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Innovative Paths of Ideological and Political Education in Higher Education in the Era of Media Convergence and Their Impact on Students' Ideological Concepts

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SUMMARY: *Media convergence has changed the environment in which ideological and political education is carried out in higher education. As students increasingly receive information through social media, short-video platforms, and other digital channels, fixed teaching approaches are often not flexible enough to respond to differences in media exposure, engagement, and feedback. To address this issue, this study proposes a dynamic framework for modeling and updating ideological and political education under changing media conditions. The framework combines pathway generation, adaptive adjustment, and outcome evaluation, and further uses feedback signals to refine pathway selection during implementation. Experimental results on four datasets show that the proposed method consistently outperforms baseline models. The largest relative gain appears on the Student Ideological Development Dataset, where the F1 Score improves by 1.22 percentage points over the strongest baseline, rising from 87.34% to 88.56%. The best absolute result is obtained on the Convergence Media Impact on Student Beliefs Dataset, where the model achieves 91.15% Accuracy. These results indicate that ideological and political education can benefit from a framework that remains responsive to media-driven change while preserving alignment with educational goals.*

KEYWORDS: *Ideological and Political Education; Media Convergence; Higher Education; Dynamic Pathway Optimization; Educational; Data Modeling*

1 Introduction

Media convergence has changed the environment of ideological and political education in higher education[1]. Once spread through social media, short video platforms and so on, educational content will no longer mainly rely on traditional classrooms[2]. Students are exposed to ideological information in a more fragmented, fast-paced and interactive media environment[3]. This change has increased the access to educational content, and made student participation diverse and unpredictable[4]. Media convergence also creates new conditions for updating teaching content and strengthening the interaction between educators and students [5].Therefore, it is necessary to rethink the ideological and political education and its implementation methods in contemporary colleges and universities[6].

Early digital approaches to ideological education were built on fixed delivery structures[7]. Educational content was arranged in predefined categories or sequences. This design supported consistency in teaching[8]. It also improved standardization to some extent[9]. The limitation

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was equally clear. The system responded weakly to differences across students[10]. It also adapted poorly to shifts in the social environment or in external demand[11]. Student engagement was difficult to maintain in settings that required interaction, feedback, and situational adjustment [12]. Later studies moved toward adaptive methods[13]. These methods adjusted content according to student behavior or learning signals[14]. Statistical evidence was used to identify patterns in interaction and preference[15]. This made content adjustment more flexible [16]. In practice, the main value of this shift was personalization[17]. Ideological content could then be connected more closely to actual learning conditions [18]. Still, these methods remained strongly constrained by the quality and coverage of the input data. Incomplete data weakened the decision basis[19]. Imbalanced data could distort the output. Noisy data further reduced stability and increased the risk of bias [20]. The computational burden also limited deployment in large-scale settings with restricted technical resources. More recent work has introduced neural network models to process complex educational data. Their advantage lies in modeling nonlinear relations among student behavior, media exposure, and content characteristics[21]. This makes them suitable for ideological and political education tasks. Transfer learning further improves adaptation when labeled data is limited [22]. These gains do not remove the main concerns. Neural models are often hard to interpret. They usually require more computational resources. Their outputs are not always easy to align directly with educational goals. The current issue is no longer prediction performance alone. It is also the need to keep the model transparent, controllable, and usable in real educational settings[23].

Given the limitations, this study constructs a framework for ideological and political education under media convergence. This framework mainly aims to integrate path generation, adaptive update and result evaluation together, so that the model can respond to media observations, student interactions and situational feedback. This method does not rely on fixed teaching tricks or single model assumptions, so that path adjustment is consistent with educational goals, and it is sensitive to changes in the learning environment. The main contributions of this study are summarized as follows:

- We propose a dynamic framework for ideological and political education under media convergence, which links pathway generation with feedback-driven adjustment.
- We provide a unified modeling process that can incorporate heterogeneous educational signals while maintaining alignment with instructional objectives.
- Experiments on four datasets show that the proposed method achieves consistent improvements over baseline models and remains effective across different task settings.

2 Method

2.1 Overview

Media convergence has changed how ideological and political education is delivered and received in higher education. In this study, the method section is organized around three connected parts: the theoretical basis of the problem, the core model, and the strategy used to refine content delivery during deployment. Section 2.2 defines the problem setting and introduces the main variables used throughout the paper. It describes how educational content, media platforms, and student engagement are represented in a shared analytical framework, and it clarifies the structural conditions under which these factors interact. These formulations provide the basis for the model design in the following subsection. Section 2.3 presents the Ideological Pathway Synthesizer, which serves as the core model of this study. The model contains three coordinated modules: the Manifold Constraint Optimizer, which keeps generated pathways aligned with ideological and instructional objectives; the Agent-based Conceptual Navigator, which captures the evolving interaction between students and educational content; and the Probabilistic Impact Modeler, which estimates how media convergence may influence students' ideological development. These modules work together to generate pathways that are adaptive, constrained, and educationally usable. Section 2.4 then introduces the optimization strategy used to update pathway selection over time. This part combines structure-aware fusion with Dynamic Ideological Pathway Optimization so that the model can respond to feedback, engagement signals, and changes in the media environment. Rather than treating ideological education as a fixed delivery process, the strategy allows pathway adjustment during implementation, which improves precision and keeps the instructional process responsive to actual learning conditions.

2.2 Preliminaries

Media convergence has changed the conditions under which ideological and political education operates in higher education. This subsection introduces a mathematical framework for describing how students' ideological concept profiles evolve under media influence, and it provides the basis for the Ideological Pathway Synthesizer.

Let S denote the set of students, where each student $s \in S$ is associated with an ideological concept profile $\mathbf{v}_s \in \mathrm{R}^n$. The vector $\mathbf{v}_s$ contains n dimensions, each representing a specific ideological attribute. The media convergence environment is modeled as a manifold $\mathrm{M} \subset \mathrm{R}^n$, which represents the diverse and changing media influences acting on students. A set of constraints C is introduced to describe the admissible transformations of ideological concepts under these influences.

