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# Strengthening Cultural Confidence in the Innovation of the Discourse System of Ideological and Political Education in Higher Education in the Era of Artificial Intelligence

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**SUMMARY:** *Artificial intelligence has caused changes in higher education, and traditional ideological and political discourse has become difficult to handle. Many situations are: existing methods are not flexible enough when teaching conditions change, and have weak connections with cultural values. Words may be formally correct, yet seem divorced from students' actual experiences, and are limited to the role of strengthening cultural identity. This study develops an adaptive method to improve the university's ideological and political discourse system. Combining data analysis and dynamic adjustment, this method enables discourse strategies to respond to changing educational environments without departing from cultural guidelines. Instead of fixing discourse design, it takes the continuous coordination of educational goals, student participation and value transmission as the core.The empirical results on different datasets are relatively stable. On the HE ideology course dataset, the proposed method achieves an accuracy of 90.23% and an F1 score of 89.09%, which is 1.56 percentage points higher than the strongest baseline.On the AI-augmented political discourse dataset, the accuracy rate is 91.89%, the F1 score is 90.94%, which is 1.55 percentage points higher than the best comparative model. Overall, these findings indicate that AI-based methods can provide assistance for improving ideological and political education in higher education, and can also provide practical support for strengthening cultural identity amid rapid technological changes.*

***KEYWORDS:*** *Artificial intelligence, Ideological and political education, Higher education, Cultural confidence, Discourse system*

## 1 Introduction

In the context of artificial intelligence, renewing the discourse system of ideological and political education in higher education has become an increasingly practical issue[1]. On the one hand, rapid technological change is reshaping teaching methods, communication patterns, and students' access to information. On the other hand, higher education is under growing pressure to strengthen students' cultural confidence in a more complex media and technological environment[2]. AI offers new possibilities for improving educational practice, especially in terms of interaction, personalization, and information processing. At the same time, its widespread use also raises concerns about how cultural identity and value orientation can be maintained in the educational process[3]. For this reason, innovation in the discourse system should not stop at the technical level. It also needs to consider how cultural confidence can be reinforced while new technologies are being introduced into teaching and communication[4].

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Early attempts to improve the discourse system in ideological and political education were largely built on structured frameworks based on predefined rules and explicit logical organization[5]. These approaches helped establish consistency in content delivery and provided a relatively stable basis for knowledge transmission. However, their limitations became more apparent as educational contexts continued to change[6]. In many cases, such methods were not flexible enough to respond to shifting cultural discussions or to the diversity of students' experiences, which reduced their practical impact in real teaching settings[7]. Because these frameworks depended heavily on fixed structures, they often struggled to keep pace with contemporary cultural contexts and more complex forms of ideological expression[8]. This also made it harder for such systems to keep students engaged in a sustained way, which is why more adaptive approaches gradually became necessary. Later work began to move away from purely rule-based designs and turned to adaptive algorithms trained on structured educational data. Compared with earlier methods, these approaches made discourse generation more flexible across different learners and teaching settings, and they were generally more useful in practice. By capturing patterns in educational content, they allowed discourse systems to respond more directly to students' backgrounds and learning needs[9]. Even so, the limitations of these methods were still easy to see. In many cases, the discourse they generated could respond to context, but only to a limited extent. It often remained acceptable at the surface level while failing to convey cultural and ideological meaning in a sufficiently deep way. This suggests that flexibility, by itself, does not solve the problem[10]. Cultural sensitivity needs to be built into discourse design more explicitly if the content is expected to connect with students in a meaningful way. There have been some recent advances in neural network architectures. Models based on pre-trained architectures often perform better when the task requires context and language coherence. They are trained on large datasets, can generate discourses more similar to editorial scenarios, and can also reflect stronger cultural nuances[11]. However, actual differences still exist in them. The computational cost is high, and model performance is not always satisfactory in tasks involving highly specific cultural contexts or fine-grained ideological expression. In other words, progress is clear, but it is not yet enough to fully support the needs of contemporary educational environments[12].

