



Research on Prediction of Ideological and Political Education effect of physical Education Course based on machine learning and structural equation model

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SUMMARY: *Aiming at the problems of result lag, mechanism difficulty and data heterogeneity existing in the effectiveness evaluation of ideological and political education in physical education courses, this paper constructs a prediction method combining machine learning and structural equation model. Twenty-eight physical education classes in three universities were selected as objects, and classroom behavior logs, exercise task performance, interaction records, reflective texts and scale data were collected. After cleaning, 796 effective samples, 12736 classroom behavior fragments were obtained, and 58 input features were extracted. The model used algorithms such as random forest and gradient boosting tree to identify key features, and then used structural equation model to describe the chain between teacher support, classroom engagement, responsibility and value identification. The results show that the R², RMSE, MAE and MAPE of the proposed model on the test set are 0.914, 4.86, 3.71 and 5.94%, respectively. Compared with XGBoost, the R² is increased by 0.049 and RMSE is decreased by 1.02. The research shows that the collaboration of machine learning and structural equation model can simultaneously improve the accuracy and explanatory power of the prediction of the ideological and political education effect of physical education courses.*

KEYWORDS: *Physical education curriculum ideological and political; Education effectiveness prediction; Machine learning; Structural equation model*

1 Introduction

With the continuous advancement of education digitization and intelligent analysis technology, curriculum evaluation in colleges and universities is shifting from empirical inductive judgment to data-supported recognition. As a teaching field with the attributes of physical practice, situational interaction and value guidance, the effect of ideological and political education is not only reflected in the improvement of classroom satisfaction or skill performance, but also reflected in the comprehensive generation of students in multiple dimensions such as rule consciousness, responsibility, cooperation spirit, will quality and collective identity. If the evaluation is still mainly based on teacher observation, questionnaire mean comparison or after-class summary, it is often difficult to reveal the role chain between different teaching elements, and it is also difficult to find the key turning point in the formation of education effectiveness in time. Therefore, using computer technology to deeply mine the ideological and political data

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of physical education courses and construct an analysis framework with both explanatory and predictive capabilities has become a direction worthy of promotion in the current research on physical education evaluation [1-3].

Compared with general courses, the ideological and political education process of physical education courses has more obvious characteristics of dynamic and situational embedding. Students' action participation, peer collaboration, teachers' feedback response, competition compliance performance and task adherence in the classroom are not isolated behavior segments, but will affect each other in continuous teaching situations and jointly shape value cognition and behavior tendency. Garcia-Ceberino et al. [4] pointed out that there was a stable structural correlation between psychological need satisfaction and sports participation stickiness. Wen and Cai [5] and Zhang et al. [6] revealed multiple mediation paths in physical education situations from the perspectives of teachers' beliefs, supportive behaviors, self-efficacy and positive emotions. This shows that the effect of ideological and political education in physical education is not directly determined by a single variable, but is affected by multi-dimensional factors such as teacher support, classroom experience, behavior investment, and emotional identity. If only linear statistical methods are used to deal with such problems, it is easy to ignore the indirect effect and hierarchical relationship between the latent variables, and then weaken the grasp of the education mechanism itself.

In recent years, machine learning has shown strong application potential in the field of education prediction. The reviews of Albreiki et al. [7], Sekeroglu et al. [8] and Issah et al. [9] show that student performance prediction based on classification and regression algorithms has gradually expanded from performance prediction to more complex task scenarios such as behavior recognition, risk early warning and learning support. Ahmed et al. [10] and Guevara-Reyes et al. [11] further emphasize that explainable machine learning is driving educational decision making from "giving results only" to "explaining rationale at the same time". For the ideological and political education of physical education course, the data such as class attendance, exercise load, interaction frequency, cooperation task completion, reflection text and stage evaluation results have the characteristics of multiple sources, heterogeneous structure and significant nonlinear relationship. The traditional regression model is difficult to fully describe its internal model, while machine learning has obvious advantages in feature screening, nonlinear fitting and combination prediction. It can provide more sensitive technical tools for the identification of education effectiveness.

However, there are limitations to relying on machine learning alone. The ideological and political research of physical education curriculum is not satisfied with obtaining a high-precision prediction value, but needs to explain "what potential factors are playing a role" and "through what path each variable affects the educational effectiveness". This requirement determines that the research cannot stay at the level of black-box computing. Structural equation model has mature advantages in dealing with latent variable measurement, path analysis and intermediary mechanism testing, and can transform abstract concepts such as rule awareness, value identity, learning engagement and teacher support into estimable structural relationships. Jansson et al. [12], Leyton Roman et al. [13] and Ntoumanis and Standage [14] all showed that structural equation model has strong adaptability for revealing the association between psychological perception, motivation generation and learning results in physical education classroom. Hair et al. [15] and Kline [16] also pointed out that structural equation model is not only suitable for theoretical testing, but also can provide a relatively clear causal explanation framework for complex educational phenomena.

Based on this, the integration of machine learning and structural equation modeling forms a technical path that is more suitable for this research topic. On the one hand, machine learning can identify high-contribution features from multi-source educational data with the help of

computer algorithms, and improve the prediction accuracy of the ideological and political education effect of physical education courses. On the other hand, structural equation model can model the interaction mechanism between latent variables, and make up for the deficiency of pure algorithm prediction in theoretical explanation level. After the collaboration of the two, it can not only deal with the complex nonlinear relationship in classroom data, but also maintain the mechanism interpretability required by educational research, so that "prediction" and "explanation" are no longer separated from each other. Bond et al. [17] research on the application of artificial intelligence in higher education also reminds us that educational intelligence analysis must take into account both technical efficiency, educational logic and ethical prudence if it is to truly serve the improvement of teaching, which provides a realistic reference for the method selection of this research.

Based on the above understanding, this paper focuses on the prediction problem of ideological and political education effectiveness of physical education, tries to construct an analytical framework combining machine learning and structural equation modeling, integrates classroom behavior data, teaching evaluation data and questionnaire measurement data in the scene of physical education, identifies the key factors affecting educational effectiveness, reveals their action paths, and forms a prediction model with transferability. The research aims to answer two core questions. First, whether the effectiveness of ideological and political education in physical education curriculum can be predicted with high accuracy by using computer methods; Second, whether the structural influence mechanism behind the prediction results can be clearly explained. Research on these two problems could not only help to improve the scientific nature of the ideological and political evaluation of physical education courses, but also provide more reliable data support for the optimization, process intervention and precise education of physical education in colleges and universities.

