Application of TabNet Interpretable Model in the Evaluation of Student Satisfaction and Value Formation in Textile Ideological and Political Courses

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ABSTRACT With the rapid advancement of intelligent information processing and data-driven decision-making technologies, interpretable artificial intelligence has become increasingly important for complex evaluation tasks in engineering education and future intelligent communication systems. In textile universities, accurately assessing student satisfaction and value formation in ideological and political courses remains challenging because of the nonlinear interactions among multiple educational factors and the limited interpretability of conventional models. To address these issues, this study proposes an interpretable evaluation framework based on the TabNet deep learning architecture. A multi-task learning strategy is employed to simultaneously predict student satisfaction and value formation while providing transparent attribution of influential factors through sequential attention mechanisms. Using questionnaire data collected from 832 textile students, the proposed model achieves a satisfaction prediction accuracy of 91.3% and a value prediction mean squared error of 0.653, outperforming conventional machine learning approaches. The analysis identifies textile ethics integration, craftsmanship guidance, and professional identity as the dominant factors affecting educational outcomes and further reveals significant nonlinear interaction effects and population heterogeneity across majors and grade levels. The proposed framework provides an accurate and explainable methodology for intelligent educational assessment and offers valuable references for data-driven decision support, adaptive information processing, and interpretable learning models in future smart sensing and communication-oriented engineering applications.

INDEX TERMS tabnet, interpretable deep learning, student satisfaction, value formation, intelligent evaluation

I. INTRODUCTION

WITH the deepening of ideological and political education in colleges and universities, constructing a scientific and effective evaluation system for the effectiveness of such education has become a key element in furthering educational and teaching reform. In engineering majors, ideological and political courses not only serve as a platform for theoretical instruction but also undertake the crucial task of guiding students to internalize values and undergo behavioral transformation. Therefore, their evaluation systems must be closely integrated with the professional talent training goals. Textile colleges and universities, as pivotal institutions for engineering education with Chinese characteristics, have a unique, practice-oriented student body [1,2]. Thus, establishing an evaluation framework that can accurately and multi-dimensionally reflect textile students' satisfaction and value formation processes is an urgent requirement to improve the specificity and effectiveness of in-course ideological and political education [3,4]. Nonetheless, current evaluation approaches in textile ideological and political classes generally rely on conventional questionnaire statistics and descriptive analyses, which are severely limited in meeting the intricate demands of professional contexts. The primary deficiencies of existing methods are their irrationality and lack of explanatory power, rendering them inadequate for the specific needs of textile education evaluation. On one hand, conventional methods such as linear regression or similar modeling techniques fail to capture the complexities of industry indicators—like the integration of textile ethics cases, the level of craftsmanship, and student feedback—due to their inherent linear assumptions. Insufficient explanatory power degrades overall predictive function, a problem exacerbated in contexts with multiple, nonlinear drivers [5,6]. On the other hand, the explanatory power of these methods remains at the macro level and cannot provide fine-grained attribution analysis, making it difficult to accurately identify teaching shortcomings in the evaluation results [7,8]. Traditional machine learning models, either due to poor adaptation to nonlinearity or their black box nature, hinder the ability to trace decision paths and fail to meet the needs of textile ideological and political course evaluation. To resolve this dilemma, it is essential to apply intelligent models that achieve both high predictive performance and high interpretability. TabNet, a deep learning framework specifically designed for structured tabular data, aligns well with the assessment needs of textile ideological and political courses. TabNet leverages a unique sequential attention mechanism and feature selection gating structure, achieving an effective synthesis of prediction quality and interpretability [9,10]. The primary advantage of the TabNet model is its ability to autonomously identify and quantify the relative importance of industry-specific features. For example, it can articulate the degree of integration of textile technology history and the influence of corporate social responsibility cases on students' interpretations. Additionally, tracking attention weights dynamically helps visually map attribution pathways at both individual and group levels, clearly explaining the role of each feature variable in final satisfaction or value scores. This is particularly useful in educational assessment contexts, which benefit from rich explanatory accounts. Moreover, research has shown that TabNet performs favorably when processing high-dimensional, discrete, structured datasets and can effectively capture nonlinear associations between features [11,12]. This paper innovatively employs the TabNet model to evaluate student satisfaction and value formation in textile ideological and political courses, establishing an interpretable artificial intelligence evaluation framework for professional contexts. The study adopts a multi-task learning framework to concurrently predict student satisfaction and value formation scores, enabling joint modeling and comprehensive evaluation of teaching effectiveness. Furthermore, by leveraging the model's interpretability, the study identifies key driving factors—such as the use of textile ethics cases and the strength of craftsmanship guidance—that contribute to teaching effectiveness in a nuanced manner, examining nonlinear threshold and interaction effects. This research aims to promote the transformation of the ideological and political education assessment paradigm from an empirical, judgment-based approach to a data-driven, interpretable, and precise, intervention-based intelligent approach.