In view of these limitations, we propose an approach that combines deep learning techniques with cultural knowledge to improve the discourse system of ideological and political education. The goal is to strengthen cultural specificity while keeping the method practical enough for real educational use. By introducing cultural information into the training and adjustment process, the proposed method aims to generate discourse that is more consistent with educational objectives and more closely connected to students' cultural understanding. In this way, the approach is intended not only to improve adaptability in changing educational contexts but also to support the development of cultural confidence among students. This study makes three main contributions:

- We propose a method that brings deep learning and cultural knowledge into the same framework, so that educational content can respond better to different contexts while remaining connected to the cultural aims of ideological and political education.
- We show that the method is not limited to a single teaching setting and can still maintain reasonable efficiency across different educational scenarios.
- Through experiments, we find that the proposed approach leads to better student engagement and stronger cultural understanding than the comparison methods used in this study.

# 2 Method

## 2.1 Overview

The integration of artificial intelligence into higher education is creating new demands on the discourse system of ideological and political education. In this section, we describe the overall methodology used to improve adaptability and strengthen cultural confidence under changing technological conditions. The discussion is organized into three parts, covering the theoretical basis of the problem, the core design of the proposed model, and the strategy used for its implementation in educational settings. Section 2.1 states the problem and also provides a mathematical foundation for subsequent analysis. The interaction between cultural factors and educational processes is important, as it determines the organization of discourse systems and adjusts constraints. The model in subsection 2.3 does not fix the discourse. It adapts to changing needs and cultural backgrounds, without destroying discourse coherence and associating reports, analyses and decisions. Section 2.4 mentions implementation. Incorporating model outputs into educational planning, subsequent adjustments are aligned with institutional needs. In this way, the analytical side of the method is tied more closely to teaching practice, while the overall goal of strengthening cultural confidence is kept in view. Taken together, this section provides the methodological basis for the study. The following subsections explain each part in detail and show how the proposed approach can be used to improve the discourse system of ideological and political education in the context of ongoing technological change.

## 2.2 Preliminaries

In the setting of artificial intelligence, improving the discourse system of ideological and political education can be viewed as a constrained optimization problem. The central concern is how to organize discourse content so that it remains pedagogically effective while staying aligned with cultural values. In this study, cultural confidence is treated as the degree to which educational discourse reflects cultural identity in a way that is coherent, recognizable, and meaningful to students. We denote the discourse system by $\mathcal{D} = \{d_1, d_2, \dots, d_n\}$, where each $d_i$ represents one discourse element. In practice, such an element may correspond to a topic unit, a value-oriented statement, or a pedagogical component associated with a specific teaching objective and cultural context. The problem is not simply to select these elements independently, but to arrange them in a way that improves their overall cultural consistency and educational function.

To describe the space of feasible discourse arrangements, we introduce a manifold $\mathcal{M}$. Each point on $\mathcal{M}$ corresponds to one possible configuration of discourse elements in an educational setting. Under this formulation, the task is to find a configuration that leads to stronger cultural confidence without weakening pedagogical effectiveness. We measure this objective through a cultural confidence function $C: \mathcal{M} \to \mathbb{R}$, which evaluates the cultural alignment of a given discourse configuration. The optimization problem is written as

$$\mathbf{d}^* = \operatorname*{argmax}_{\mathbf{d} \in \mathcal{M}} C(\mathbf{d}), \tag{1}$$

where $\mathbf{d}$ denotes a candidate configuration of discourse elements.