2 Theoretical basis and core technology

2.1 Prediction methods of educational effect driven by Machine learning

The prediction of educational effect driven by machine learning is essentially to transform the multi-source behavior information in the learning process into computable features, and then establish the nonlinear mapping relationship between "input features and outcome variables" through the algorithm. For the ideological and political education of physical education curriculum, the prediction object is not limited to skill performance or classroom standard rate, but also should cover the education results such as rule awareness, cooperation tendency, responsibility undertaking, adhere to quality and value identity. Because such results are often affected by multi-dimensional factors such as classroom participation frequency, exercise load level, peer interaction density, teacher feedback intensity, and emotional tendency of reflective texts, traditional linear statistical methods are difficult to fully describe the coupling relationship. Machine learning has obvious advantages in feature selection, pattern recognition and complex relationship fitting. Albreiki et al. [11] and Sekeroglu et al. [12] pointed out that the task of educational prediction has been gradually expanded from single performance estimation to process behavior recognition and risk warning. Ahmed et al. [15] and Wang and Yu [18] further show that predictive models incorporating interpretable mechanisms are more conducive to instructional intervention decisions.

In the ideological and political scenario of physical education courses, the original data usually come from teaching platform logs, classroom check-in records, action acquisition equipment, questionnaire scales and text reflection materials. In order to improve the usability of the model, it is necessary to complete missing repair, outlier removal, time alignment and

feature coding, and then organize continuous variables, categorical variables and text-derived variables into a unified feature vector. Let the input feature of the i th student be $x_i \in \mathbb{R}^p$ and its ideological and political education effectiveness label be y_i , then the machine learning prediction model can be formulated as

$$\hat{y}_i = f(x_i; \theta) \quad (1)$$

where $f(\cdot)$ represents the prediction function and θ is the model parameter. In order to keep a balance between the fitting ability and the generalization ability of the model, it is usually trained with the objective of minimizing the empirical risk, and its optimization form can be written as:

$$\min_{\theta} \mathcal{L} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 + \lambda \Omega(\theta) \quad (2)$$

where \mathcal{L} is the overall loss function, the former term measures the prediction error, the latter term is the regularization constraint, λ is the penalty coefficient, and $\Omega(\theta)$ is used to suppress overfitting caused by high model complexity.

As shown in Figure 1, the prediction of the effectiveness of ideological and political education in physical education courses driven by machine learning is not to directly send data into the classifier or regressor, but to undergo a closed-loop process of "data collection - feature construction - model training - result interpretation - teaching feedback". This process emphasizes two levels of computer support: one is to realize the unified cleaning and coding of multi-source heterogeneous information with the help of data processing programs, and the other is to estimate and sort the education results through supervised learning algorithms. Common models include random forests, support vector machines, gradient boosted trees, and lightweight neural networks. Among them, the tree model is more suitable for processing medium-scale mixed feature data, and it is convenient to output feature importance. Kernel method has better adaptability to complex boundaries. Neural networks are more resilient in modeling high-dimensional behavioral features. For this study, the value of machine learning is not only to improve the prediction accuracy, but also to identify the key features with more significant impact on education effectiveness from a large number of surface behavioral variables, so as to provide data basis for the setting of latent variables and path construction of the subsequent structural equation model. In other words, machine learning undertakes the task of "extracting high-value signals from complex observations", which lays a quantifiable foundation for subsequent mechanism explanation, rather than replacing educational theory analysis itself.

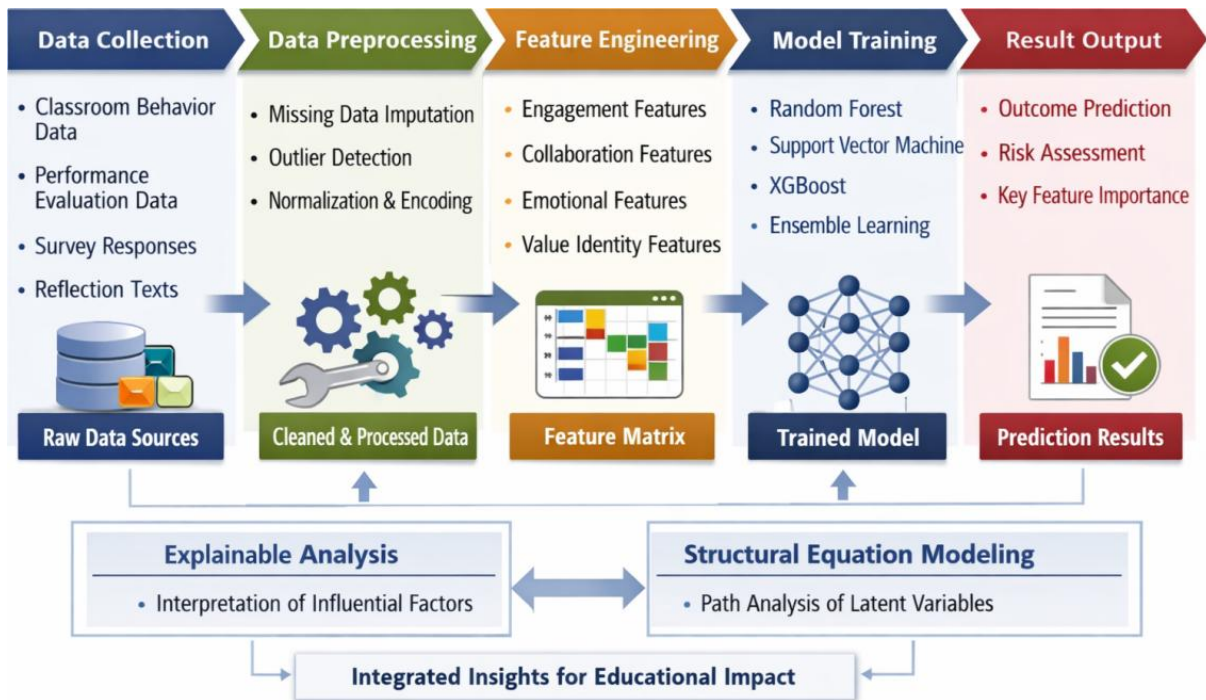


Figure 1: The flow chart of the prediction of the effectiveness of ideological and political education in physical education courses driven by machine learning

2.2 Principle of latent variable analysis of structural equation model

In the research on the effectiveness of ideological and political education in physical education courses, many key factors cannot be read directly like scores. Students' value identity, rule awareness, responsibility commitment, classroom engagement and teacher support perception often belong to potential psychological or behavioral structures, which need to be indirectly described by questionnaire items, classroom observation records and platform behavior indicators. The advantage of structural equation model is that it can link these latent variables that can not be observed directly with explicit variables that can be collected and coded, and further identify the path relationship between the latent variables. Jansson et al. research shows that the learning perception and satisfaction in physical education classroom can construct a stable potential structure through the scale [12]. Leyton Roman et al. found that there was a clear structural correlation between responsibility empowerment, classroom experience and student satisfaction [13]. This shows that under the ideological and political scenario of physical education curriculum, structural equation model is not only suitable for explaining the formation mechanism of educational effectiveness, but also suitable for providing structural constraints for prediction models.