II. TABNET'S INTERPRETABLE EVALUATION MODEL DESIGN

A. DATA PREPROCESSING AND FEATURE ENGINEERING

To build an interpretable evaluation model for ideological and political courses in textiles, data preprocessing and feature engineering are fundamental steps to ensure model effectiveness. First, to address missing values, K-Nearest Neighbors (K-NN) imputation is used to preserve sample integrity and reduce information loss [13,14]. For any missing feature x_i, its estimated value is determined by the weighted mean of the five samples with the closest Euclidean distance:

$$\hat{x}_i = \frac{\sum_{j\in N_k(i)} w_j x_j}{\sum_{j\in N_k(i)} w_j}, \quad w_j = \frac{1}{d(i,j)} \tag{1}$$

Here, $N_k(i)$ represents the k nearest neighbors of the i-th sample, and $d(i,j)$ is the distance between samples. Next, categorical variables are one-hot encoded and converted into binary vectors to avoid imposing artificial ordinal relationships:

$$\mathrm{One}(c) = [0,\ldots,1,\ldots,0]^T \in \mathbb{R}^m \tag{2}$$

In formula (2), c is the category value, and m is the total number of categories for the variable. For numerical variables, Z-score standardization is used to eliminate dimensional differences:

$$x' = \frac{x-\mu}{\sigma} \tag{3}$$

Here, x' is the standardized value, x is the original numerical variable, μ is the sample mean, and σ is the sample standard deviation, ensuring all features are on the same scale to improve model convergence stability. The final constructed input feature vector covers teaching dimensions, professional integration, value identification, and student background. This paper designs the "professional-value coupling index" as a composite feature:

$$PVVI = \alpha \cdot C_{\text{case}} + \beta \cdot E_{\text{spirit}} \tag{4}$$

Here, C_{case} represents the frequency of industry case studies, and E_{spirit} represents the strength of explicit guidance on the spirit of craftsmanship. α and β are weight coefficients used to quantify the degree of integration between course content and the values of the textile profession. This feature system fully reflects the practical orientation and industry attributes of textile ideological and political courses, providing structured input with domain significance for subsequent modeling. The input feature system is shown in Table 1. To track the dynamic changes in teaching characteristics and support subsequent correlation analysis, this study supplemented time-series annotation of core teaching characteristics during feature engineering. For key variables related to teaching and professional integration, such as Frequency of Case Teaching (F2) and Integration of Textile Ethics Cases (F5), we combined the time series collected throughout the academic year, matched end-of-term questionnaire data with mid-term teaching logs, and annotated the cumulative implementation duration (e.g., Intensity of Craftsmanship Guidance (F6) was annotated as "8 weeks (midterm)" and "16 weeks (end-of-term)"). For short-term stable characteristics such as Professional Identity (F15), we added a "baseline-reference" label: the enrollment survey score served as the baseline, and the end-of-term questionnaire score served as the "post-intervention" value. This annotation preserves the structural properties of

TABLE 1. Input Feature System

Feature Category	Feature Number	Feature Name	Characteristic Description and Calculation Method
Teaching Process	F1	Frequency of Teacher Interaction	Standardized score for the number of questions and discussions asked in class (1–5 points)
Teaching Process	F2	Frequency of Case Study Use	Average number of teaching cases used per semester (standardized)
Teaching Process	F3	Course rhythm	Mean student subjective evaluation of the course progress (1–5 points)
Teaching Process	F4	Teacher Approachability	Comprehensive student rating of the instructor's communication attitude and level of care (1–5 points)
Professional Integration	F5	Integration of Textile Ethics Case Studies	Frequency and depth of integration of textile industry ethics issues (e.g., labor rights and pollution control) in the course (1–5 points)
Professional Integration	F6	Strength of Craftsmanship Guidance	Frequency and depth of instructor's explicit mention of "craftsmanship" and industry role models (e.g., model workers, inheritors of intangible cultural heritage) (1–5 points)
Professional Integration	F7	Proportion of Sustainable Development Topics	Number of class hours covering topics such as green production, environmentally friendly materials, and the circular economy ratio
Professional Integration	F8	Integration of Professional Practice	Score of the close integration of ideological and political content with professional internships, graduation projects, etc. (1–5 points)
Values Identification	F9	Patriotic Sentiment	Degree of recognition of concepts such as "serving the country through industry" and "strengthening the country through science and technology" (1–5 points)
Values Identification	F10	Professional Dedication	Self-assessment of future career commitment and sense of responsibility (1–5 points)
Values Identification	F11	Integrity and Law-abiding Awareness	Degree of recognition of the importance of academic integrity and compliance with laws and regulations (1–5 points)
Values Identification	F12	Sustainable Development Perspective	Degree of emphasis on environmental protection and resource conservation (1–5 points)
Student Background	F13	Professional Focus	Textile Engineering (0), Fashion Design (1)
Student Background	F14	Year Level	Freshman (1), Sophomore (2), Junior (3), Senior (4)
Student Background	F15	Professional Identity	Comprehensive score of students' love and recognition of their major and their willingness to engage in related work in the future (1–5 points)

the features and captures their temporal dynamics, providing a basis for analyzing temporal associations between features and outcome variables, and distinguishing the effectiveness of teaching interventions.

