognition of integrity as an externalization of this cognition into the concrete behavior.

2.2 Cognition Generation Mechanism Oriented by Moral Education and Talent Cultivation

The development of integrity cognition in college students can be modeled as an abstract process with stage-based and cyclical attributes under the tutelage of the objective of moral education and talent development. This process can be described as comprising of three essential stages of value input, cognitive processing and behavioral feedback based on a thorough examination of educational practice and cognitive development and thus this constitutes a closed-loop operational mechanism. As shown in Figure 1.

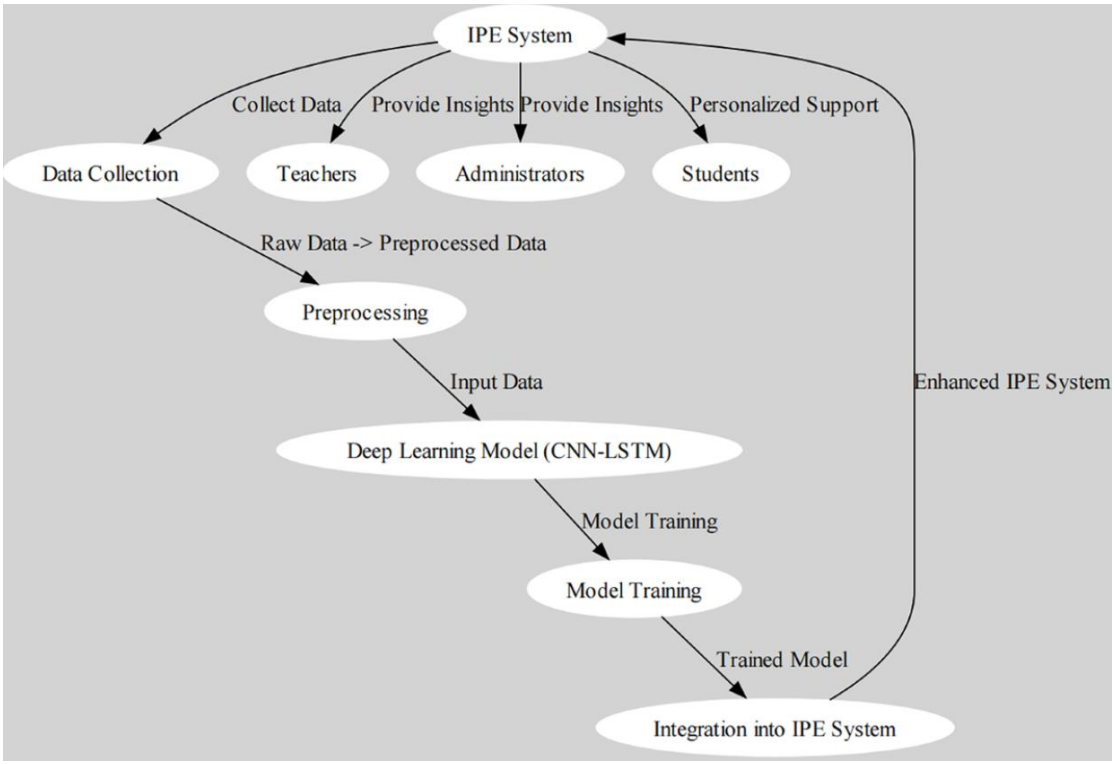

Figure 1: Model of the Integrity Cognition Generation Mechanism under the Guidance of Moral Education and Talent Cultivation

2.3 Methodological Foundations of Data Mining in Educational Cognition Research

Within the framework of educational digitalization, data mining technology can have a new methodical contribution to the investigation of integrity cognition. Data mining can identify latent patterns in large volume, multidimensional data, and produce structured analysis of

multifaceted cognitive processes as compared to conventional research techniques that require questionnaires and interviews [5]. In particular, association rule mining is primarily employed to determine the most important factors that affect the development of integrity cognition and their relationships with each other. It examines the co-occurrence nature and level of association among the variables, thus unveiling the possible links between the educational interventions and cognitive outcomes. The cluster analysis categorizes students into various types depending on variations in cognitive levels, behavioral performance, and value orientations hence, offering a foundation to differentiated education. The text semantic analysis is based on the semantic analysis of feedback texts and online expressions by students and allows retrieving emotional tendencies and value expression features, thereby facilitating the determination of implicit cognitive structures. It is upon this foundation that path modeling forms causal relationship models among variables, in order to provide a systematic explanation of the mechanism of formation of integrity cognition [6].