Structural equation model usually consists of two parts: measurement model and structure model. The measurement model is used to describe the correspondence between latent variables and observed indicators, and its basic form can be written as:

$$x = \Lambda_x \xi + \delta, \quad y = \Lambda_y \eta + \varepsilon \quad (3)$$

where, x represents the exogenous observation variable vector, which can correspond to measurement indicators such as teacher support, classroom organization, and interaction frequency. y represents the endogenous observation variable vector, which can correspond to the outcome indicators such as responsibility awareness, cooperation performance and value identification. ξ and η are exogenous and endogenous latent variables, respectively. Λ_x and

Λ_y are the factor loading matrices. δ and ε are measurement error terms. This formula shows that explicit variables are not isolated observations, but externalized results of latent variables at the level of specific indicators.

On this basis, the structural model further characterizes the action path between the latent variables, whose expression is:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (4)$$

In the formula, B is the path coefficient matrix between endogenous latent variables, which is used to describe the influence of "classroom engagement" on "value identification". Γ is the influence coefficient matrix from exogenous latent variable to endogenous latent variable, which is used to represent the effect strength of antecedents such as teacher support and instructional design. ζ is the structural residual term, which represents the perturbation information that the model fails to account for. Through this model, the chain process of "teaching support - behavior investment - education effectiveness" in the ideological and political education of physical education curriculum can be transformed into an estimable path structure, instead of staying in the experience judgment.

From the perspective of computational implementation, structural equation modeling is essentially an iterative approximation of the difference between the sample covariance matrix and the model implied covariance matrix. Its core fitting objective can be expressed as:

$$F = \min[S - \Sigma(\theta)] \quad (5)$$

where, S is the sample covariance matrix, which comes from the questionnaire data, behavioral characteristic data or their standardized results. $\Sigma(\theta)$ is the implied covariance matrix of the model generated by the parameters θ . F is the fitted function value. Essentially, the process of parameter estimation is to continuously adjust the path coefficients, factor loadings and error terms in the computer environment, so that the model output is as close to the real sample structure as possible. Hair et al. pointed out that structural equation model can simultaneously complete measurement test and path test in the study of complex variable relationship [19]. Kline also emphasizes that its value lies not only in testing hypotheses, but also in revealing potential mechanisms [20]. In terms of this study, this method can transform the abstract education goal of ideological and political education in physical education curriculum into a structure system that can be modeled, interpreted, and connected with machine learning results, which provides a solid method foundation for the construction of subsequent fusion prediction models.

2.3 Related research progress at home and abroad

Around the prediction of educational effect and physical education curriculum evaluation, the existing research roughly formed two types of technical context. One kind of research is centered on machine learning, focusing on the computational modeling ability of learning behavior data, score data and platform logs. The other type of research focuses on structural equation modeling, and focuses on identifying the path relationship and action mechanism between latent variables. The former advances faster in the prediction level, while the latter has more advantages in the explanation level. However, the two have been developed in parallel for a long time, and have not yet been fully coupled in the research on the effectiveness of ideological and political education in physical education courses.

In the direction of machine learning, Albreiki et al. [11], Sekeroglu et al. [12] and Issah et al. [13] pointed out through systematic reviews that student performance prediction has been

extended from traditional performance estimation to more complex scenarios such as learning engagement identification, risk early warning and decision support. Ahmed et al. [15], Guevara-Reyes et al. [16] and Islam et al. [17] further emphasize that interpretable machine learning is becoming an important trend in educational data mining. From the perspective of computational implementation, random forest, support vector machine, gradient boosting tree and neural network can fit high-dimensional, heterogeneous and nonlinear learning data, and are suitable for processing multi-source information such as platform interaction logs, classroom behavior records and stage evaluation results. However, most of these studies focus on general academic performance or online learning performance. Aiming at the complex scene of physical practice, emotional experience and value shaping characteristics of the ideological and political education of physical education courses, the existing models still have the problems of insufficient explanation of variables and insufficient reveal of potential mechanisms.

In the direction of structural equation model, Jansson et al. [2] constructed a scale around perceived learning and satisfaction in physical education classroom and conducted a structural test. Jansson et al. [3] further analyzed the perceived differences between different groups. Garcia-Ceberino et al. [4] discussed the structural relationship between psychological need satisfaction and sports persistence behavior. Wen and Cai [5], Zhang et al. [6] and Guo et al. [7] revealed multiple mediation paths in physical education from the perspectives of teacher support, student engagement, self-efficacy and positive emotions. This kind of research provides strong support for understanding the psychological generation mechanism in physical education curriculum, and also shows that latent variable analysis has high adaptability in physical education research. However, its limitations are also obvious. On the one hand, structural equation models usually rely on questionnaire scale or cross-sectional data, which is difficult to fully absorb complex computational data such as teaching platform logs, classroom behavior sequences and text reflections. On the other hand, its goal is more towards theoretical verification, rather than forward prediction oriented to teaching intervention.

From the practical needs of the ideological and political research of physical education curriculum, it is difficult to fully respond to the two questions of "can it accurately predict" and "why this result" by using a single method. As shown in Table 1, machine learning is better at extracting effective signals from massive observational variables, and structural equation models are more suitable for revealing the path structure among teacher support, classroom participation, sense of responsibility, and value identity. Although the current domestic and foreign literatures have accumulated foundations in education prediction and physical education classroom mechanism analysis respectively, there is still a lack of a comprehensive framework that can unify multi-source data calculation, feature recognition and latent variable interpretation around the effectiveness of ideological and political education in physical education courses. Because of this, the integration of machine learning and structural equation model is not only a method superposition, but also a supplement and promotion of the ideological and political research paradigm of physical education curriculum.

Table 1: Comparison of technical characteristics of related studies at home and abroad

Research Type	Representative Studies	Main Techniques	Applicable Advantages	Existing Limitations
Traditional educational prediction studies	Albreiki et al. [11]; Sekeroglu et al. [12]; Issah et al. [13]	SVM, RF, XGBoost, etc.	Capable of handling structured data and convenient for classification and regression prediction	Insufficient in revealing latent variable relationships, with limited explanatory power for specific scenarios
Explainable machine learning studies	Ahmed et al. [15]; Guevara-Reyes et al. [16]; Islam et al. [17]	Explainable AI, feature importance analysis	Balances predictive performance and decision support, and is suitable for educational management applications	Mostly focuses on general academic performance, with insufficient coverage of physical education and ideological-political contexts
Structural analysis studies in physical education	Jansson et al. [2][3]; García-Ceberino et al. [4]	Scale development, SEM path analysis	Able to reveal the structural relationships among perceived learning, psychological needs, and classroom outcomes	Relies on questionnaires and cross-sectional data, with relatively weak predictive capability
Studies on influence mechanisms in physical education classes	Wen and Cai [5]; Zhang et al. [6]; Guo et al. [7]	Mediation analysis, structural equation modeling	Suitable for analyzing the action chains of teacher support, engagement, emotion, and related factors	Difficult to integrate high-dimensional computational data such as platform logs and behavioral sequences
Proposed integrated path in this study	This study	Machine learning + structural equation modeling	Simultaneously balances multi-source data prediction capability and latent mechanism interpretation	Needs to address feature alignment, model collaboration, and unified expression of results