B. TABNET BACKBONE NETWORK ARCHITECTURE DESIGN

To achieve joint modeling of student satisfaction and value formation in textile ideological and political education courses, this paper constructs a deep neural network architecture based on TabNet [15]. The model adopts a multi-step decision structure, consisting of an embedding layer, a feature transformation module, and multiple attention blocks in series [16,17]. The input feature vector is first mapped to a high-dimensional space through a linear embedding layer:

$$e = W_e x + b_e, \quad e \in \mathbb{R}^d \tag{5}$$

Where $d = 64$ is the hidden layer dimension. The model then proceeds through $T = 4$ parallel decision steps, each consisting of a feature transformation block and an attention gating unit. The decision dimension n_d and attention dimension n_a are set to 64 and 32, respectively. n_d remains the same as the hidden layer dimension for consistent feature representation, and n_a is set to half of n_d to achieve efficiency and sparsity in attention computation. The feature selection coefficient γ is set to 1.2, reducing feature overlap among decision steps and enhancing differentiated mining of industry features such as textile ethics cases and craftsmanship guidance. The sparse regularization coefficient λ_{sparse} is set to 0.001, meeting the model's requirement to suppress redundant features without causing excessive sparsity or loss of key industry features. Feature transformation uses a combined BN and GLU structure to enhance nonlinear expression capabilities:

$$BN(z) = \gamma \cdot \frac{z - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{6}$$

$$GLU(z) = (W_1 z + b_1) \otimes \sigma(W_2 z + b_2) \tag{7}$$

Here, $\otimes$ represents the Hadamard product and σ is the Sigmoid function. The GLU structure allows the model to perform feature screening at the channel level, which is particularly suitable for identifying key teaching factors that affect students' value internalization [18]. The residual vector o_t output by each decision step is accumulated into the final representation:

$$O = \sum_{t=1}^{T} o_t \tag{8}$$

This design simulates the step-by-step reasoning process of humans and aligns with the logic of the gradual influence of multiple factors in educational evaluation.

C. SEQUENTIAL ATTENTION MECHANISM AND TEXTILE FEATURE SELECTION

The core innovation of the TabNet model is its sequential attention mechanism, which simulates the gradual focusing behavior of human decision-making and dynamically selects the feature subset with the greatest impact on the current prediction during multi-step reasoning. This achieves both sparse activation and interpretability [19,20]. In this paper, this mechanism is used to identify key teaching factors affecting student satisfaction and value formation in textile ideological and political courses. In the t-th decision step, the model first calculates the attention weight vector $a_t \in \mathbb{R}^d$ of the current step based on the hidden state h_{t-1} from the previous moment:

$$a_t = \text{sparsemax}(W_a h_{t-1} + b_a) \tag{9}$$

Here, h_{t-1} is the hidden state from the previous moment, and the sparsemax function ensures that the output vector is sparse:

$$\text{sparsemax}(z)_i = \max(z_i - \tau(z), 0) \tag{10}$$

Here, $\tau(z)$ is a threshold function controlling the number of activated features. This mechanism ensures the model focuses on only a few key features at each decision step, avoiding averaging across all input features. To enhance the model's focus on core features of the textile industry, this paper incorporates a sparsity regularization term into the total loss function, defined as the weighted sum of the number of activated features in all decision steps:

$$L_{\text{sparse}} = \lambda \sum_{t=1}^{T} \|a_t\|_1 \tag{11}$$

Here, $\|a_t\|_1$ is the L1 norm of the attention weight vector, and λ is the regularization coefficient. By minimizing L_{sparse}, the model is able to select fewer, more discriminative features during training, effectively reducing reliance on redundant or noisy features beyond key industry indicators such as textile ethics integration and craftsmanship guidance. This weight vector a_t acts as a mask on the input features, retaining only key dimensions for subsequent calculations:

$$\tilde{x}_t = a_t \otimes x \tag{12}$$

The weighted feature is then passed to the next feature transformation module and produces the residual contribution for the current step. The entire process is iterated for T = 4 steps, aggregating all residuals to yield the final representation. This gradual focusing mechanism enhances the model's ability to capture complex nonlinear relationships and, crucially, provides a transparent attribution analysis pathway, meeting the fundamental requirement of transparency in ideological and political education evaluation by recording the decision path for educational ideologies and practices.