3 Data Sources and Methodological System

3.1 Construction of Multi-Source Data

The development of the integrity cognition of college students under the influence of the purpose of moral education and nurturing of talents is characterized by important features of situational embeddedness and dynamic development, and their data form is characterized by complex features of multiple sources, multimodality, and perpetual change. Thus, the most important basis of data mining analysis is the construction of a multi-source data system that would encompass the whole process of cognitive formation. This study, using the real-life functioning of education, synthesizes systematically structured and unstructured data to construct a four-dimensional integrated data model of learning-experience-expression-evaluation [7]. The data sources, in particular, primarily consist of the following four categories (1) Data on the learning of ideological and political courses, such as course grades, course learning behavior patterns, classroom interaction frequency, and stage-based assessment outcomes, which can indicate the level of mastery of the students at the normative cognition level, and the level of learning engagement (2) Records of engagement in campus integrity education activities, such as thematic practical activities, project-based Online platforms create comments and feedback texts based on the course evaluation systems, learning platform discussion sections, and online communities on campuses, which can be used to provide information about the depth of student participation and the intensity of situational experience in value identification formation. These data have high subjective expression and emotional inclination features, and are crucial data sources to determine the implicit cognitive structure of students in terms of standardized scales, behavioral tendency measurements, and overall teacher-based assessments, which offer quantitative evidence to support the cognitive structure.Coming to Figure 2, data of various sources is standardized and combined under a single set of coding rules and labeling systems, and an analytic data, dynamically structured, is created by reconstruction of time series. Not only does this data structure capture the cognitive changes of the students at various stages, but also indicates possible connections between the different kinds of data, which in turn offers continuous and systematic support to the future path modeling.

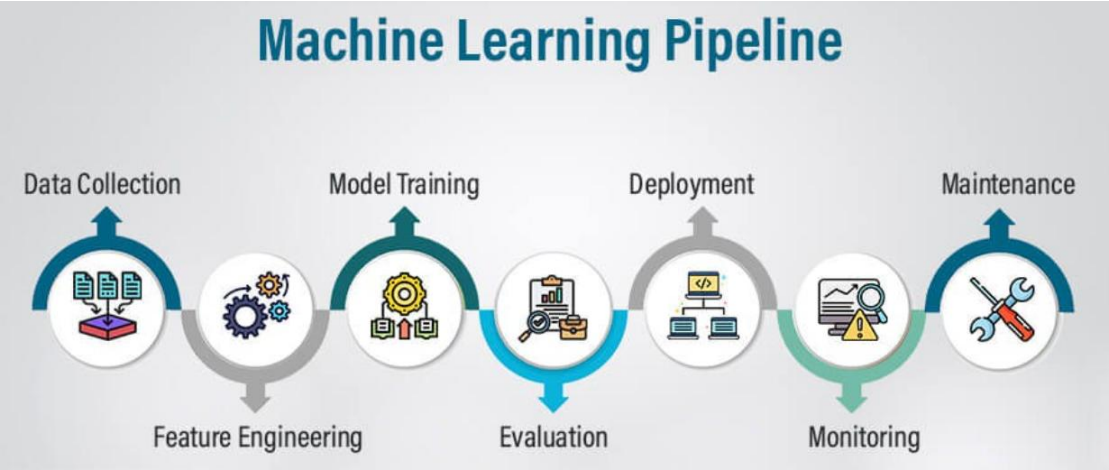

Figure 2: Schematic Diagram of the Multi-Source Data Construction and Integration Framework

3.2 Data Processing Workflow

3.2.1 Data Cleaning and Standardization Stage

The lost data, outliers and duplicated records should be deleted. The lost data can be substituted by the mean imputation or model-based prediction imputation according to the characteristics of the variable. Outliers are detected and adjusted by combining the statistical distribution with the actual educational conditions. Furthermore, the consistency between different data sources is achieved through the use of a standardised data format and dimension normalisation [8].

Continuous indicators from different platforms were transformed to a comparable scale using the min-max normalization in Eq. (1).

$$x_{i,k}^{*} = \frac{x_{i,k} - \min(x_k)}{\max(x_k) - \min(x_k) + \varepsilon} \tag{1}$$

In Eq. (1), $x_{i,k}$ is the original value of indicator k for student i, $x_{i,k}^{*}$ is the normalized value, and ε prevents division by zero when an indicator has no observed dispersion.