3 Construction of prediction model for ideological and political education effect of physical education course

3.1 Model architecture design integrating machine learning and structural equation modeling

The formation of ideological and political education effect in physical education curriculum is

not the result of linear accumulation of single indicators, but the comprehensive product of classroom organization, teacher support, student participation, cooperative behavior, emotional experience and value identification in continuous teaching situations. If check-in times, sports scores, discussion frequencies or questionnaire scores are directly input into a certain type of prediction model, although surface results can be obtained, two types of deviations are prone to occur. One is the semantic inconsistency between multi-source heterogeneous data, which leads to the model misrecognizing noise as valid signals. Another is that the potential education mechanism is compressed in the black-box calculation process, and it is difficult to explain "why this prediction result is generated". Based on this, this paper constructs a prediction architecture that integrates machine learning and structural equation model under the ideological and political scene of physical education curriculum, so that it has the ability to extract behavioral features and explain the relationship between latent variables, so as to realize the unity of "predictable" and "interpretable".

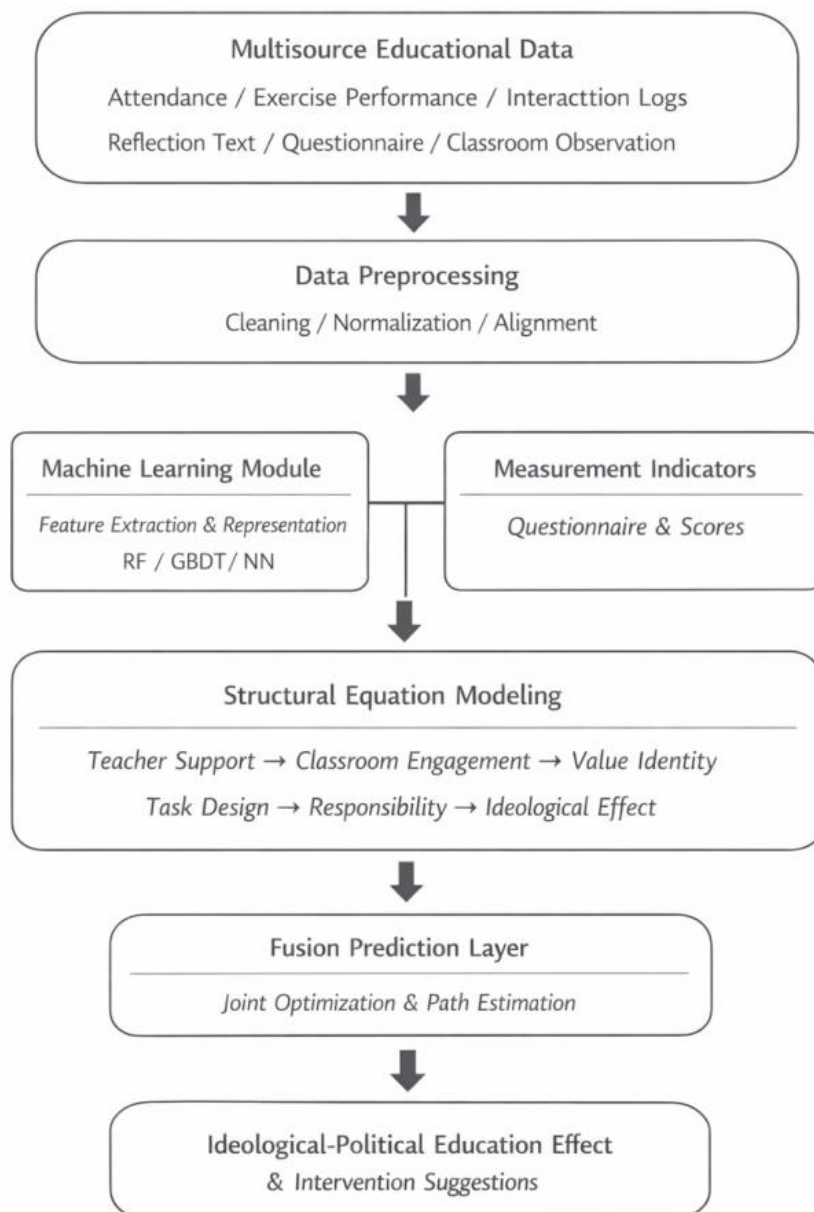


Figure 2: The overall framework of the ideological and political education effectiveness prediction of physical education courses by combining machine learning and structural equation model

As shown in Figure 2, the overall model is composed of a data input layer, a feature calculation layer, a latent variable modeling layer, a fusion decision layer, and a result output layer. The data input layer mainly receives three types of information. The first is the objective behavior data generated by the teaching platform and the classroom terminal, such as attendance records, exercise completion rate, interaction frequency, group collaboration trajectory and phasic exercise performance. The second is the subjective perception data formed by the course questionnaire and classroom observation, such as teacher support, rule identification, classroom engagement and responsibility bearing tendency. The third is semi-structured information such as reflective texts, class comments and process evaluation materials. Due to the problems of missing raw data, different scales and inconsistent time granularity, the system first completed outlier identification, standardization processing, time alignment and feature coding in the computer environment, and then entered the subsequent modeling module. The goal is not simply to improve data cleanliness, but to ensure that the behavioral, psychological, and outcome variables are placed in the same analytical coordinates.

The machine learning module undertakes the tasks of high-dimensional feature compression and key variable identification. Let the original input vector for the i th student be $x_i \in \mathbb{R}^P$. After applying the machine learning feature mapping function, we obtain the low-dimensional representation h_i :

$$h_i = \phi(x_i; \Theta) \quad (6)$$

where $\phi(\cdot)$ represents the feature learning function, which can be implemented by random forests, gradient boosting trees, or lightweight neural networks; Θ is a model parameter; h_i is the compressed core feature representation. This equation shows that the machine learning module does not directly output the final education effect, but extracts more discriminative behavioral signals from complex observation variables, which provides an input basis for subsequent structural analysis. Compared with directly using all the original variables, this step can reduce the interference of redundant information, and also help to improve the transfer stability of the model in different classes and different teaching units.

On this basis, the structural equation modeling module explicitly models the latent variable relationships. The variables such as rule consciousness, cooperative responsibility and value identity in the ideological and political education of physical education curriculum are difficult to be directly captured by a single measurement, and need to be reflected by multiple observation indicators. In this paper, the core features selected by machine learning and the scale measurement indicators are incorporated into the latent variable system to form a structural relationship closer to the real teaching process. Its basic expression is:

$$\eta = B\eta + \Gamma\xi + \Lambda h + \zeta \quad (7)$$

where, ξ is an exogenous latent variable, which can correspond to teacher support, classroom organization and task design. η is an endogenous latent variable, which can correspond to classroom engagement, sense of responsibility and value identity. B is the path coefficient matrix between endogenous latent variables. Γ is the influence coefficient matrix of exogenous latent variable on endogenous latent variable. Λ is the mapping matrix of machine learning feature representation h to the latent variable system. Let ζ be the structural residual term. Compared with the traditional structural equation model, the feature representation generated

by machine learning is embedded into the latent variable modeling process explicitly, so that the behavior data can enter the structural explanation chain instead of staying in the external description.