Not every configuration is appropriate in practice. Educational discourse is shaped by pedagogical requirements, cultural constraints, and institutional boundaries, so the feasible set must be restricted accordingly. We represent these restrictions by a set of constraint functions $\{g_1, g_2, \dots, g_k\}$, with each $g_j: \mathcal{M} \to \mathbb{R}$ corresponding to one requirement. The problem then becomes

$$\mathbf{d}^* = \underset{\mathbf{d}\in\mathcal{M}}{\operatorname{argmax}} C(\mathbf{d}) \quad \text{subject to} \quad g_j(\mathbf{d}) \le 0,\ \forall j. \tag{2}$$

For analysis, it is useful to divide the discourse system into smaller segments rather than treat it as a single whole. Let $\mathcal{S} = \{s_1, s_2, \ldots, s_m\}$ denote the resulting set of discourse segments, where each $s_i \subseteq \mathcal{D}$. This makes it possible to examine how different parts of the discourse contribute to the overall configuration and whether some segments play a more important role than others in shaping cultural confidence.

Each segment $s_i$ is assigned a confidence score $P(s_i)$, which reflects its estimated contribution to cultural confidence. Based on these segment-level scores, the confidence of a full discourse configuration is computed as

$$C(\mathbf{d}) = \sum_{i=1}^{m} P(s_i) \cdot w_i, \tag{3}$$

where $w_i$ denotes the relative importance of segment $s_i$ in the overall discourse system.

## 2.3 Counterfactual Event Planner

Figure 1 shows the overall design of the proposed method. The model is used to analyze and adjust the discourse system of ideological and political education under conditions shaped by artificial intelligence. The main idea is to connect cultural guidance, discourse organization, and adaptive analysis within a single framework, so that the resulting discourse remains relevant to current educational settings without losing its cultural orientation.

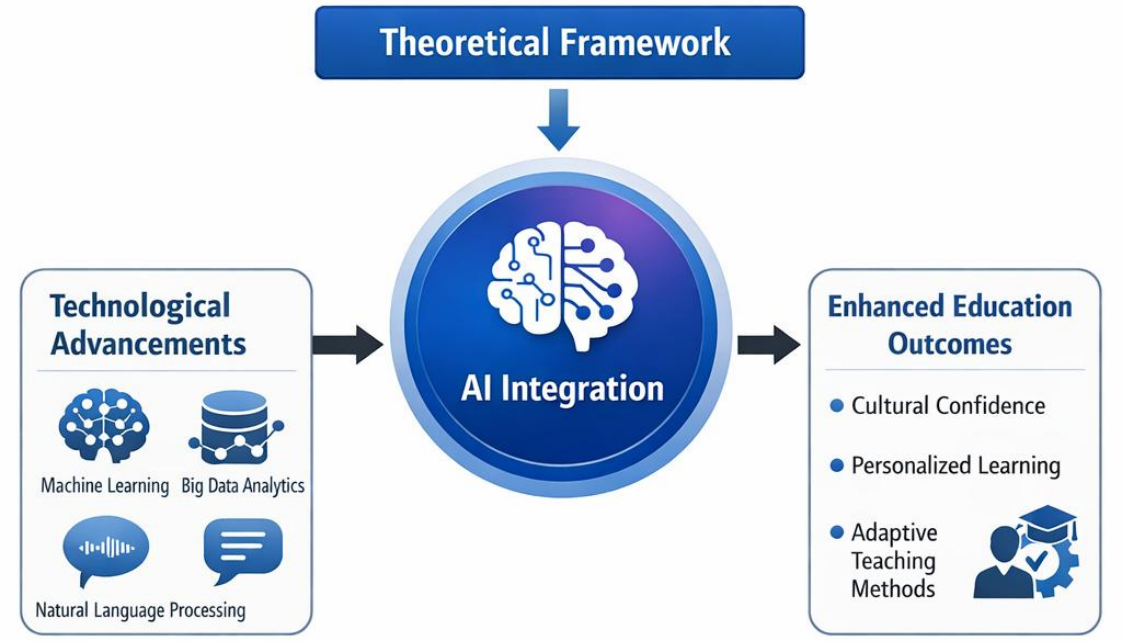


*Figure 1: Overall workflow of the proposed method in ideological and political education. The figure contains three connected parts. On the left are the main technical supports of the method, namely machine learning, big data analysis, and natural language processing. In the middle, AI integration links these technologies to the discourse system. On the right, the figure shows the educational outcomes associated with this process, including cultural confidence, personalized learning, and adaptive teaching methods.*