3.2.2 Feature Extraction and Dimensionality Reduction Stage

The raw data are converted into a system of indicators that show the nature of integrity cognition by forming interpretable feature variables. As a case in point, an engagement index is derived out of learning behavior data, sentiment polarity and value related keywords out of textual data, and cognitive scoring dimensions out of questionnaire data are constructed. Based on this fact, the dimensionality reduction techniques are used to minimize redundancy in data and maximize efficiency of a model and ease in interpreting the result.

After normalization, the cognitive profile of student i was expressed as the feature vector in Eq. (2).

$$\mathbf{z}_i = [N_i, V_i, B_i, E_i, S_i, P_i]^T \tag{2}$$

Here, N is normative cognition, V is value identification, B is behavioral tendency, E is learning engagement, S is sentiment tendency extracted from text, and P is practical-activity participation.

3.2.3 Model Training and Validation Stage

According to the research objectives, suitable data mining algorithms are chosen for the model. For the classification of cognitive types, clustering analysis is applicable; for detecting the important influencing factors, association rule mining is used; and for studying the relationships in cognitive pathways, path models should be established. In the training of the model, methods like cross-validation are applied to assess the stability and generalization ability of the model, guaranteeing the accuracy and repeatability of the analytical results [9].

3.2.4 Result Interpretation and Path Analysis Stage

The model results are systematically matched to the theoretical framework, and major variables and their paths of action are analyzed in-depth. By comparing the features of various cognitive types and their evolutionary processes, some important nodes and mechanisms in the formation of integrity cognition can be identified, which will provide a foundation of educational intervention strategies.

4 Classification and Feature Analysis of Integrity Cognition

4.1 Analysis of Clustering Results

Based on the construction of multi-source data and feature extraction, the K-means clustering algorithm was applied to classify college students' integrity cognition into different types. The clustering variables largely consist of normative cognition scores, value identification index scores, behavioral tendency scores, and learning engagement levels. Structural grouping of samples was attained using distance measurement in a multidimensional feature space. Ultimately, college students' integrity cognition was categorized into three typical types, as shown in Table 1.

For clustering, the normalized student-level feature vector was estimated by minimizing the within-cluster sum of squared distances in Eq. (3).

$$J = \sum_{c=1}^{K} \sum_{i \in C_c} \|\mathbf{z}_i - \boldsymbol{\mu}_c\|_2^2, \quad K = 3 \tag{3}$$

Table 1: Classification Results of College Students' Integrity Cognition Types

Type	Feature Description	Behavioral Tendency	Proportion (%)
High-identification type	High degree of value internalization, stable cognitive structure, and strong consistency between normative understanding and value identification	Consciously complies with norms, with sustained and consistent behavior	34.5
Situation-dependent type	Moderate cognitive level, unstable value identification, easily influenced by external situations	Behavioral orientation fluctuates with environmental changes, showing selective compliance	41.2
Low-cognition type	Insufficient normative understanding, weak value identification, and incomplete cognitive structure	Unstable behavior, prone to decision-making that deviates from norms	24.3

4.2 Association Analysis of Influencing Factors

The multi-source data were analyzed using association rule mining to further determine the most important factors that affect the distribution of the types of integrity cognition. Statistically significant strong association rules were extracted by setting thresholds of support and confidence and presented in Table 2.

Support and confidence were calculated using Eq. (4), where A is a condition combination, B is a cognitive type, and n is the sample size.

$$support(A \Rightarrow B) = \frac{|\{i{:}A_i{=}1,\ B_i{=}1\}|}{n},\ confidence(A \Rightarrow B) = \frac{|\{i{:}A_i{=}1,\ B_i{=}1\}|}{|\{i{:}A_i{=}1\}|} \quad (4)$$

Table 2: Association Rule Analysis of Influencing Factors of Integrity Cognition

Rule ID	Condition Combination	Support	Confidence
R1	High engagement + high satisfaction with ideological and political courses → High-identification type	0.42	0.78
R2	High exposure to negative online information → Low-cognition type	0.35	0.71
R3	Participation in practical activities + mentor guidance → High-identification type	0.38	0.82