In order to avoid the separation between prediction accuracy and structural fitting, we further design a joint optimization objective, which unifies the prediction error of machine learning and the fitting deviation of structural equation model into the same training framework. The joint loss function is written as:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\text{pred}} + \lambda_2 \mathcal{L}_{\text{sem}} + \lambda_3 \|\Omega\|_2^2 \quad (8)$$

In the formula, $\mathcal{L}_{\text{pred}}$ represents the prediction error of educational effectiveness, which can be in the form of mean square error or cross entropy. \mathcal{L}_{sem} represents the fitting loss of the structural model, which is used to constrain the agreement between the latent variable path and the observed covariance; $\|\Omega\|_2^2$ is the parameter regularization term; $\lambda_1, \lambda_2, \lambda_3$ are the weight coefficients. The key implication of this formula is that the goal of model training is not only to "predict better" numerically, but also to make sure that the latent variable relationship "makes sense" statistically. This is also the key to distinguish the fusion architecture of this paper from a single prediction model.

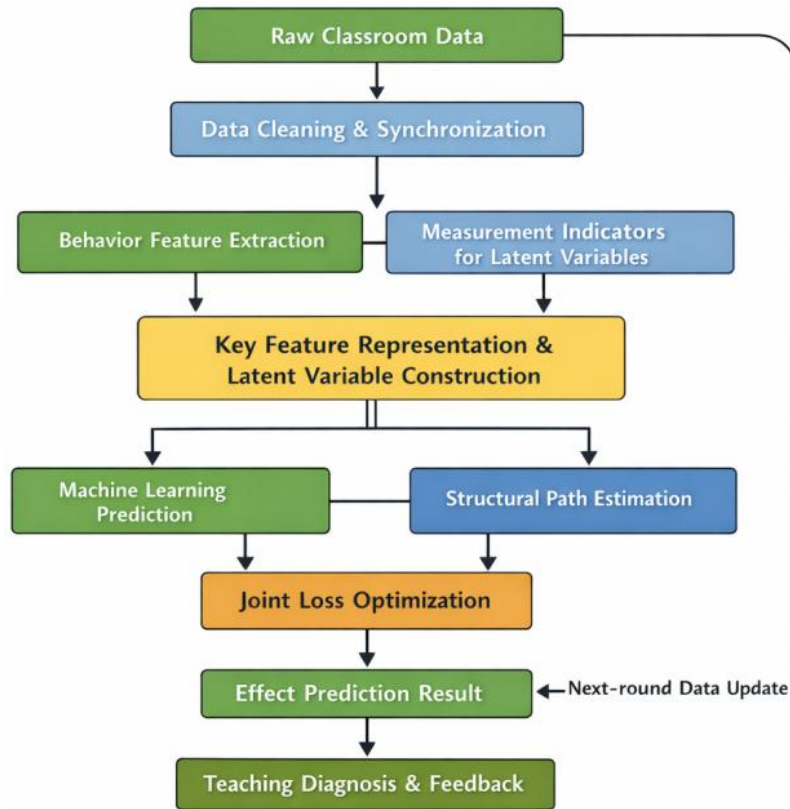


Figure 3: Collaborative operation process of ideological and political education effectiveness prediction in physical education courses

As shown in Figure 3, in the system operation process, the original classroom data is not processed once, but continuously updated along the closed loop of "data cleaning - feature extraction - latent variable estimation - fusion prediction - teaching feedback". The teacher side can identify the key links with weak education effectiveness according to the model output, such as insufficient cooperation behavior, low responsibility commitment or unstable rule

identification. The management end can make targeted adjustments to the curriculum design, evaluation methods and intervention nodes according to the structural path differences of different teaching classes. In other words, the value of this framework is not only to generate a score, but also to transform the ideological and political education formation mechanism of physical education curriculum into an observable, computable and traceable analysis chain.

3.2 Model optimization method under the scenario of ideological and political education in physical education

In the prediction of the effect of ideological and political education in physical education, model optimization can not only be understood as parameter adjustment or error compression, but also make the calculation process fit the real operation logic of physical education. Compared with general online learning data, physical education course data has stronger scene, volatility and stage differences: the behavior intensity of the same student in warm-up, skill practice, confrontation and cooperation, reflection and summary is not consistent, and the ideological and political results such as rule awareness, responsibility commitment and value identity will not appear synchronously. If the whole process data is still processed with a uniform weight, the model tends to over-amplify the high-frequency action information, but weakens the signals that are also important to the education effect, such as cooperative interaction, reflective expression and classroom emotion. Based on this, this paper optimizes the fusion model in scenes around four levels of multi-source data alignment, stage adaptive modeling, structural constraint enhancement and lightweight deployment.

At the data representation level, this paper constructs a multimodal time alignment mechanism for physical education classroom, which maps attendance records, exercise load, group collaboration behavior, classroom question and answer, reflective text and teacher observation and evaluation into a unified teaching time window. Considering that the data sampling frequency of different modalities is not consistent, let the m -th mode feature in the t -th time window be $z_t^{(m)}$, and its quality weight be $q_t^{(m)}$, then the fusion representation can be written as:

$$u_t = \sum_{m=1}^M q_t^{(m)} W_m z_t^{(m)} \quad (9)$$

where, u_t is the unified feature vector of the t -th teaching period; W_m represents the linear mapping matrix of different modes. $q_t^{(m)}$ is used to reflect the data integrity and information credibility of the mode in the current period. In this way, platform logs, text features, and classroom observations are no longer separate pieces of data, but can jointly represent the classroom state of students in the same computational coordinates. For the ideological and political research of physical education courses, this step is particularly important, because many educational signals are not directly reflected in the performance of actions, but are implied in the interactive process and reflection content.

Completing data alignment alone is still not enough. The physical education course has obvious differences in teaching stages. The skill training stage emphasizes action execution and persistence, the cooperative competition stage is easier to manifest rule consciousness and responsibility, and the course summary stage is more conducive to recognizing value understanding and emotional identification. In response to this feature, this paper introduces a stage adaptive attention mechanism to dynamically adjust the feature weights according to different teaching links. Its expression is:

$$\alpha_t^{(m)} = \frac{\exp(\mathbf{v}^\top \tanh(\mathbf{A}u_t + \mathbf{B}s_t))}{\sum_{j=1}^M \exp(\mathbf{v}^\top \tanh(\mathbf{A}u_t^{(j)} + \mathbf{B}s_t))} \quad (10)$$

where, $\alpha_t^{(m)}$ is the attention coefficient of the MTH feature in the TTH stage; s_t represents the coding vector of teaching stage, which can correspond to different links such as warm-up, practice, competition and reflection. \mathbf{A} , \mathbf{B} , and \mathbf{v} are learnable parameters. The significance of this mechanism is that different classroom stages no longer share a rigid set of variable importance, but the model automatically adjusts the focus of attention according to the teaching situation, so as to reduce the recognition bias caused by "too strong action data and too weak ideological and political signals".