For convenience, the ideological concept profile can be written in component form as

$$\mathbf{v}_s = \left[v_{s,1}, v_{s,2}, \ldots, v_{s,n}\right]^\top, \tag{1}$$

where $v_{s,j}$ denotes the value of student s on the j-th ideological attribute. This representation allows different ideological dimensions to be modeled in a unified state space.

The media convergence environment is further represented as

$$\mathrm{M} = \left\{\mathbf{v} \in \mathrm{R}^n \mid g_k(\mathbf{v}) \leq 0,\ k=1,2,\ldots,K\right\}, \tag{2}$$

where $g_k(\mathbf{v})$ denotes the k-th structural condition imposed on the ideological state space. In this form, the manifold is not treated as an unconstrained domain, but as a feasible region shaped by educational and media-related conditions.

The evolution of a student's ideological concept profile over time is described by a dynamical system:

$$\frac{d\mathbf{v}_s}{dt} = f(\mathbf{v}_s, \mathrm{M}, \mathrm{C}, t), \tag{3}$$

where f determines the rate of change of the ideological concept profile based on the current state $\mathbf{v}_s$, the media environment M, the constraint set C, and time t. To make this dependence more explicit, we further write

$$f(\mathbf{v}_s, \mathrm{M}, \mathrm{C}, t) = \mathbf{A}(t)\mathbf{v}_s + \mathbf{B}(t)\mathbf{m}_s(t) - \mathbf{R}(\mathbf{v}_s, \mathrm{C}), \tag{4}$$

where $\mathbf{A}(t)$ describes the internal evolution of the ideological state, $\mathbf{m}_s(t)$ denotes the media influence vector received by student s at time t, $\mathbf{B}(t)$ measures the strength of media impact, and $\mathbf{R}(\mathbf{v}_s, \mathrm{C})$ represents the restriction induced by the constraint set C.

For discrete observations, the same process can be written as

$$\mathbf{v}_s^{(t+1)} = \mathbf{v}_s^{(t)} + \Delta t\, f\left(\mathbf{v}_s^{(t)}, \mathrm{M}, \mathrm{C}, t\right), \tag{5}$$

where Δt denotes the time interval between two consecutive updates.

To account for uncertainty in media influence, we further introduce a stochastic process $\mathbf{X}_s(t)$, which represents random fluctuations in the ideological concept profile of student s. Its behavior is characterized by the conditional distribution

$$P(\mathbf{X}_s(t) \mid \mathrm{M}, \mathrm{C}). \tag{6}$$

The observed ideological state can then be written as

$$\tilde{\mathbf{v}}_s(t) = \mathbf{v}_s(t) + \mathbf{X}_s(t), \tag{7}$$

where $\tilde{\mathbf{v}}_s(t)$ denotes the realized state after stochastic perturbation. This separates the deterministic evolution of ideological concepts from the uncertainty introduced by media exposure and contextual variation.

Assuming a zero-mean perturbation for simplicity, we further have

$$\mathrm{E}[\mathbf{X}_s(t) \mid \mathrm{M}, \mathrm{C}] = \mathbf{0}, \tag{8}$$

and

$$\mathrm{Cov}[\mathbf{X}_s(t) \mid \mathrm{M}, \mathrm{C}] = \mathbf{\Sigma}_s(t), \tag{9}$$

where $\mathbf{\Sigma}_s(t)$ denotes the covariance structure of the stochastic fluctuation. This allows uncertainty to vary across students and time.

The influence of media convergence is quantified through a set of impact functions $\mathrm{I} = \{I_1, I_2, \ldots, I_m\}$. Each function $I_i : \mathrm{R}^n \to \mathrm{R}$ measures the contribution of one media element to the ideological concept profile. The total impact on student s is written as

$$I_{\text{total}}(\mathbf{v}_s) = \sum_{i=1}^{m} I_i(\mathbf{v}_s). \tag{10}$$

To make the impact structure more explicit, we define

$$I_i(\mathbf{v}_s) = \omega_i\, \phi_i(\mathbf{v}_s, \mathbf{z}_i), \tag{11}$$

where ω_i denotes the weight of the i-th media element, $\mathbf{z}_i$ denotes its feature representation, and $\phi_i(\cdot)$ is a response function measuring how that element affects the ideological state. The total impact can then be rewritten as

$$I_{\text{total}}(\mathbf{v}_s) = \sum_{i=1}^{m} \omega_i\, \phi_i(\mathbf{v}_s, \mathbf{z}_i). \tag{12}$$

In addition, the normalized contribution of each media element is defined as

$$\bar{\omega}_i = \frac{\omega_i}{\sum_{j=1}^{m} \omega_j}, \tag{13}$$

so that the relative influence of different media sources can be compared directly within the same framework.

Based on this formulation, the Ideological Pathway Synthesizer seeks to optimize students' ideological concept profiles by navigating the manifold M under the constraints C.

2.3 Ideological Pathway Synthesizer

This subsection describes the Ideological Pathway Synthesizer, which functions as the central component of the framework. Figure 1 presents its structure. The model is built from three coordinated modules. Each module handles a specific stage of pathway generation under media convergence.