**Cultural constraint optimization.** Figure 2 illustrates this part of the method. The main idea is to keep discourse adjustment within a culturally acceptable range, so that changes in

content do not disrupt semantic continuity or ideological coherence. In other words, discourse is not allowed to vary without restriction; its adjustment is carried out under explicit cultural constraints. Let $\mathcal{M}$ denote the manifold of feasible cultural narratives, and let $\mathbf{C}$ denote the associated constraint set. The optimization problem is defined as

$$\min_{\mathbf{x}\in\mathcal{M}} \quad \mathcal{L}(\mathbf{x}, \mathbf{C}), \tag{4}$$

where $\mathcal{L}$ measures how far a discourse configuration departs from the required cultural conditions. Here, $\mathcal{M}$ represents the set of discourse configurations that remain acceptable in cultural terms, while $\mathbf{C}$ collects the educational and ideological constraints imposed on them. The objective is to update $\mathbf{x}$ by reducing the loss while keeping the discourse within this feasible space. This constrained formulation is useful because discourse evolution is not completely free in practice. Cultural narratives usually have internal structure, and abrupt deviations may weaken semantic consistency or make the discourse less coherent in ideological terms. For this reason, the optimization is performed on the manifold rather than in an unconstrained Euclidean space.

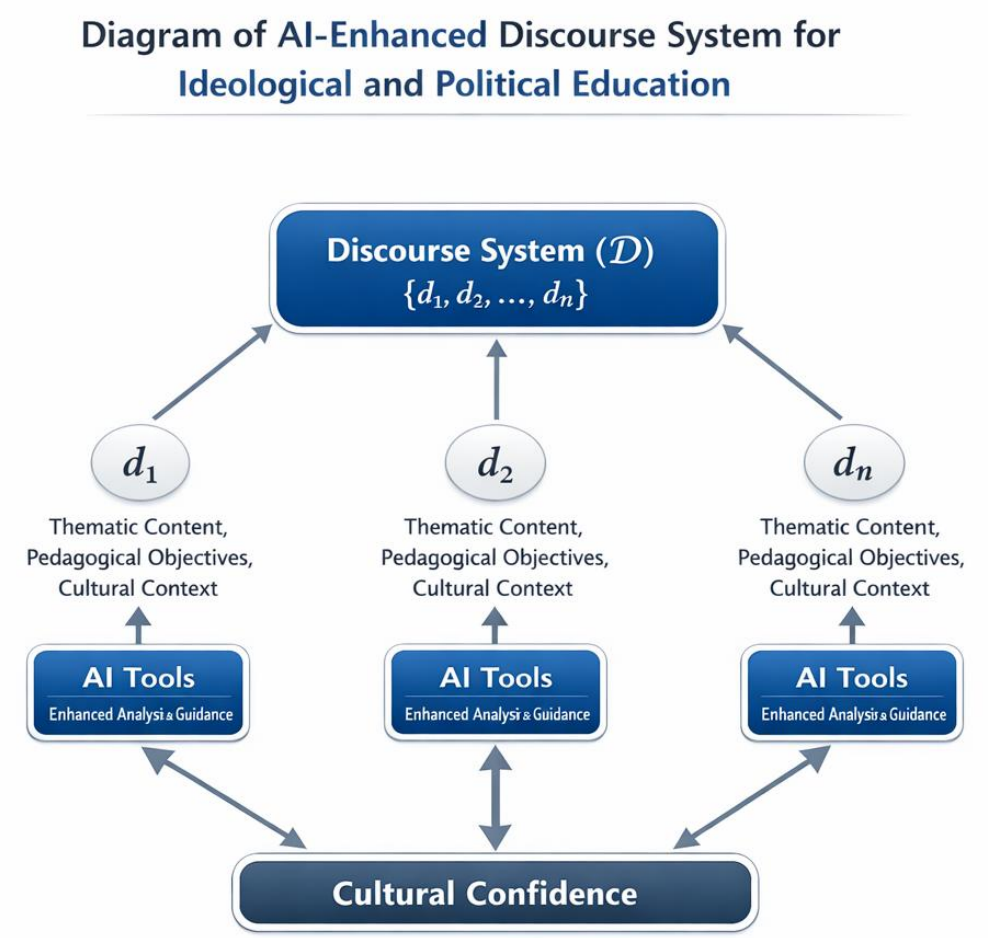


*Figure 2: Constrained optimization process under cultural and ideological requirements. The figure shows how different discourse elements are connected to thematic content, pedagogical objectives, and cultural context, and how AI-based adjustment is used to keep the discourse system consistent with cultural confidence.*

**Discourse segmentation.** This part of the method breaks the discourse into smaller units so that different components can be analyzed and adjusted in a more targeted way. If the whole discourse is treated as a single block, many local differences are difficult to capture. Segmenting it into separate parts makes the analysis easier to handle, especially in more complex educational settings.

Let $\mathcal{A} = \{a_1, a_2, \dots, a_n\}$ denote the set of agents, where each agent is responsible for one part of the discourse. For agent $a_i$, the corresponding discourse segment $\mathcal{D}_i$ is defined as