Considering that the fusion framework of "machine learning + structural equation modeling" is adopted in this paper, the optimization process also needs to address the possible disconnection between the prediction layer and the explanation layer. To this end, we introduce a structural consistency constraint in the training phase to keep the high-contribution features extracted by machine learning in harmony with the direction of the latent variable path. The joint objective function is defined as:

$$\mathcal{J} = \mathcal{L}_{\text{cls}} + \beta \sum_{r=1}^R (\hat{\gamma}_r - \gamma_r^*)^2 + \mu \|\mathbf{P}\|_1 \quad (11)$$

In the formula, \mathcal{L}_{cls} is the classification or hierarchical prediction loss of educational effectiveness. $\hat{\gamma}_r$ represents the influence strength of the RTH path learned by the model. γ_r^* is the target path coefficient estimated by the structural equation model. \mathbf{P} is the feature selection parameter matrix; β and μ are the weight coefficients. This formula shows that the model optimization is no longer only aiming at prediction accuracy, but synchronously constraining the consistency of path interpretation and the sparsity of feature selection. In this way, the output of the model could not only answer the question "whose education effectiveness may be weak", but also further suggest "insufficient classroom input, unstable rule identification, or insufficient teacher support transmission".

In addition, considering the strong on-site feedback demand of physical education evaluation, the model should also take into account both computational efficiency and deployment feasibility. At the implementation level, this paper adopts the operation strategy of "offline training + online inference": the multi-modal feature learning, structural path estimation and hyperparameter search are completed in the offline stage, and only the core inference module is retained in the online stage to support the rapid output of results in or after class. For teachers, the practical significance of this design was that the model did not have to wait until the end of the whole semester to give a conclusion, but could continue to update students' educational effectiveness portraits within a number of teaching weeks, providing a more timely basis for classroom intervention and teaching adjustment.

As shown in Table 2, the optimization method in this paper is not launched for a single algorithm index, but corresponds item by item around the real problem in the ideological and political scene of physical education courses. Data asynchronism, stage differences, insufficient mechanism explanation, and difficulties in identifying scarce samples constitute several links that are most prone to deviation when the model lands. By introducing time alignment, stage attention, structural consistency constraints and lightweight deployment strategies, the model can better adapt to the data characteristics of "strong context, strong interaction and strong process" in the ideological and political education of physical education courses, and also

provide methodological support for the performance improvement of the subsequent experimental part.

Table 2: Model optimization methods and their effects under the ideological and political education scenario of physical education courses

Optimization Stage	Technical Method	Specific Processing Content	Role in the Prediction Task
Unified representation of multi-source data	Multimodal temporal alignment and quality-weighted fusion	Maps behavioral logs, exercise load, questionnaires, reflective texts, and classroom observations into a unified time window	Reduces information fragmentation caused by asynchronous sampling and improves input consistency
Dynamic adaptation to teaching stages	Stage-adaptive attention mechanism	Adjusts feature weights according to stages such as warm-up, practice, competition, and reflection	Strengthens truly effective educational signals at different stages and reduces the problem of rigid weighting
Coordination of prediction and interpretation	Structural consistency constraints	Keeps machine learning feature contributions aligned with the directional paths of the structural equation model	Enhances the interpretability of model results and their educational validity
Enhanced identification of scarce samples	Stratified sampling, cost-sensitive learning, and sample augmentation	Increases the training weights of low-frequency samples such as responsibility-taking, rule consciousness, and deep reflection	Improves the recognition of critical but infrequent behaviors
Improved classroom application efficiency	Separation of offline training and online inference	Performs complex training in the backend while retaining a lightweight inference module on the classroom side	Supports relatively rapid instructional feedback and continuous updating

4 Experiment and result analysis

In order to test the actual performance of the fusion model in the prediction of the ideological and political education effect of physical education courses, this paper selected 28 physical education classes from 3 universities as research objects, and the samples covered four courses of basketball, volleyball, track and field and physical training. The data collection period was from September 2024 to June 2025. A total of 842 student samples were obtained, and 796 valid samples were retained after removing the records with serious missing and misplaced timestamps. After focusing on "students-weeks-teaching link", 12736 pieces of classroom behavior fragment data were formed. The input data included 58 features such as attendance rate, motor task completion rate, frequency of classroom interaction, participation in

cooperative practice, number of rule violations, feedback response time of teachers, emotion score of reflective text, and teacher support, sense of responsibility and value identity measured by the scale. The model training environment is Python 3.10, and Pandas, scikit-learn, PyTorch and semopy are mainly used for data preprocessing, machine learning modeling and structural path estimation. All samples were divided into training set, validation set and test set according to 7 : 2 : 1, and 5-fold cross validation was used to optimize parameters on the training set to reduce the accidental fluctuation of model evaluation.

From the overall prediction results, the method of combining machine learning and structural equation model is superior to the single prediction model, and also significantly superior to the SEM model only used for mechanism explanation. Table 3 shows the comparison results of different models on the test set. It can be seen that the R² of the proposed model reaches 0.914, RMSE is 4.86, MAE is 3.71, and MAPE is controlled at 5.94%, which are the optimal values among the comparison models. Compared with XGBoost, the R² of the proposed model is increased by 0.049 and RMSE is decreased by 1.02. Compared with random forest, the decrease of RMSE reaches 24.9%. This shows that when the ideological and political data of physical education courses contain behavior logs, scale indicators and text features at the same time, although only relying on the tree model or shallow neural network can complete the result fitting, it is difficult to fully absorb the structural information provided by the latent variable relationship. While retaining the ability of feature learning, the fusion model incorporated the path relationship between teacher support, classroom engagement, responsibility and value identity into the prediction constraint, so it performed better in stability and explanation consistency.

Table 3: Comparison of prediction results of ideological and political education effectiveness of different models in physical education courses

Model	R ²	RMSE	MAE	MAPE / %
Linear Regression	0.742	7.58	6.14	10.82
Random Forest	0.831	6.47	5.02	8.36
XGBoost	0.865	5.88	4.41	7.21
MLP	0.852	6.05	4.63	7.48
SEM Single Model	0.781	7.06	5.61	9.47
Proposed Integrated Model	0.914	4.86	3.71	5.94

In this paper, the actual value of education effectiveness of a teaching class in the test set was extracted based on the weighted comprehensive evaluation scale and behavioral indicators from week 2 to week 11, and compared with the predicted value of the model. The results are shown in Figure 4. It can be found that the output curve of the model in this paper is overall consistent with the real change trend. In the fifth week of collaborative competition teaching and the ninth week of course reflection enhancement, although the real value fluctuates obviously, the prediction curve can still follow quickly, and there is no lag phenomenon common in the single model. Especially in the fifth week, the actual score increased from 78.6 to 82.4, and the predicted value of the model increased from 77.9 to 81.6, with the deviation maintained within 1 point. In week 9, when the true value fell back to 79.8, the model predicted a value of 80.5, which also maintained a good fit. This shows that the model has a good ability to capture the phenomenon of stage interaction enhancement and short-term transition of responsibility behavior in physical education classroom.