D. MULTI-TASK OUTPUT LAYER CONSTRUCTION

To comprehensively evaluate the teaching effectiveness of ideological and political courses in textiles, this paper adopts a multi-task learning (MTL) framework and builds a dual-output head based on a shared backbone network to complete both student satisfaction classification and value formation score regression [21,22]. This design captures the multidimensionality of student feedback: satisfaction reflects their subjective feelings about the teaching process, while the value score measures the degree to which their core values are internalized. Although related, the two are not interchangeable. The comprehensive representation $O \in \mathbb{R}^{64}$ of the model backbone is fed into two independent fully connected layers. For satisfaction prediction, it is defined as a three-class classification problem, with a Softmax activation function outputting the probability distribution:

$$P_{\text{sat}} = \text{Softmax}(W_s O + b_s), \quad P_{\text{sat}} \in \mathbb{R}^3 \tag{13}$$

The loss function is categorical cross entropy:

$$L_{\text{cls}} = -\sum_{i=1}^{3} y_i \log p_i \tag{14}$$

Here, y is the one-hot encoding of the true label. For value formation score prediction, it is treated as a continuous variable regression task with an output range of points and a linear activation:

$$s_{\text{val}} = W_v O + b_v, \quad s_{\text{val}} \in \mathbb{R} \tag{15}$$

The corresponding loss function is mean squared error:

$$L_{\text{reg}} = \frac{1}{N} \sum_{i=1}^{N} \left(y_i^{\text{val}} - s_i^{\text{val}}\right)^2 \tag{16}$$

To balance the gradient updates of both tasks, the total loss function is a weighted sum:

$$L_{\text{total}} = \lambda L_{\text{cls}} + (1 - \lambda) L_{\text{reg}} \tag{17}$$

This multi-task structure enables the model to learn both the shared and task-specific features. This is particularly relevant for textile courses, where students may find the teaching methods unengaging and report low satisfaction, yet still identify with the core values. The MTL framework thus more realistically and comprehensively reflects educational outcomes, avoiding the one-sidedness of single-metric evaluations. Interpretability is a significant feature of the proposed model for assessing ideological and political education. To achieve this, the model incorporates an interpretability module into the TabNet framework, aiming to transform the black-box deep learning decision-making process into an interpretable and trustworthy examination of educational mechanisms. The core of this module is to record the attention weight sequence $\{a_1, a_2, \ldots, a_T\}$ for each sample across T decision steps and perform aggregate analysis. First, it calculates the global feature importance (GFI), the average cumulative attention weight of each feature across the entire test set:

$$I_j = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} a_{t,j}^{(n)} \tag{18}$$

Here, $a_{t,j}^{(n)}$ denotes the attention weight of the n-th sample on the j-th feature at step t. This module enhances model transparency, converting data analysis outcomes into actionable teaching recommendations and forming a closed loop from data intelligence to educational intelligence, thus offering a valuable decision-support tool for the precise implementation of ideological and political education in courses.

III. EXPERIMENTAL DESIGN

A. DATA SOURCES AND TEXTILE INDEX MARKING

This research implemented a repeated cross-sectional data collection method targeting students at Qinhuangdao Vocational and Technical College over a four-year period

(2021–2024). Data were collected using a standardized questionnaire at the end of each semester for ideological and political education courses. The questionnaire covered 44 items across four modules: teaching process, professional integration, value identification, and student background, ensuring data consistency and comparability. The survey was anonymous, with no personally identifiable information recorded. Each academic year's participants were students from different batches within the corresponding grade level. A total of 920 questionnaires were distributed over four years. After removing 88 invalid responses (incomplete, contradictory, etc.), 832 valid questionnaires remained, resulting in a valid response rate of 90.4%. The sample size represents cumulative data from all participating students across grade levels over four years: 216 first-year students, 221 second-year students, 211 third-year students, and 184 fourth-year students. This study employs a rolling validation method to partition the data and verify model performance: the 832 samples were divided into four consecutive time windows (one for each academic year from 2021–2024), and iterative validation was conducted sequentially, using the first k windows as the training set and the (k+1)th window as the validation set. Specifically, Round 1 used the 2021 student sample as the training set and the 2022 sample as the validation set; Round 2 used 2021–2022 as the training set and 2023 as the validation set; Round 3 used 2021–2023 as the training set and 2024 as the validation set. This method prevents time-series data leakage and ensures the robustness and practicality of the model evaluation results.

B. BASELINE MODEL COMPARISON EXPERIMENT

To validate the superiority of the proposed TabNet model in assessing ideological and political education courses in textiles, this paper selected four typical machine learning algorithms excelling in structured data modeling as baseline models: logistic regression (LR), support vector machine (SVM), multilayer perceptron (MLP), and eXtreme Gradient Boosting (XGBoost). Logistic regression, a classic linear classification model, is used for baseline comparison, with a three-class LR model for satisfaction prediction and a linear regression model for value scores. The SVM uses a radial basis function kernel to capture nonlinear patterns. The MLP, a classic feedforward neural network, is constructed with two hidden layers and employs dropout to prevent overfitting. XGBoost, a popular gradient boosting tree algorithm, is used for both classification and regression, with key hyperparameters optimized via grid search. TabNet's hyperparameter grid search maintains the same standards as the baseline models. Key hyperparameters are tuned based on the characteristics of the textile ideological and political course data: decision dimension nd and attention dimension na, feature selection coefficient γ ([1.0, 1.2, 1.5]), sparse regularization coefficient λsparse ([0.0001, 0.001, 0.01]), learning rate ([1e-4, 1e-3, 5e-3]), and batch size ([16, 32, 64]).