$$\mathcal{D}_i = \bigcup_{j=1}^{m} \mathcal{S}_j(a_i), \tag{5}$$

where $\mathcal{S}_j(a_i)$ denotes the segment generated by agent $a_i$. In practice, each agent operates with its own local objective and context, so the resulting segmentation can reflect both thematic structure and educational relevance.

The segments are analyzed separately, but they cannot be treated as completely independent. To keep the discourse coherent as a whole, all agents interact through a shared state $\mathcal{G}$, which represents the current global context. Its update rule is

$$\mathcal{G}_{t+1} = \mathcal{G}_t + \sum_{i=1}^{n} \Delta \mathcal{G}_i, \tag{6}$$

where $\Delta\mathcal{G}_i$ denotes the contribution made by agent $a_i$ at time $t$. This shared state keeps local segmentation decisions connected to the broader discourse context, which becomes especially important when the educational setting or discussion focus changes over time. To evaluate segmentation quality, we define a coherence score $\mathcal{C}(\mathcal{D})$ as

$$\mathcal{C}(\mathcal{D}) = \frac{1}{|\mathcal{D}|} \sum_{i=1}^{|\mathcal{D}|} \mathrm{sim}\,(\mathcal{D}_i, \mathcal{D}_{i+1}), \tag{7}$$

where $\mathrm{sim}(\mathcal{D}_i, \mathcal{D}_{i+1})$ measures the similarity between neighboring segments. A larger value of $\mathcal{C}(\mathcal{D})$ means that continuity is better preserved after segmentation. This gives a direct way to check whether dividing the discourse locally still keeps the overall structure coherent.

## 2.4 Counterfactual Pacing and Policy-driven Coordination

Figure 3 presents the strategy used to apply the proposed method in actual educational settings. The focus here is not only on generating discourse, but also on adjusting its pace and direction as educational conditions change. In ideological and political education, discourse has to remain responsive to shifts in teaching context while still following broader institutional and policy requirements. For this reason, the strategy combines counterfactual analysis with policy-oriented coordination.