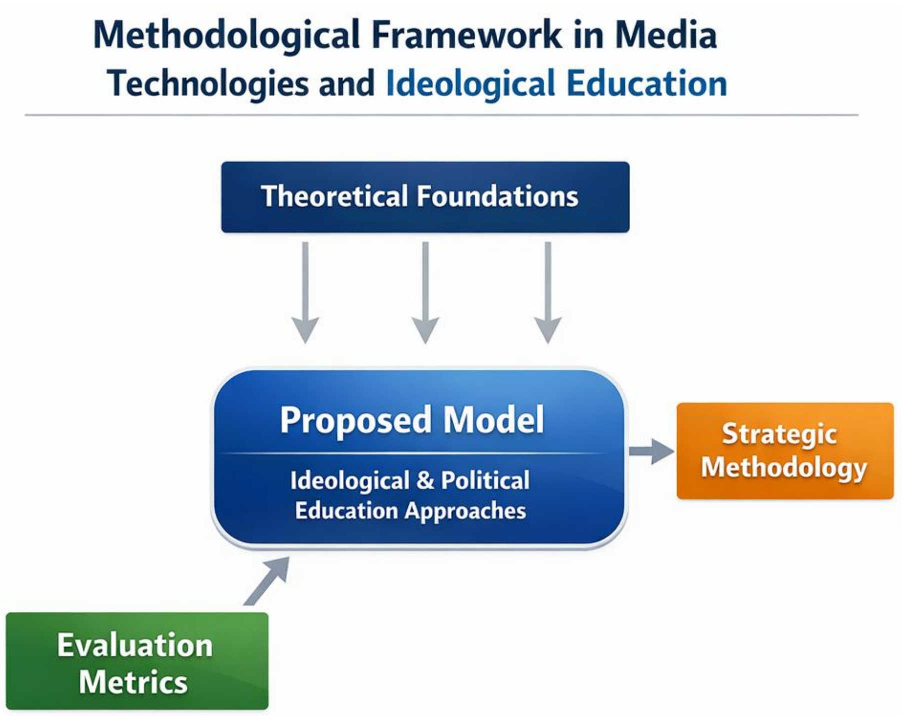

Figure1: The synthesis architecture contains three modules. The manifold constraint optimizer enforces feasibility. The agent-based concept navigator generates pathways. The probabilistic impact modeler estimates outcomes. Together they support generation, adjustment and evaluation within the creative policy process.

Manifold Constraint Optimizer: This module ensures that generated pathways remain aligned with predefined educational objectives and ideological constraints. Figure 2 shows how the process is formulated. Pathway generation is not treated as a free search. Student states are embedded into the same representation space. Media influences are integrated into this space. Instructional requirements are encoded as constraints within the same structure. Feasible pathways are selected within this unified framework. Let M denote the manifold of ideological concepts. Let **C** denote the constraint set. The optimization problem is defined as

$$\min_{\mathbf{x}\in M} \quad L(\mathbf{x},\mathbf{C}) \tag{14}$$

Here **x** represents a candidate ideological pathway on the manifold M. The function $L(\mathbf{x},\mathbf{C})$ measures the deviation from the target ideological objective under the imposed constraints.

To make the pathway representation explicit, we define

$$\mathbf{x}=[\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_T], \tag{15}$$

where $\mathbf{x}_t \in \mathrm{R}^n$ denotes the ideological state at step t, and T is the pathway length.

The manifold constraint is written as

$$\mathrm{M}=\{\mathbf{x} \mid g_k(\mathbf{x}_t)\leq 0,\ t=1,\ldots,T,\ k=1,\ldots,K\}, \tag{16}$$

where $g_k(\mathbf{x}_t)$ denotes the k-th feasibility condition at state $\mathbf{x}_t$.

The loss function is further decomposed as

$$\mathrm{L}(\mathbf{x},\mathbf{C})=\mathrm{L}_{\mathrm{target}}(\mathbf{x})+\lambda\mathrm{L}_{\mathrm{constraint}}(\mathbf{x},\mathbf{C}), \tag{17}$$

where $\mathrm{L}_{\mathrm{target}}(\mathbf{x})$ measures the deviation from the desired ideological objective and $\mathrm{L}_{\mathrm{constraint}}(\mathbf{x},\mathbf{C})$ measures the degree of constraint violation. The coefficient λ controls the trade-off between target alignment and feasibility.

The target deviation term is defined as

$$\mathrm{L}_{\mathrm{target}}(\mathbf{x})=\sum_{t=1}^{T}\|\mathbf{x}_t-\mathbf{x}_t^*\|_2^2, \tag{18}$$

where $\mathbf{x}_t^*$ denotes the target ideological state at step t. This term penalizes pathways that move too far away from the intended educational direction.

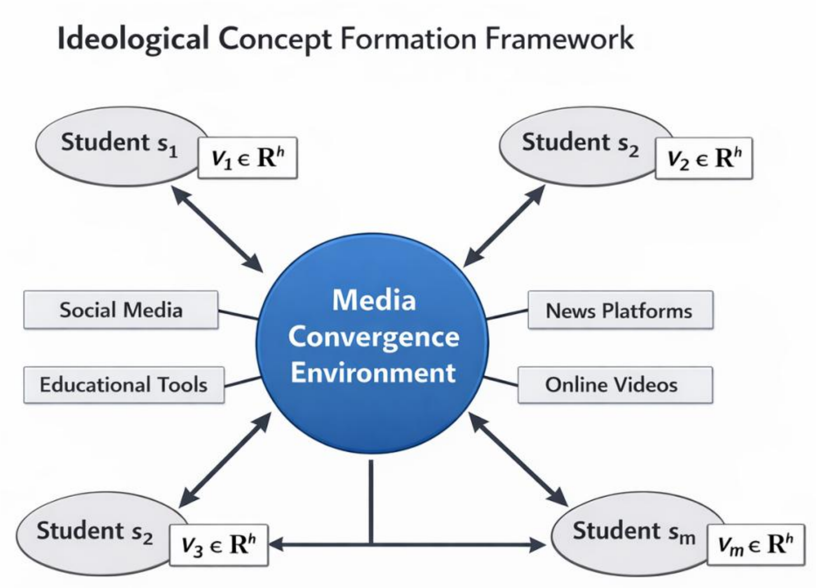

Figure 2: Conceptual representation of ideological pathway generation under media convergence. The figure illustrates how student states, media influences, and educational constraints are organized within the pathway synthesis process.