5 Data Mining Model of the Formation Path of Integrity Cognition

5.1 Path Modeling

According to the classification of types and identification of the factors above, a Structural Equation Modeling (SEM) approach is further presented to quantitatively model the process of integrity cognition formation. The model considers the following core system of variables: value input-cognitive processing -behavioral tendency-cognitive reinforcement. It develops relationships among latent variables and observed variables, which results in a systematic representation of the cognitive generation mechanism. The value input has a strong positive impact on cognitive processing with a standardized path coefficient of 0.63, which means that issues like curriculum education, institutional norms and campus culture can effectively enhance the way people understand and assimilate information related to integrity [10]. The effect coefficient of cognitive processing on the behavioral tendency is 0.71 which shows that the extent of cognitive internalization is a direct determinant of the stability of behavioral decision making and a key mediating factor between external input and behavioral output. The path coefficient of behavioral feedback on cognitive reinforcement is 0.58 which implies that practical experience and evaluation mechanisms can have a reverse regulatory effect on the existing cognitive structure, thus allowing the cognitive system to dynamically adjust to the current circumstances. In the sense of the general framework of the model, the cognitive processing phase falls in the middle of the pathway and is a major mediator between the value input and the behavioral tendency. This finding suggests that merely utilizing external sources of knowledge is not enough in order to reach cognitive stability, and, instead, one has to support deep processing to ensure that people accomplish the conversion process between understanding and identification. Moreover, the presence of the behavioral feedback pathway also points towards the cyclic character of the cognitive system whereby behavioral

consequences in turn reflect on cognitive structures and thus constitute a dynamic evolutionary process.

The structural path model was formulated as Eq. (5), where *VI* represents value input, *CP* stands for cognitive processing, *BT* indicates behavioral tendency, *CR* denotes cognitive reinforcement and *X* is the vector of control variables.

$$CP_i = \beta_1 VI_i + \gamma_1 X_i + \varepsilon_{1i}; BT_i = \beta_2 CP_i + \gamma_2 X_i + \varepsilon_{2i}; CR_i = \beta_3 BT_i + \gamma_3 X_i + \varepsilon_{3i} \quad (5)$$

5.2 Dynamic Evolution Characteristics

According to the path model, a time-series analysis was carried out to study the long-term changes of integrity cognition. The results show a definite developmental trend. At first, the integrity cognition rises quickly due to the great educational influence which helps the students to learn the fundamental norms and values within a short time [11]. In the middle stage, a change occurs: when the students face more complicated social environments, their existing cognitive structures are affected by situational stress, conflicting interests and peer pressure, leading to a decrease in cognitive stability. Eventually, with the increase of experiences and more dependable feedback systems, the value orientations and behavioral patterns become more firm. This developmental process indicates that the integrity cognition is improved by repeated influences, conflicts, integration and stabilization. Therefore, appropriate intervention measures should be taken according to the developmental stage to enhance the continuity and stability of cognitive growth [12].

6 Path Optimization Strategies under the Guidance of Moral Education and Talent Cultivation

6.1 Data-Driven Precision Education Mechanism

With the help of the results of data mining, it is a significant direction to develop a precision education mechanism depending on the individual differences of students to strengthen the internalization effect of integrity cognition. It can be turned into differentiated intervention by making use of multi-source educational data and dynamically defining the cognitive structures of students, i.e., by changing the homogeneous supply to differentiated intervention [13].

6.1.1 Construction of Multidimensional Data Profiles and Identification of Cognitive Stratification

A multidimensional profile system of college students integrity cognition is built based on the data on learning behavior, indicators of cognitive assessment and the data on emotional expression. Through a comprehensive evaluation of normative cognition level, strength of value identification, and stability of behavioral tendencies, students are classified into different groups such as high-identification type, situation-dependent type, and low-cognition type. Meanwhile, a time dimension is also added so that the cognitive changes in the students can be longitudinally monitored and their developmental stages and evolutionary patterns could be detected and, as a result, dynamic stratified control of the cognitive structures could be attained.

6.1.2 Design of Differentiated Educational Intervention Strategies

According to cognitive stratification, different educational programs are arranged for various student categories. For the high-ability students, efforts are made to reinforce their leading position and to carry out volunteer activities and practical projects. For the students whose

situations need special attention, more situational training and structured reflection are required to enhance their cognitive stability. For the students with low intelligence, the intervention starts with the acquisition of basic norms and gradually constructs a more comprehensive cognitive structure by means of systematic courses and individual guidance. Such differentiated arrangements facilitate the reasonable distribution of educational resources. [14].

6.1.3 Dynamic Optimization Mechanism of Educational Decision-Making

The effectiveness of educational interventions is constantly checked on the basis of data analysis results, and educational strategies dynamically changed with the results of feedback. Through the development of a closed-loop decision-making mechanism, a cyclical cycle of data collection-analysis and evaluation-strategy adjustment-re-implementation is achieved, thus constantly enhancing the targeting and effectiveness of educational interventions. Simultaneously, predictive models are incorporated to draw future-oriented estimations concerning the trends of cognitive development of the students so that a scientific understanding of educational decisions can be made.