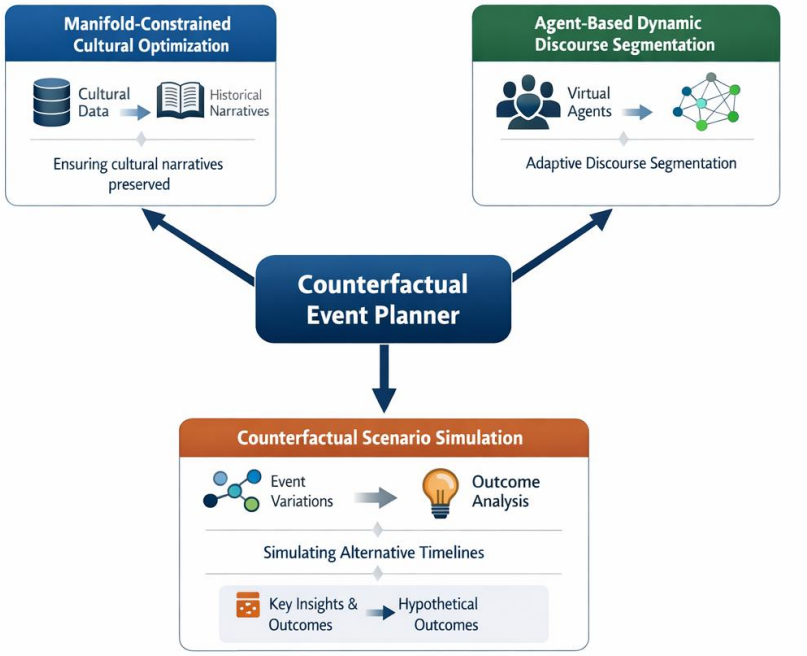


*Figure 3: Overall strategy for applying the proposed method in ideological and political education. The framework combines discourse adjustment, contextual analysis, and policy coordination so that discourse can remain adaptive while preserving cultural and educational consistency.*

**Counterfactual scenario analysis** Figure 4 shows how alternative discourse scenarios are evaluated in the proposed strategy. The idea is to compare possible discourse paths before a specific adjustment is adopted, so that the resulting strategy is not based only on the current state but also on plausible alternatives. This is useful in ideological and political education, where different discourse choices may lead to different responses under the same educational objective.

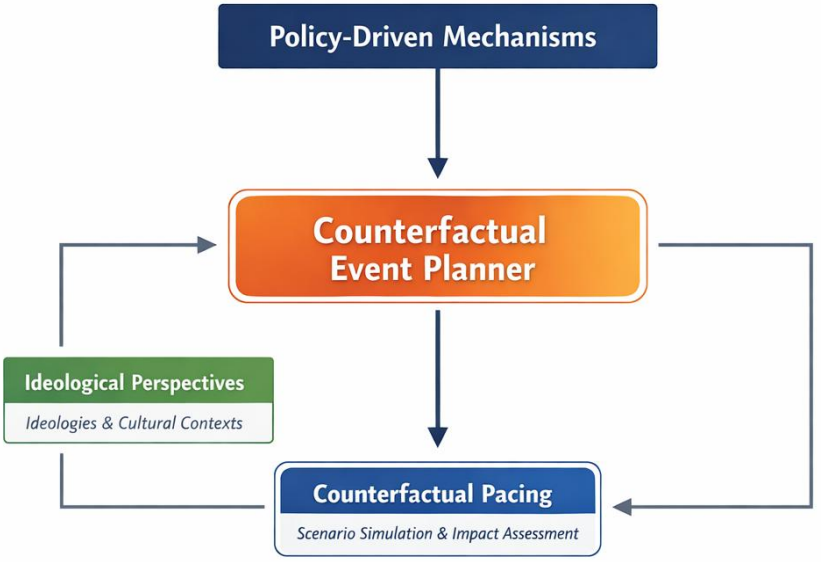


*Figure 4: Illustration of counterfactual scenario analysis within the proposed strategy. The framework compares alternative discourse paths under cultural, educational, and policy-related constraints so that strategy updates can be evaluated before implementation.*

Let $S$ denote the set of candidate discourse scenarios, and let $C$ represent the relevant cultural and educational constraints. Scenario selection is formulated as the following constrained optimization problem:

$$\max_{s \in S} \quad f(s) \quad \text{subject to} \quad g(s) \leq C, \tag{8}$$

where $f(s)$ measures the relevance of scenario $s$, and $g(s)$ represents the corresponding feasibility condition. Under this formulation, the model favors scenarios that are both educationally meaningful and feasible within the given discourse context.