Agent-based Conceptual Navigator: This module uses a multi-agent mechanism to describe how ideological pathways evolve through interaction in a changing media environment. Each agent a_i operates in a conceptual space S_i under a rule set R_i, and its state is updated according to both local interaction and external media signals. The basic navigation process is written as

$$\mathbf{p}_i(t+1)=\mathbf{p}_i(t)+\Delta\mathbf{p}_i(t) \tag{19}$$

where $\mathbf{p}_i(t)$ denotes the position of agent a_i at time t, and $\Delta\mathbf{p}_i(t)$ denotes the corresponding update. To make the update process more explicit, we further decompose it as

$$\Delta\mathbf{p}_i(t)=\alpha\mathbf{u}_i(t)+\beta\mathbf{m}_i(t)+\gamma\mathbf{e}_i(t) \tag{20}$$

where $\mathbf{u}_i(t)$ represents interaction-driven movement from neighboring agents, $\mathbf{m}_i(t)$ represents the influence of media exposure, and $\mathbf{e}_i(t)$ represents environmental or contextual feedback. The coefficients α, β, and γ control the relative contribution of these factors.

The interaction term $\mathbf{u}_i(t)$ is defined as

$$\mathbf{u}_i(t)=\sum_{j\in \mathrm{N}_i} w_{ij}(t)\left(\mathbf{p}_j(t)-\mathbf{p}_i(t)\right) \tag{21}$$

where N_i denotes the neighborhood of agent a_i, and $w_{ij}(t)$ is the interaction weight between agents a_i and a_j at time t. This term captures how neighboring agents shift the conceptual position of the current agent through local interaction.

To represent media-driven movement more directly, we define

$$\mathbf{m}_i(t)=\sum_{k=1}^{K}\eta_{ik}(t)\,\mathbf{z}_k(t) \tag{22}$$

where $\mathbf{z}_k(t)$ denotes the influence vector of the k-th media source and $\eta_{ik}(t)$ denotes the exposure intensity of agent a_i to that source. This allows the model to capture the fact that agents may move differently in conceptual space when they are exposed to different media inputs.

Based on the updated position, the pathway score for agent a_i is computed as

$$s_i(t)=\phi\left(\mathbf{p}_i(t),\mathrm{R}_i,\mathrm{C}\right) \tag{23}$$

where $\phi(\cdot)$ denotes a scoring function that evaluates whether the current conceptual position remains aligned with the local rule set R_i and the global constraint set C.

Probabilistic Impact Modeler: This module estimates the potential effect of candidate pathways on students' ideological development. A Bayesian formulation is used to represent uncertainty in the estimation process and to evaluate pathway effects in a more stable way. Let Θ denote the parameters associated with ideological impact, and let $\mathbf{y}$ denote the observed outcomes. The predictive model is written as

$$P(\mathbf{y}\mid\Theta)=\int P(\mathbf{y}\mid\mathbf{x},\Theta)P(\mathbf{x}\mid\Theta)\,d\mathbf{x} \tag{24}$$

where $\mathbf{x}$ denotes a candidate pathway and $P(\mathbf{y}\mid\mathbf{x},\Theta)$ is the likelihood of observing outcome $\mathbf{y}$ under that pathway.

The posterior distribution of the impact parameters is defined as

$$P(\Theta\mid\mathbf{y},\mathbf{x})=\frac{P(\mathbf{y}\mid\mathbf{x},\Theta)P(\Theta)}{P(\mathbf{y}\mid\mathbf{x})} \tag{25}$$

where $P(\Theta)$ is the prior distribution over ideological impact parameters and $P(\mathbf{y}\mid\mathbf{x})$ is the marginal likelihood. This formulation allows the model to update its assessment of pathway impact after observing outcome data.

To evaluate the expected ideological effect of a pathway, we define

$$E(\mathbf{y} \mid \mathbf{x}) = \int \mathbf{y}\, P(\mathbf{y} \mid \mathbf{x}, \Theta)\, P(\Theta \mid \mathbf{x})\, d\Theta\, d\mathbf{y} \tag{26}$$

which gives the expected outcome under pathway **x** after accounting for uncertainty in the parameter space. This quantity is useful when comparing candidate pathways with different estimated effects.

The uncertainty associated with pathway impact is measured by the predictive variance

$$\mathrm{Var}(\mathbf{y} \mid \mathbf{x}) = \int \| \mathbf{y} - E(\mathbf{y} \mid \mathbf{x}) \|^2 P(\mathbf{y} \mid \mathbf{x}, \Theta) P(\Theta \mid \mathbf{x})\, d\Theta\, d\mathbf{y} \tag{27}$$

which describes how stable or unstable the expected educational effect is for a given pathway.

2.4 Dynamic Ideological Pathway Optimization

This subsection defines dynamic ideological pathway optimization. It extends the Ideological Pathway Synthesizer through pathway updating and content delivery. Figure 3 shows the overall structure.

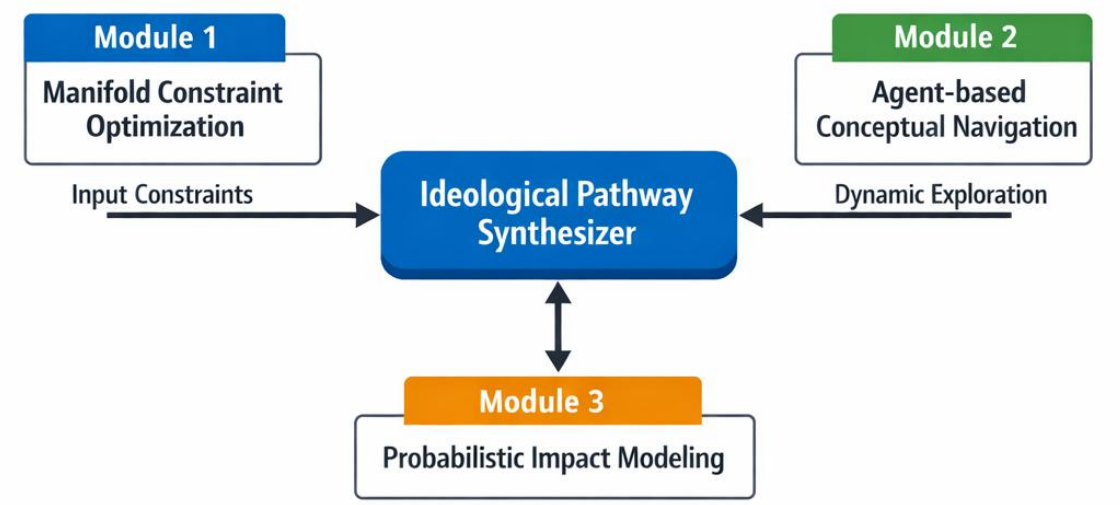

Figure 3: Overall structure of Dynamic Ideological Pathway Optimization. The strategy extends the Ideological Pathway Synthesizer through media-influence estimation, feedback-driven updating and adaptive pathway adjustment. Pathway selection then responds to changing educational conditions under media convergence.