IV. RESULT ANALYSIS

A. IDENTIFICATION OF CORE INFLUENCING FACTORS IN THE TEXTILE INDUSTRY

In assessing student satisfaction and value formation in textile ideological and political education courses, identifying key influencing factors is crucial for optimizing teaching strategies. The TabNet model calculates global feature importance, quantifying each feature's contribution to assessment results and thereby identifying the core driving factors. Figure 1 shows the importance distribution of 15 features. The results in Figure 1 demonstrate that textile ethics integration (16%) and guidance regarding craftsmanship (15%) are the top two influencing factors, contributing to nearly one-third of the total explanatory power. Professional identity and case study frequency follow in influence, showing that both value orientation and teaching dimensions strongly affect model results. In contrast, professional orientation and grade level contribute little explanatory power, suggesting that structural or demographic attributes are not meaningful factors. Overall, this distribution highlights the concentrated explanatory power of factors related to ethical integration and professional practice, underscoring their primary roles in shaping observed patterns. Figure 2 explores how the importance of core characteristics changes over time in school through comparisons and trend analysis across grade levels: Figure 2(a) and 2(b) compare the performance of first-year and senior students, and sophomores and juniors, respectively, on three key characteristics. The results show that the importance of these three characteristics gradually increases as students progress through their studies, indicating that senior students place greater emphasis on ethical integration, skill development, and professional self-perception. Figure 2(c) and 2(d) further demonstrate that the weights of ethical textile integration and professional identity continue to rise from the first to fourth year. These trends illustrate how students' ethical consciousness and identity construction evolve, with mentorship, experience, and course design increasingly shaping their perspectives. Generally, the relevance of values shifts as students progress, rather than remaining static.

B. MINING NONLINEAR INTERACTION EFFECTS

Student satisfaction and value formation result from interactions among multiple factors, which are not purely linear but exhibit complex, nonlinear relationships. The interaction of professional identity and case relevance, beyond performance, is presented in Figure 3: Figure 3(a) shows a three-dimensional surface with a clear synergistic effect: predicted satisfaction increases nonlinearly with higher professional identity and case relevance. Figure 3(b) further breaks down this effect by grouping students into low, medium, and high professional identity levels. Across five points of case relevance, students with high professional identity consistently report higher predicted satisfaction, ranging from 3.5 to 7.9. The relationship to case relevance widens the gap between groups, highlighting the importance of relevant