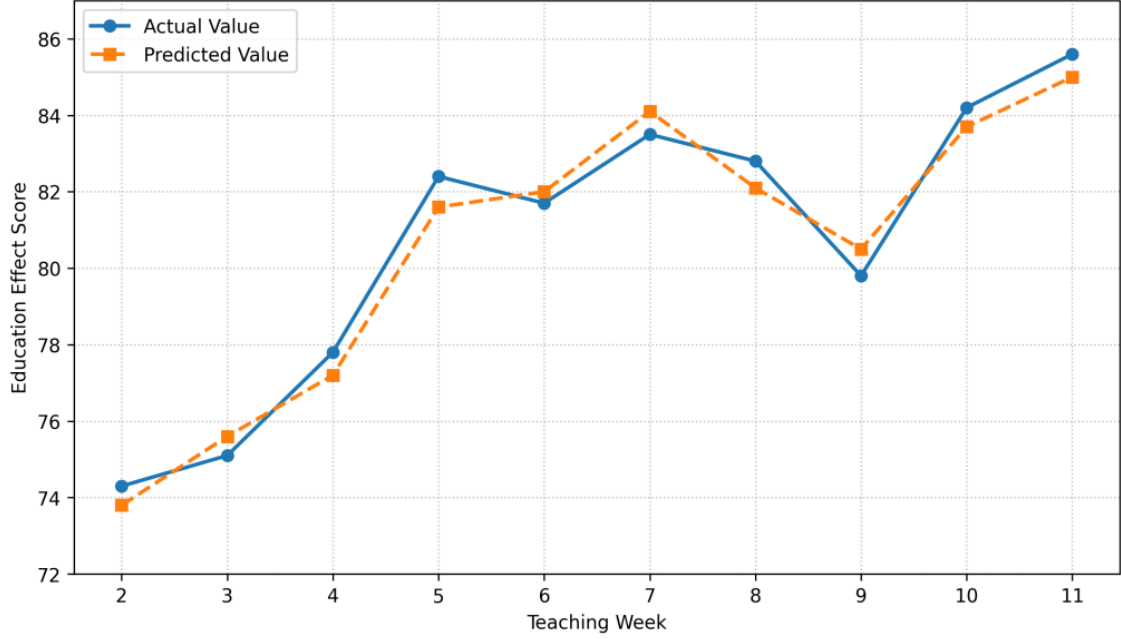


Figure 4: Comparison of actual value and predicted value of education effectiveness in consecutive teaching weeks

If the experimental perspective is shifted from "overall prediction" to "module contribution", the advantages of the fusion architecture will be clearer. In this paper, we further carry out ablation experiments to successively remove structural path constraints, text reflection features, and stage adaptive attention modules, and the results are shown in Table IV. The R2 of the full model was 0.914, but dropped to 0.883 after removing the structural path constraint, indicating that the latent variable relationship is not ancillary information, but can effectively reduce the local bias caused by pure data fitting. After removing the text reflection feature, the MAPE increased from 5.94% to 6.83%, indicating that although language materials did not account for the main amount of data, they had a complementary role in identifying value identification and responsibility awareness. After removing stage attention, RMSE rises to 5.61, indicating that there are indeed differences in signal strength in different links of physical education class, and uniform weight processing will weaken the model's ability to adapt to situation changes.

Table 4: Results of ablation experiments for the proposed model

Model Variant	R ²	RMSE	MAE	MAPE / %
Full Model	0.914	4.86	3.71	5.94
Without Structural Path Constraints	0.883	5.42	4.09	6.57
Without Reflective Text Features	0.896	5.17	3.94	6.83
Without Stage-adaptive Attention	0.871	5.61	4.28	6.95

In addition to the accuracy comparison, the path estimation results in the structural equation model part also support the theoretical setting in the previous section. The standardized path coefficient of teacher support on classroom engagement was 0.61, the path coefficient of classroom engagement on responsibility was 0.47, and the path coefficient of responsibility on value identification was 0.52. The three core paths were all significant at the 0.001 level. The fitting index of the model performs well, $\chi^2/df=2.31$, CFI=0.948, TLI=0.936, RMSEA=0.041, indicating a high consistency between the structural path and the sample data. By cross-comparing these path results with the feature importance of machine learning output, it can be

found that "cooperative interaction frequency", "teacher immediate feedback", "rule violation correction rate" and "responsibility word density of reflective text" are the variables with high contribution degree, which are basically consistent with the role chain identified by the structural model. In other words, the prediction results are not due to random data fitting, but can be explained more clearly by the educational mechanism.

Figure 5 further demonstrates the distribution of prediction errors for different teaching stages. The MAE was 3.42 in the warm-up phase, 3.65 in the skill practice phase, 4.18 in the cooperative competition phase, and 3.27 in the course summary and reflection phase. The relatively high error in the cooperative competition stage does not mean that the model is invalid, but it is more likely to show that students' behavior is more active, the situation disturbance is stronger, and the fluctuation of rule awareness and responsibility performance is more obvious in this stage. Even so, the full model maintains a low error at this stage without significant distortion, which indicates that the stage adaptation mechanism set up in the previous section is effective.