Probabilistic Modeling of Media Influence: This module represents media influence as an updateable probabilistic process. Figure 4 shows the corresponding structure. Let X denote the set of media conditions. Let Y denote the ideological response. Their relation is defined by the conditional distribution

$$P(Y \mid X) \tag{28}$$

For a specific media condition x, the response distribution becomes

$$P(Y \mid x) \tag{29}$$

Let θ denote the parameter vector of media influence. Given observed data D, the posterior distribution is

$$P(\theta \mid D) = \frac{P(D \mid \theta) P(\theta)}{P(D)} \tag{30}$$

The marginal likelihood is written as

$$P(D) = \int P(D \mid \theta) P(\theta) \, d\theta \tag{31}$$

The predictive distribution under condition x is then defined as

$$P(Y \mid x, D) = \int P(Y \mid x, \theta) P(\theta \mid D) \, d\theta \tag{32}$$

The expected ideological response under condition x is

$$E(Y \mid x) = \int Y \, P(Y \mid x, D) \, dY \tag{33}$$

Substituting the predictive term gives

$$E(Y \mid x) = \int Y \, P(Y \mid x, \theta) P(\theta \mid D) \, d\theta \, dY \tag{34}$$

This formulation connects media conditions with pathway adjustment through the posterior estimate of ideological response.

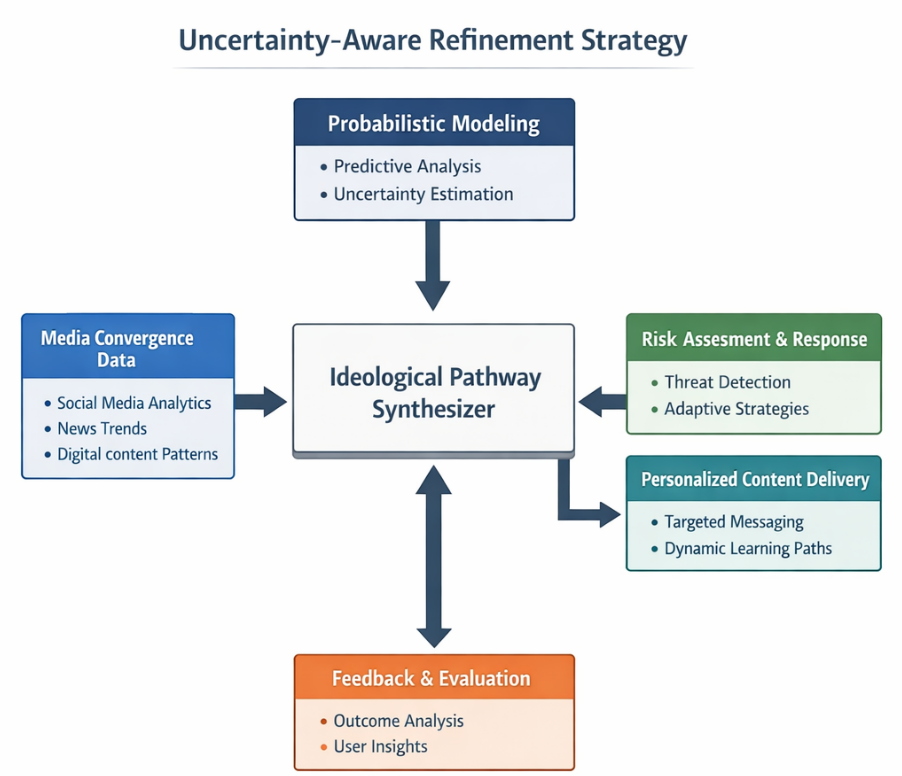

Figure 4: The diagram shows the components of Dynamic Ideological Pathway Optimization in the Ideological Pathway Synthesizer. Probabilistic modeling supports predictive analysis and uncertainty estimation. Structure-aware data fusion integrates media convergence data. Ideological trend prediction supports personalized content delivery. Feedback and evaluation guide continuous updating. Risk assessment supports response under changing media conditions.

Structure-aware Data Fusion: This module maps heterogeneous inputs into a unified representation. The update process uses media input and auxiliary information together. Let X denote the media-related input. Let Z denote the auxiliary source. The fusion function is defined as

$$F(X,Z)=\alpha X+\beta Z \tag{35}$$

The coefficients satisfy

$$\alpha+\beta=1 \tag{36}$$

The weight of the media-related input is determined by source reliability

$$\alpha=\frac{q_X}{q_X+q_Z} \tag{37}$$

The weight of the auxiliary source is

$$\beta=\frac{q_Z}{q_X+q_Z} \tag{38}$$

The fused signal at time t is

$$F_t=F(X_t,Z_t) \tag{39}$$

The integrated educational state is then written as

$$\mathbf{h}_t=\psi(F_t) \tag{40}$$

Adaptive Pathway Update: This module uses the Agent-based Concept Navigator to describe state change under media exposure and instructional intervention. Each agent corresponds to one student. The student state at time t is denoted by $\mathbf{s}_{i,t}$. The transition process follows a Markov decision formulation. The next state depends on the current state and the selected action

$$P\left(\mathbf{s}_{i,t+1} \mid \mathbf{s}_{i,t},\mathbf{a}_t\right) \tag{41}$$

The state transition itself is written as

$$\mathbf{s}_{i,t+1}=f\left(\mathbf{s}_{i,t},\mathbf{a}_t,\boldsymbol{\epsilon}_t\right) \tag{42}$$

where f is the transition function and $\boldsymbol{\epsilon}_t$ represents stochastic disturbance.