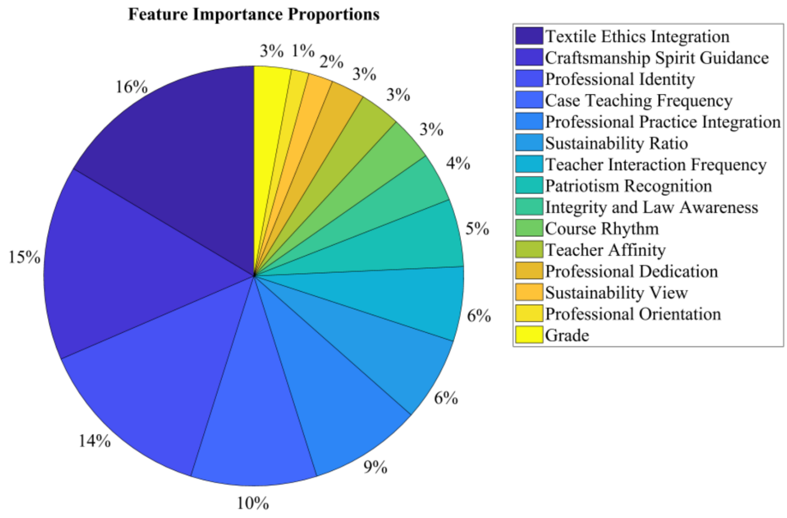

FIGURE 1. Importance distribution of features

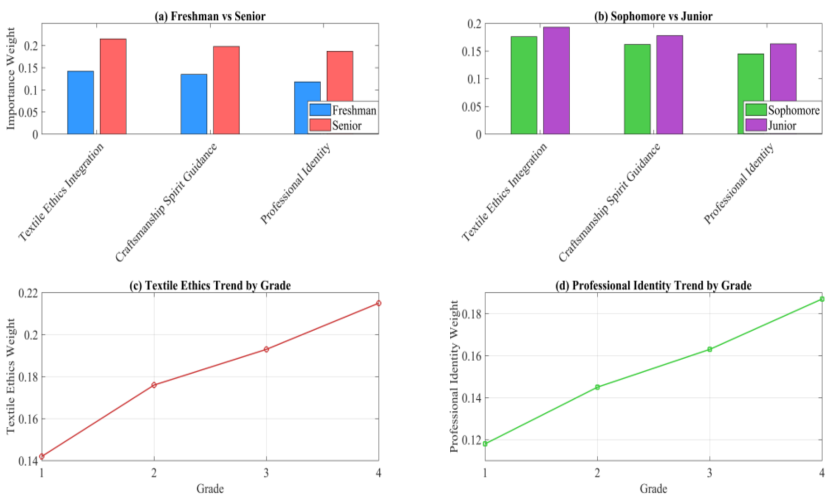

FIGURE 2. Comparison and trend analysis by grade

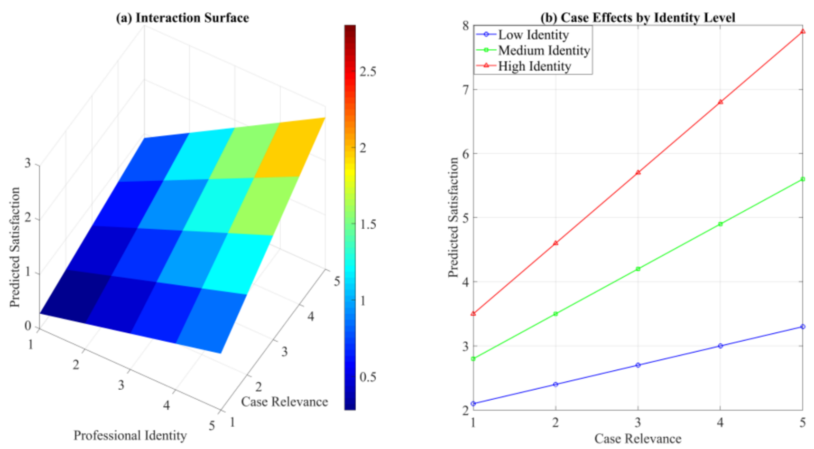

FIGURE 3. Interaction effect between professional identity and case relevance

case learning for students with strong professional identity. Thus, students highly invested in their professional identity can benefit significantly from instructional strategies that intentionally and deeply incorporate relevant case learning, whereas students with lower professional identity benefit less. Figure 4 depicts the interaction between craftsmanship guidance and course rhythm, displaying the distribution of SHapley Additive exPlanations (SHAP) interaction values and comparing differences in the effects of craftsmanship guidance on value scores across various course rhythms. Figure 4 illustrates the interaction between the intensity of craftsmanship guidance and course pace on student value scores. The SHAP interaction heat map suggests that the interaction effect is near zero when both craftsmanship guidance and course pace are at the median (score of 3). Deviations from the median show a positive and negative distribution effect, indicating substantial non-linearity in the interaction between course pace and craftsmanship. With a slower pace, increasing craftsmanship intensity from 1 to 5 raises the value score from 2.2 to 4.5; with a faster pace, the same increase boosts the score from 3.0 to 7.8—almost a doubling at a high pace. Thus, a high course pace amplifies the positive effect of craftsmanship on value scores much more than a low pace. These findings suggest that merely increasing craftsmanship intensity does not maximize benefits when the course pace is too slow; well-planned pacing is crucial for maximizing positive outcomes.

C. POPULATION HETEROGENEITY ANALYSIS

Students from different professional backgrounds have varying experiences, knowledge structures, and career plans, leading to group heterogeneity in their needs and responses to ideological and political education courses. By analyzing groups by professional focus, we can identify different group priorities and inform differentiated teaching. Figure 5 compares students majoring in textile engineering and fashion design: Figure 5 shows that fashion design students place significantly more emphasis on aesthetic value guidance, while textile engineering students focus more on sustainable development issues. Additionally, fashion design students are more sensitive to faculty friendliness. The value score distribution in Figure 5(b) further confirms these differences: fashion design students score higher in aesthetic values, while textile engineering students score higher in patriotism, professionalism, and integrity. These differences are closely related to the training objectives and industry characteristics of each major, providing a clear basis for implementing customized ideological and political education courses in textile disciplines. Students at different grade levels vary in cognitive maturity and professional exposure, and the distinct training orientations of textile engineering and fashion design may further amplify these group characteristics. Therefore, it is necessary to explore the impact of the interaction between grade and major on the evaluation results of ideological and political courses. Figure 6 shows changes in the attention weights assigned by students of different majors and grades to core driving factors. Figure 6 clearly illustrates dynamic changes in the importance of core characteristics based on the interaction between grade and major. For textile engineering majors, the weights of textile ethics integration and craftsmanship guidance increase with grade, reaching 0.20 and 0.19, respectively, in the senior year. Meanwhile, the weight of aesthetic value guidance decreases to 0.06 in the senior year, reflecting the growing demand for industry ethics and professionalism. For fashion design majors, the weight of sustainable development remains constant, while the weight of aesthetic values guidance varies with grade, reaching 0.15 in the senior year. This indicates that art majors continue to emphasize both aesthetic values and industry sustainability. These disparities suggest that, to design effective and differentiated teaching strategies, ideological and political education courses for textile majors must consider both grade progression and the unique features of each major.