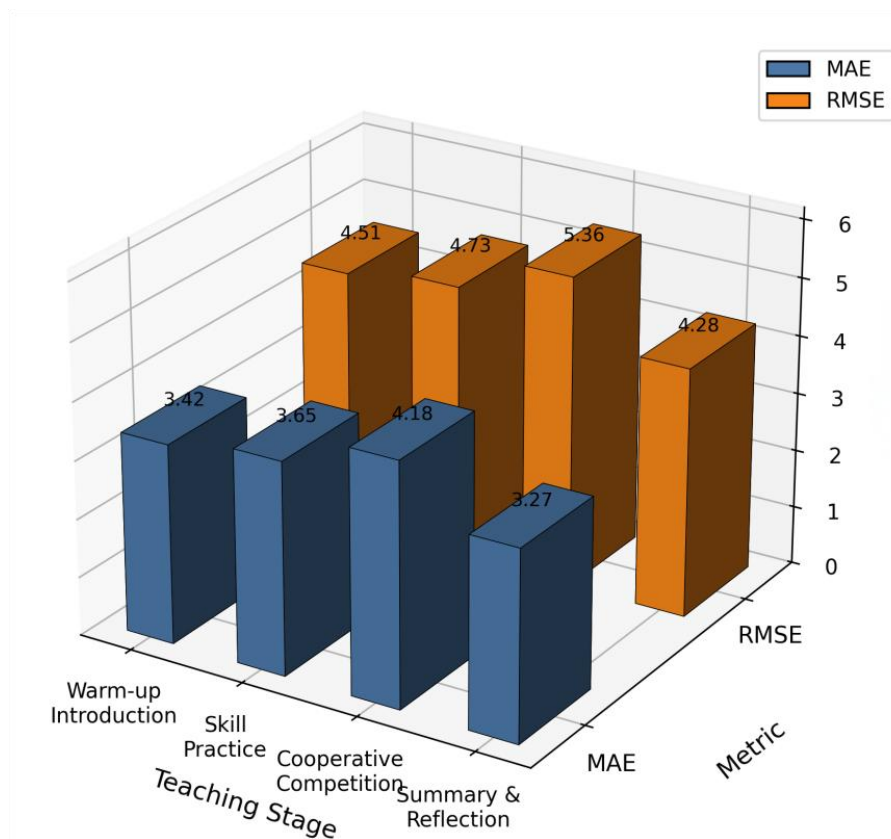


Figure 5: Comparison of prediction errors in different teaching stages

Based on the above results, it can be believed that the fusion model constructed in this paper is better adapted to the task of predicting the effectiveness of ideological and political education in physical education courses. On the one hand, it is better than the comparison model in a number of error indicators, indicating that the combination of machine learning and structural equation model is not a formal splicing, but indeed improves the prediction performance. On the other hand, the path estimation and feature contribution can corroborate each other, which makes the model output more interpretable. For the ideological and political evaluation of physical education courses, this is particularly important, because the research goal is not only to judge who has higher or lower educational effectiveness, but also to identify the specific links that affect the formation of differences, so as to provide operable data basis for teachers

to improve classroom organization, adjust interaction methods and optimize value guidance strategies.

5 Discussion

From the experimental results, the prediction framework combining machine learning and structural equation model proposed in this paper shows a relatively stable advantage in the identification of the effectiveness of ideological and political education in physical education courses. On the test set, the R^2 of the proposed model is 0.914, RMSE, MAE and MAPE are 4.86, 3.71 and 5.94%, respectively, which are better than those of linear regression, random forest, XGBoost, MLP and the comparison schemes using SEM alone. Among them, compared with XGBoost, R^2 is increased by 0.049 and RMSE is decreased by 1.02. Compared to random forest, RMSE decreases by nearly a quarter. This shows that although the ideological and political data of physical education courses can be fitted by general machine learning methods, the model often can only identify surface correlations without the constraint of latent variable relationships. The performance improvement of the proposed model is not only from the increase of the number of features, but also mainly from the collaborative modeling of the 'prediction layer' and the 'explanation layer'. On the one hand, the model uses computer algorithms to process classroom behavior logs, interaction records, text reflection and scale data to complete high-dimensional feature screening and nonlinear mapping. On the other hand, with the help of structural equation model, the relationship among teacher support, classroom engagement, responsibility and value identification is brought into the same framework. The path estimation results showed that the standardized coefficient of teacher support on classroom engagement was 0.61, the coefficient of classroom engagement on responsibility was 0.47, and the coefficient of responsibility on value identification was 0.52, and all reached a significant level. That is to say, the reason why the model predicts more accurately is not only because "the calculation is more complex", but also because it calculates the more critical role chain in the ideological and political education of the physical education curriculum.

This was further verified by ablation experiments. After removing the structural path constraint, the model R^2 decreased from 0.914 to 0.883. After removing phase adaptive attention, RMSE increased to 5.61. After removing the text reflection feature, the MAPE rises to 6.83%. These variations suggest that structural relationships, stage differences, and linguistic materials are not marginal information, but rather important sources that jointly support the prediction of educational effectiveness. Especially in the cooperative competition stage, the model MAE is 4.18, which is higher than 3.42 in the warm-up introduction stage, but still remains within the acceptable range, indicating that it has certain adaptability to the classroom situation with high interaction and strong fluctuation. At the same time, the model in this paper still has limitations. One type of problem comes from insufficient low-frequency samples, such as taking the initiative to take responsibility, deep reflection expression and other high-value behaviors, which are not high in the sample, and easily affect the adequacy of model learning. The other type of problem comes from cross-curriculum transfer. The current sample mainly covers basketball, volleyball, track and field and physical training, and has not yet entered the teaching scenarios with greater differences such as martial arts and swimming. Therefore, follow-up research needs to continue to expand data sources, enhance the modeling ability of scarce samples, and improve the generalization level of the model across different sports.

6 Conclusions

Under the background of the ideological and political evaluation of physical education courses gradually moving towards data and intelligence, this paper focuses on the problem that the educational effect is "predictable but difficult to explain, observable but difficult to quantify", and constructs an analysis framework combining machine learning and structural equation model. The framework integrated classroom behavior logs, sports performance, interaction records, reflective texts and scale measurement results into the calculation process. Through the collaboration of feature learning and latent variable path modeling, the comprehensive prediction of ideological and political education effect of physical education curriculum was realized.

(1) This paper takes 28 physical education classes in 3 universities as the research object, and collects the curriculum data from September 2024 to June 2025. There were 842 original samples, 796 valid samples were retained after cleaning, and 12736 classroom behavior fragments were formed, and 58 input features were extracted. The data sources covered the attendance rate, task completion rate, interaction frequency, rule violation times, teachers' feedback response time, emotional scores of reflective texts, teachers' sense of support, sense of responsibility, value identity and other indicators, which better reflected the education process of "behavior-experience-identity" linkage generation under the ideological and political scene of physical education curriculum.

(2) Experimental results show that the R2 of the proposed model on the test set reaches 0.914, and the RMSE, MAE and MAPE are 4.86, 3.71 and 5.94%, respectively, which are better than those of various comparison models. Compared with XGBoost, R2 is increased by 0.049 and RMSE is decreased by 1.02. Compared with random forest, the RMSE decreases by 24.9%. This shows that the combination of the nonlinear fitting ability of machine learning and the path interpretation ability of structural equation model is more suitable for dealing with the multi-source, heterogeneous and implicit feature structure in the ideological and political data of physical education courses.

(3) Ablation experiments further verify the necessity of the model design. After removing the structural path constraint, the model R2 decreased from 0.914 to 0.883. After removing phase adaptive attention, RMSE increased to 5.61. After removing the text reflection feature, the MAPE rises to 6.83%. Meanwhile, the structural path analysis showed that the standardized coefficient of teacher support on classroom engagement was 0.61, the coefficient of classroom engagement on responsibility was 0.47, and the coefficient of responsibility on value identification was 0.52. It can be seen that the model in this paper not only improves the prediction accuracy, but also enhances the educational interpretation power of the results, which can provide computational support for the improvement and precise intervention of ideological and political teaching in physical education courses.

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