To evaluate the quality of each action, we define the immediate pathway reward as

$$r_t=g\left(\mathbf{s}_{i,t},\mathbf{a}_t,\mathbf{s}_{i,t+1}\right) \tag{43}$$

where $g(\cdot)$ measures the short-term educational gain after the transition. A larger reward indicates that the selected action is more consistent with the intended ideological objective.

The long-term pathway value is then defined as

$$V\left(\mathbf{s}_{i,t}\right)=\mathrm{E}\left[\sum_{k=t}^{T}\gamma^{k-t}r_k \,/\, \mathbf{s}_{i,t}\right] \tag{44}$$

where $\gamma \in (0,1)$ is the discount factor. This quantity measures the cumulative effect of future actions from the current state onward and helps the model choose pathway adjustments that are beneficial beyond a single step.

Based on the state value, the update policy is written as

$$\pi^*\left(\mathbf{a}_t \mid \mathbf{s}_{i,t}\right)=\arg\max_{\pi} \mathrm{E}\left[V\left(\mathbf{s}_{i,t}\right)\right] \tag{45}$$

which selects the action policy that maximizes the expected long-term educational effect. To make the pathway update process explicit, the adjusted ideological pathway at time t+1 is further defined as

$$\mathbf{x}_{t+1}=\mathbf{x}_t+\rho\, \Phi\left(\mathbf{s}_{i,t},\mathbf{a}_t,\tilde{\mathbf{h}}_t\right) \tag{46}$$

where $\mathbf{x}_t$ denotes the current pathway, $\tilde{\mathbf{h}}_t$ denotes the fused contextual representation obtained from media and auxiliary data, $\Phi(\cdot)$ denotes the update function, and ρ is the step size controlling the adjustment magnitude.

3 Experimental Setup

3.1 Dataset and Data Preprocessing

3.1.1 Datasets

The experiments were conducted on four public datasets related to ideological analysis and media-aware educational modeling. The Student Ideological Development Dataset contains 11,520 student records with 3 target categories and 27 variables. Its variables describe student demographics, academic performance, extracurricular participation, peer influence, and belief indicators. Labels were derived from standardized ideological development scores. Two trained education researchers annotated the samples under a fixed coding protocol. Inconsistent labels were resolved through consensus review. Samples with more than 20% missing fields were removed. Samples with fewer than two observation rounds were removed. Samples with duplicated student identifiers were also removed. The final split followed a chronological 7:1:2 partition at the student level. The Media Influence on Political Education Dataset contains 13860 samples with 3 categories and 25 variables. These variables describe media exposure frequency, source type, political knowledge, engagement, and media literacy outcomes. Labels were determined from post-assessment scores under the threshold rules released with the dataset. Records with incomplete media logs were excluded. Records with exposure frequency below three observations per week were excluded. Records with invalid assessment pairs were excluded. The final split used an 8:1:1 random partition with student-level isolation. The Higher Education Ideological Trends Dataset includes 9,740 samples with 4 categories and 30 variables. Its variables describe faculty ideology, student ideology, curriculum content, campus activities, and policy indicators. Labels were annotated by domain experts under a unified ideological trend rubric. Institutions with incomplete policy records were removed. Institutions with activity frequency below five occurrences were removed. Institutions with duplicated semester entries were removed. A stratified 8:1:1 split was then applied at the institution level. The Convergence Media Impact on Student Beliefs Dataset contains 12,430 samples with 3 target classes and 24 variables. These variables describe media consumption, content exposure, and psychological response. Labels were generated from composite belief-shift scores under deterministic ranking rules. Samples with missing core fields were filtered out. Samples with completion time shorter than 120 seconds were filtered out. Samples with repeated response patterns were filtered out. The final split followed a random 8:1:1 partition with respondent-level isolation.

3.1.2 Data Preprocessing

A unified preprocessing pipeline was applied to all four datasets. Duplicate records were first removed according to student or institution identifiers and timestamps. Samples with missing values in core target-related fields were then excluded, followed by rule-based filtering of abnormal entries. In particular, records with more than 20% missing attributes, survey completion time shorter than 120 seconds, zero-variance response vectors, or inconsistent multi-round identifiers were discarded. For numerical variables, standardization to zero mean and unit variance was performed using statistics computed only from the training split. Ordinal variables were aligned to fixed ascending scales so that larger values consistently indicated stronger ideological tendency, belief strength, or media influence. Categorical variables were mapped to fixed indices after identity alignment across the three data splits, and categories with fewer than 50 samples were merged into a shared background class. For textual fields and media-description fields, tokenization was performed with a fixed vocabulary, and the maximum sequence length was set to 128. Sequence-based student histories were truncated or padded to 20 observations with a stride of 5. Missing non-core numerical values were filled with training-set medians, and missing categorical values were replaced with the most frequent category in the training set. All model inputs were derived directly from the original structured variables and textual fields, without introducing external feature extractors. During training, inverse-frequency class weighting was applied according to the label distribution of the training split. The same preprocessing statistics, encoding mappings, and token indices were reused for validation and test data without recalculation, which ensured split isolation and made the comparison across methods consistent.

3.2 Implementation Details

All experiments were implemented in PyTorch and run on a unified server platform equipped with NVIDIA Tesla V100 GPUs. Mixed-precision training, Adam optimization, cosine annealing learning-rate scheduling, and fixed random initialization were used throughout the experiments. The model was trained for 100 epochs with a batch size of 32. Checkpoint selection and early stopping were both determined by validation performance. The detailed implementation settings are listed in Table 1. Given that the input data consist of structured variables, textual fields, and sequence-based student histories, the model was implemented as a multimodal pathway modeling framework rather than an image-based architecture. Structured features were encoded as fixed-dimensional vectors, textual fields were represented through token embeddings, and sequential student records were processed with consistent temporal truncation and padding rules. The fused representation was then passed to task-specific prediction layers for classification. For fairness, all baseline methods and the proposed method were trained and evaluated under the same data splits, preprocessing pipeline, optimization settings, and computing environment. Hyperparameters for all methods were tuned only on the validation set, and final results were reported on the same held-out test set with identical evaluation metrics.