D. MODEL PERFORMANCE DIFFERENCES AND VISUALIZATION OF INDIVIDUAL ATTRIBUTION PATHS

Individual-level attribution analysis is crucial for understanding differences in student satisfaction and value formation. Using the attention mask tracking of the TabNet model, it is possible to produce characteristic influence paths for individual samples, revealing the factors contributing to low satisfaction or value formation. Comparing TabNet's performance to baseline models further validates its advantages in individual prediction and attribution. Performance differences are shown in Figure 7.

As shown in Figure 7, TabNet performs best across all metrics: satisfaction prediction accuracy is 0.913 (7% higher than MLP and 2.6% higher than XGBoost); the F1 score is 0.897 (greater than MLP's 0.825 and 7.5% higher t han MLP), demonstrating greater flexibility with imbalance d samples. Its mean squared error (MSE) is 0.653, approximately 52.4% of MLP's MSE, also providing superior conti -nuous variable prediction accuracy. Overall, TabNet outpe rforms other models, including MLP, while preserving int erpretability, establishing a solid technical foundation for ind-ividual attribution analysis. Negative feedback among stude-nts with low satisfaction typically results from deficiencies or imbalances in certain aspects of the teaching experience, necessitating fine-grained attribution path analysis to identify main areas for improvement. Figure 8 (derived from TabNet's attention mechanism) visually presents an example of a low student satisfaction scenario (satisfaction level of 2), showing the characteristic attention distribution