6.2 Construction of a Situational Practice-Based Teaching System

6.2.1 Case-Based Situational Embedded Teaching Design

The choice of representative real-life cases imparts the content of integrity education to the contexts of particular situations, converting abstract value ideas into concrete problems that can be perceived. Case analysis helps the students to make value judgments and perform decision-making simulations in a multidimensional information background, which increases the level of cognitive processing and logical analysis capacity[15].

6.2.2 Simulated Decision-Making and Role-Playing Mechanism

Decision-making scenarios are simulated and role-playing techniques are embraced to allow the students to be exposed to the decision-making process through the lens of various roles. Students are required to face conflict of interest and value decisions in simulated situations, thus putting their own cognitive structures into practice. This process assists in increasing situational flexibility of thinking and the consistency of behavioral decision-making.

6.2.3 Construction of a Practice-Oriented Reflection Mechanism

Once the practical activities are completed, the students are then coached to reflect on their individual behaviors using reflection reports, group discussions, and mentor feedback. It is the systematic reflection that transforms practice experience into fixed cognitive forms and thus, attains the process of experiential accumulation to internalization of values[16].

6.3 Digital Feedback and Dynamic Monitoring Mechanism

6.3.1 Real-Time Collection and Integration of Multi-Source Data

Based on educational information sources, real-time learning behavior of students, interaction information and the cognitive assessment outcomes is being collected and the multi-source information is integrated using the data fusion technologies. Through the development of unified data interfaces, data interoperability across various systems is achieved and this gives comprehensive data support on cognitive monitoring.

6.3.2 Dynamic Evaluation Model of Cognitive Development Status

According to the data mining algorithms, the model of the evaluation of integrity cognition structure is developed in order to reveal the cognitive level of students in real time. The cognitive deviations and developmental bottlenecks can be determined by establishing cutoffs on the key indicators, thus facilitating accurate assessment and early detection of the cognitive statuses of the students.

6.3.3 Feedback-Based Intervention Adjustment Mechanism

In accordance with dynamic monitoring, an adjustment mechanism of intervention based on the data feedback is developed. By examining the trends of cognitive change in students, the educational content and techniques are streamlined in a timely manner, realizing dynamic control of the educational process. This process can make the process of correcting cognitive deviations significantly shorter and enhance the responsiveness and effectiveness of educational interventions.

6.4 Multi-Subject Collaborative Mechanism

6.4.1 Teacher-Led Value Guidance Mechanism

The teachers are involved in the process of shaping integrity cognition in a central guiding role. The value transmission and delivery can be improved by making optimal instructional design and enhancing the interaction process within the classroom. Meanwhile, educators are advised to support the gradual formation of the cognitive framework of students with the help of personalized instructions and constant monitoring[17].

6.4.2 Institutional Guarantee Mechanism of the Management System

Institutional guarantees of integrity education are offered through the university management departments, which enhance system design, and evaluation systems. Integrity education is integrated into the overall talent cultivation system by setting up standardized mechanisms of assessment and incentive mechanisms, thus strengthening the institutional constraint and effectiveness of its implementation.

6.4.3 Student-Centered Self-Construction Mechanism

The degree of active involvement of the students has a direct impact on the educational results in the process of cognitive formation. The students are mentored by creating mechanisms of autonomous learning and self-reflection to actively build their cognitive structures in practice, thus increasing the degree of value internalization.

6.4.4 Cross-Departmental Collaboration and Resource Integration Mechanism

By building a cross-departmental collaboration platform, information sharing and resource integration among teaching departments, administrative departments, and student organizations can be achieved. Through the operation of collaborative mechanisms, a multidimensional support system is formed, thereby enhancing the overall effectiveness and systematic level of integrity education.

7 Conclusion

The process of establishing the integrity cognition of college students has the features of

multidimensional interaction and dynamic development under the conditions of the realization of the goal of moral education and talent development. By applying data mining techniques, important nodes and contributing forces to the process of cognitive formation can be identified successfully, and a systematic path model can be built, which offers a scientific foundation to educational practice. The findings of the research depict that cognitive processing takes a central place in the whole pathway whereas behavioral feedback is significant in the process of cognitive reinforcement.Further enhancement of the combination of theoretical frameworks and data-driven techniques is needed in the future, which can facilitate the shift in integrity education towards data-driven rather than experience-driven. Simultaneously, the implementation of accuracy-based educational mechanisms and flexible feedback mechanisms will make it possible to constantly guide and optimize the cognitive growth of students and improve the overall level and educational efficiency of ideological and political education in universities.

About the Author

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