Table 1: Summary of implementation and model configuration details.

Category	Configuration
Hardware	Intel Xeon Gold 6226R CPU, 4×NVIDIA Tesla V100 GPUs (32 GB), 256 GB RAM, Ubuntu 20.04 LTS
Software	PyTorch 2.1.0, CUDA 11.8, cuDNN 8.9.2, numpy 1.24.4, scipy 1.10.1, scikit-learn 1.3.2, pandas 2.0.3
Epochs	100
Batch size	32
Optimizer	Adam
Learning rate	0.001
Weight decay	1×10^{-4}
Scheduler	Cosine annealing
Random seed	42
Mixed precision	Enabled
Gradient clipping	1.0
Early stopping	Patience = 10
Checkpoint selection	Best validation F1 score
Input modalities	Structured variables, textual fields, sequential student histories
Text sequence length	128
History length	20 observations
History stride	5
Feature fusion	structured and textual representations
Dropout	0.5
Loss	Cross-entropy

3.3 Comparison with Baseline Methods

Tables 2 and 3 report the results on four datasets with different data organizations. The proposed method shows consistent improvements over all baselines across the four evaluation metrics. On the Student Ideological Development Dataset, the model reaches 89.78% Accuracy and 88.56% F1 Score, which is about 1.2 percentage points higher than DeBERTa. The gain remains within a similar range on Recall and AUC, which indicates that the improvement is not limited to a single metric. On the Media Influence on Political Education Dataset, the margin becomes slightly larger. Accuracy increases from 89.78% to 91.12%, and F1 Score increases from 88.56% to 90.01%. The improvement is around 1.3 to 1.5 percentage points across metrics. A similar pattern can be observed on the other two datasets. On the Higher Education Ideological Trends Dataset, the method achieves 89.92% Accuracy and 88.68% F1 Score, which is about 1.2 percentage points higher than DeBERTa. On the Convergence Media Impact on Student Beliefs Dataset, the model reaches 91.15% Accuracy and 89.86% F1 Score, with improvements around 1.2 to 1.3 percentage points across all metrics. The margins remain stable across datasets with different scales and labeling schemes. The results do not show large fluctuations between metrics, which indicates that the performance gain is relatively balanced rather than concentrated on a single evaluation criterion.

Table 2: Comparison of our model with SOTA methods on Student Ideological Development and Media Influence on Political Education datasets

Model	Student Ideological Development Dataset				Media Influence on Political Education Dataset			
2-9	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
BERT	87.45 ± 0.52	86.78 ± 0.63	86.12 ± 0.58	86.45 ± 0.47	88.67 ± 0.49	88.12 ± 0.54	87.45 ± 0.60	87.89 ± 0.51
DistilBERT	86.32 ± 0.47	85.76 ± 0.59	85.01 ± 0.62	85.34 ± 0.50	87.54 ± 0.53	87.01 ± 0.61	86.34 ± 0.57	86.78 ± 0.55
ELECTRA	88.12 ± 0.44	87.56 ± 0.52	86.89 ± 0.55	87.23 ± 0.48	89.23 ± 0.46	88.67 ± 0.58	88.01 ± 0.53	88.45 ± 0.49
MobileBERT	85.67 ± 0.50	85.12 ± 0.57	84.45 ± 0.60	84.89 ± 0.54	86.78 ± 0.52	86.23 ± 0.59	85.56 ± 0.62	86.01 ± 0.56
XLNet	87.89 ± 0.48	87.34 ± 0.55	86.67 ± 0.59	87.01 ± 0.53	89.01 ± 0.50	88.45 ± 0.57	87.78 ± 0.61	88.12 ± 0.54
DeBERTa	88.56 ± 0.46	88.01 ± 0.50	87.34 ± 0.57	87.67 ± 0.51	89.78 ± 0.48	89.23 ± 0.55	88.56 ± 0.59	88.89 ± 0.52
Ours	**89.78 ± 0.40**	**89.23 ± 0.48**	**88.56 ± 0.52**	**88.89 ± 0.45**	**91.12 ± 0.42**	**90.67 ± 0.50**	**90.01 ± 0.54**	**90.34 ± 0.47**

Table 3: Comparison of our method with SOTA models on Higher Education Ideological Trends and Convergence Media Impact on Student Beliefs datasets

Model	Higher Education Ideological Trends Dataset				Convergence Media Impact on Student Beliefs Dataset			
2-9	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
BERT	87.45 ± 0.52	86.78 ± 0.63	86.12 ± 0.58	86.40 ± 0.47	88.67 ± 0.49	88.12 ± 0.55	87.34 ± 0.60	87.65 ± 0.53
DistilBERT	86.92 ± 0.47	86.35 ± 0.59	85.68 ± 0.62	85.95 ± 0.50	88.23 ± 0.44	87.78 ± 0.52	87.01 ± 0.57	87.30 ± 0.48
ELECTRA	88.12 ± 0.39	87.56 ± 0.48	86.89 ± 0.54	87.20 ± 0.42	89.34 ± 0.37	88.89 ± 0.46	88.15 ± 0.51	88.45 ± 0.44
MobileBERT	87.78 ± 0.44	87.21 ± 0.53	86.54 ± 0.59	86.82 ± 0.46	89.01 ± 0.42	88.56 ± 0.50	87.79 ± 0.55	88.10 ± 0.47
XLNet	88.45 ± 0.36	87.89 ± 0.45	87.23 ± 0.50	87.52 ± 0.39	89.67 ± 0.34	89.12 ± 0.43	88.38 ± 0.48	88.70 ± 0.41
DeBERTa	88.67 ± 0.41	88.12 ± 0.50	87.45 ± 0.56	87.74 ± 0.44	89.89 ± 0.39	89.34 ± 0.48	88.60 ± 0.53	88.92 ± 0.46
Ours	**89.92 ± 0.38**	**89.35 ± 0.47**	**88.68 ± 0.52**	**88.97 ± 0.45**	**91.15 ± 0.36**	**90.60 ± 0.45**	**89.86 ± 0.50**	**90.18 ± 0.43**