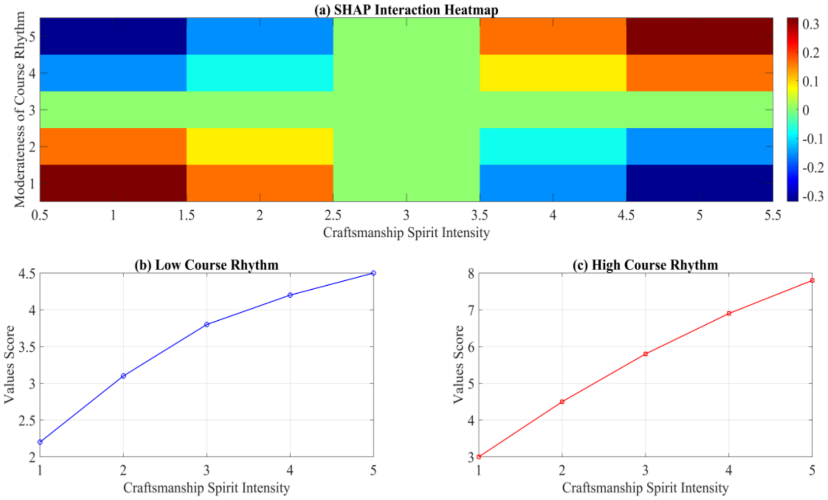

FIGURE 4. Interactive effect of craftsmanship guidance and course rhythm

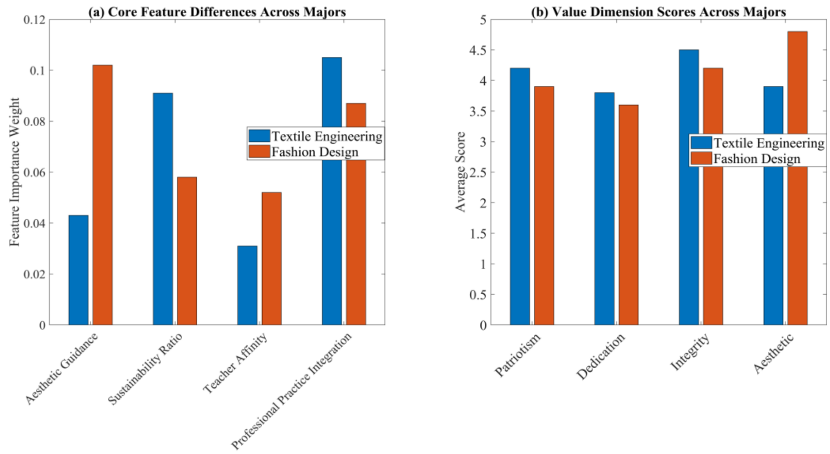

FIGURE 5. Feature importance and value scores by major

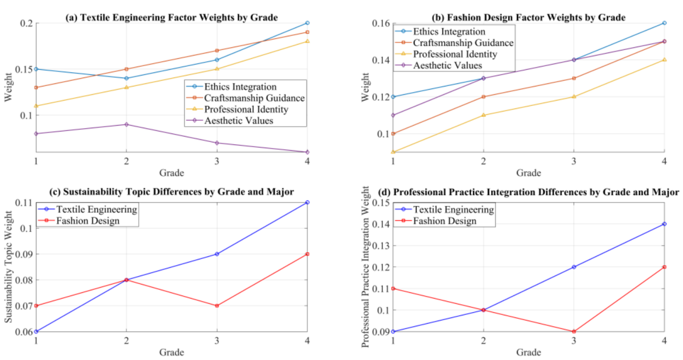

FIGURE 6. Changes in attention to core driving factors by major and grade

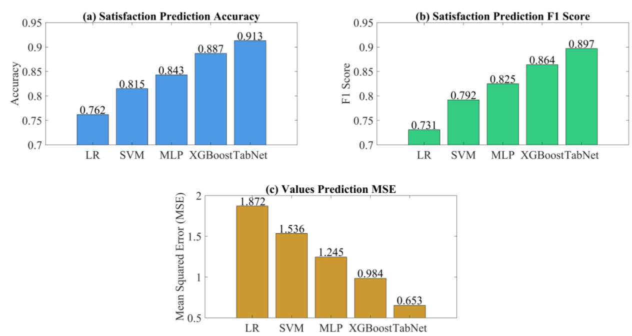

FIGURE 7. Performance differences between models

and main attribution paths utilized by the model during decision-making. This provides a visual basis for examining the mechanisms behind individual student feedback.

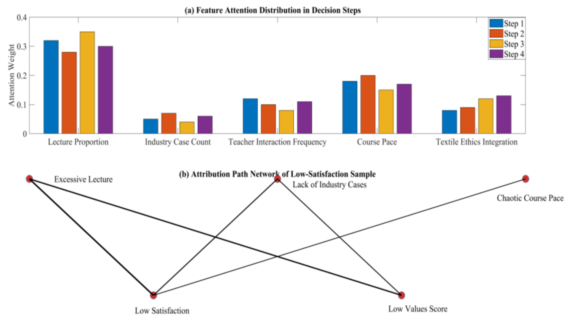

FIGURE 8. Mechanism of negative feedback formation

As illustrated in Figure 8, the attention weight for Lecture Proportion is consistently highest across all decision steps, while the attention weight for Industry Cases is always lowest. These features indicate that, regardless of decision step, the model regularly prioritizes these two salient features during reasoning. Additionally, the path network shows that excessive lectures directly lead to low satisfaction through the strongest connection and affect value scores through the second strongest connection, while a lack of industry cases exacerbates negative outcomes via a bidirectional path. These findings pinpoint precise targets for instructional improvement: affected students would benefit from less time in purely theoretical lectures, more contextually relevant instruction on textile industry ethics, and better-aligned pacing.

V. CONCLUSION

This study develops and validates a framework for evaluating student satisfaction and value development in textile ideological and political classes based on the TabNet interpretable model. The framework addresses a key challenge in traditional assessment: achieving more accurate predictions while maintaining interpretability. The results indicate that the model not only significantly outperforms baseline models in predictive metrics but, more importantly, utilizes an inherent sequential attention mechanism that reveals the explanatory mechanisms behind education quality. The analysis identifies textile ethics case integration, the intensity of craftsmanship instruction, and professional identity as three core factors driving value development, with significant nonlinear interaction effects. Furthermore, the analysis reveals substantial heterogeneity among students' value demands across majors and grade levels. In conclusion, the TabNet evaluation model proposed in this paper offers an accurate, explainable, and intelligent mechanism for implementing curriculum-based ideological and political education, and generates fine-grained attribution pathways to more precisely identify targets for teaching improvement. This approach advances the evaluation process from empirical and broad judgments to a scientific, data-driven paradigm characterized by personalized interventions. The model provides robust technical support for achieving precision education. Future research could expand the sample size, apply the framework to other disciplinary ideological and political courses, conduct comparative analyses to validate cross-scenario applicability, and further enhance the value of this intelligent evaluation tool for ideological and political education.

AUTHOR CONTRIBUTIONS

Conceptualization – Haicheng Zhang, Jing Li, Pingping Wei, Bo Dong and Qian Xia; methodology – Haicheng Zhang, Jing Li, Pingping Wei and Bo Dong; formal analysis – Haicheng Zhang and Jing Li; investigation – Haicheng Zhang; resources –Haicheng Zhang and Bo Dong; writing-original draft preparation – Haicheng Zhang, Jing Li, Pingping Wei, Bo Dong and Qian Xia; writing-review and editing – Haicheng Zhang, Jing Li, Pingping Wei and Bo Dong. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This survey was conducted in compliance with the Ethics Committee of Qinhuangdao Vocational and Technical College. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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