3.4 Ablation Study

To examine the role of each module in the proposed framework, we conducted an ablation study based on the results in Table 4 and Table 5. The three core modules, namely the Manifold Constraint Optimizer, the Agent-based Conceptual Navigator, and the Probabilistic Impact Modeler, were removed one at a time to measure their individual contributions. Table 4 reports the results on the Student Ideological Development Dataset and the Media Influence on Political

Education Dataset. In both cases, the full model achieves the best performance across all metrics. Removing the Manifold Constraint Optimizer leads to the largest drop on the Student Ideological Development Dataset, where Accuracy decreases from 89.78% to 88.45% and F1 Score decreases from 88.56% to 87.23%. On the Media Influence on Political Education Dataset, removing the same module reduces Accuracy from 91.12% to 89.67% and F1 Score from 90.01% to 88.45%. These results show that constraint control plays an important role in keeping pathway generation aligned with the target objectives. Removing the Agent-based Conceptual Navigator also lowers performance, although the drop is slightly smaller. This suggests that interaction-based pathway exploration contributes to the model, especially when the data contain dynamic relationships between student response and media exposure. The effect of removing the Probabilistic Impact Modeler is also clear. Although its removal produces a smaller decrease than the other two settings in Table 4, the full model still performs better across Accuracy, Recall, F1 Score, and AUC, which indicates that uncertainty modeling improves the stability of prediction. Table 5 shows a similar pattern on the Higher Education Ideological Trends Dataset and the Convergence Media Impact on Student Beliefs Dataset. The complete model again gives the best results in all four metrics. Across these two datasets, removing any single module causes a measurable decline, which means that the three modules are not redundant. Instead, they contribute to the framework in different ways: the Manifold Constraint Optimizer restricts the feasible pathway space, the Agent-based Conceptual Navigator captures interaction-driven adjustment, and the Probabilistic Impact Modeler provides uncertainty-aware evaluation. Taken together, the ablation results show that the performance gain of the proposed method comes from the combination of all three modules rather than from one component alone.

Table 4: Ablation study on Student Ideological Development and Media Influence on Political Education datasets

Configuration	Student Ideological Development Dataset				Media Influence on Political Education Dataset			
2-9	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w./o. Constraint Guided Pathway Synthesis	88.45 ± 0.48	87.89 ± 0.55	87.23 ± 0.58	87.56 ± 0.51	89.67 ± 0.46	89.12 ± 0.53	88.45 ± 0.57	88.89 ± 0.50
w./o. Ideological Landscape Mapping	88.78 ± 0.46	88.23 ± 0.52	87.56 ± 0.55	87.89 ± 0.49	90.01 ± 0.44	89.56 ± 0.50	88.89 ± 0.54	89.23 ± 0.47
w./o. Educational Outcome Prediction	89.12 ± 0.44	88.67 ± 0.50	88.01 ± 0.53	88.34 ± 0.47	90.34 ± 0.42	89.89 ± 0.48	89.23 ± 0.52	89.56 ± 0.45
Ours	**89.78 ± 0.40**	**89.23 ± 0.48**	**88.56 ± 0.52**	**88.89 ± 0.45**	**91.12 ± 0.42**	**90.67 ± 0.50**	**90.01 ± 0.54**	**90.34 ± 0.47**

Table 5: Ablation study on Higher Education Ideological Trends and Convergence Media Impact on Student Beliefs datasets

Configuration	Higher Education Ideological Trends Dataset				Convergence Media Impact on Student Beliefs Dataset			
2-9	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w./o. Constraint Guided Pathway Synthesis	88.45 ± 0.42	87.89 ± 0.51	87.23 ± 0.57	87.52 ± 0.48	89.67 ± 0.40	89.12 ± 0.49	88.38 ± 0.54	88.70 ± 0.47
w./o. Ideological Landscape Mapping	88.67 ± 0.39	88.12 ± 0.48	87.45 ± 0.53	87.74 ± 0.44	89.89 ± 0.37	89.34 ± 0.46	88.60 ± 0.51	88.92 ± 0.44
w./o. Educational Outcome Prediction	88.12 ± 0.45	87.56 ± 0.54	86.89 ± 0.59	87.20 ± 0.50	89.34 ± 0.43	88.89 ± 0.52	88.15 ± 0.57	88.45 ± 0.50
Ours	**89.92 ± 0.38**	**89.35 ± 0.47**	**88.68 ± 0.52**	**88.97 ± 0.45**	**91.15 ± 0.36**	**90.60 ± 0.45**	**89.86 ± 0.50**	**90.18 ± 0.43**

4 Conclusions and Future Work

This study constructs an evaluation framework for ideological and political education in the field of higher education. This framework solves a key practical problem. The current educational effects present in a media environment that is rapidly changing and constantly reshaping students' cognition. This reduces the persuasiveness of static evaluation. The proposed method provides a more suitable way to deal with this situation.Experimental results confirm its effectiveness. This method has stable advantages on the tested dataset. Its performance is strong in tasks where media expectations have a direct impact on ideological reactions. This result shows that the framework has clear value for evaluating educational processes shaped by continuous media input. The main contribution of this study is to provide a more robust evaluation path for ideological-political education under conventional media conditions.

This study has limitations. The current framework has a high practical cost. This weakness limits its use in institutions with limited technical support. The framework also highly depends on the quality of input data. Since feedback or background information is unreliable, the evaluation results may deviate from good educational judgment.There is another limitation in practical teaching. The currently output results cannot fully support direct classroom decision-making. Future work needs to be more practical. Subsequent research should reduce deployment difficulty, enhance reliability in noisy media environments, and improve interpretability, so that teachers can understand the evaluation basis and intervene in time.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Yan Zhang contributed to conceptualization, methodology, software, validation, formal analysis, investigation, data curation, original draft preparation, review and editing,

visualization, supervision, and funding acquisition. The author has read and agreed to the published version of the manuscript.

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