Not every candidate scenario is equally likely to produce a useful outcome, so we further introduce a probabilistic score for scenario evaluation. Let $P(s)$ denote the probability that scenario $s$ leads to a satisfactory discourse outcome. It is computed as

$$P(s) = \frac{\exp(\alpha \cdot h(s))}{\sum_{s' \in S} \exp(\alpha \cdot h(s'))}, \tag{9}$$

where $h(s)$ is a scoring function derived from historical information and contextual evidence, and $\alpha$ is a scaling parameter. This formulation makes it possible to compare competing scenarios in a normalized way, so that discourse adjustments can be guided by both feasibility and estimated effectiveness.

**Policy coordination** This part of the strategy is used to keep discourse adjustment consistent with institutional and educational requirements. In practice, discourse does not evolve independently of policy constraints. Changes in educational goals, administrative rules, or teaching priorities may all require corresponding changes in discourse organization. For this reason, policy coordination is introduced to connect discourse adjustment with the broader requirements of the educational setting.

Let $D$ denote the discourse flow, and let $P$ denote the set of relevant policies. The discourse is divided into segments $\{d_1, d_2, \ldots, d_n\}$, and each segment is required to satisfy a minimum level of policy alignment:

$$\forall d_i \in D, \quad \text{PolicyAlignment}(d_i, P) \geq \tau, \tag{10}$$

where $\tau$ is the threshold for acceptable alignment.

Policy requirements may change over time, so the strategy also includes a dynamic adjustment step. Let $\Delta P$ denote a policy update, and let $\Delta D$ denote the corresponding change in discourse flow. The adjusted discourse is obtained by solving

$$\Delta D = \operatorname*{argmin}_{D'} \quad \| D' - D \| \quad \text{subject to} \quad \text{PolicyAlignment}(D', P + \Delta P) \geq \tau, \tag{11}$$

where $\| D' - D \|$ measures the difference between the updated discourse and the original one. This formulation keeps the new discourse as close as possible to the previous version while still satisfying the revised policy conditions.

**Confidence estimation** This part of the strategy is used to evaluate how reliable a candidate discourse scenario is under uncertain educational conditions. Since different scenarios may lead to different outcomes even under similar settings, the model does not rely only on point estimates. Instead, it assigns each scenario a confidence value that reflects both its expected effect and the uncertainty associated with that effect.

Let $C(s)$ denote the confidence assigned to scenario $s$. It is defined as

$$C(s) = \int_{x \in X} p\,(x|s) \cdot u(x)\, dx, \tag{12}$$

where $X$ is the set of possible outcomes, $p(x|s)$ is the probability density of outcome $x$ given scenario $s$, and $u(x)$ represents the utility of that outcome. Under this formulation, the confidence score reflects not only the expected usefulness of a scenario but also the distribution of its possible results.

# 3 Experimental Setup

## 3.1 Dataset

Table 1 summarizes the datasets used in this study in terms of size, modality, and task setting. These datasets are not limited to a single type of educational analysis. Instead, they involve ideological content, political discourse, cultural context, and broader issues related to educational systems. This diversity is useful for evaluation because it allows the proposed method to be examined under different data conditions rather than in only one narrowly defined task.

*Table 1: Main statistics of the educational datasets used in this study. #Src denotes the number of sources, #Doc the number of documents, #Samp the number of samples, #Cls the number of categories, and #Scen the number of scenarios. Txt denotes text, Aud audio, Survey survey data, and Stat statistical data.*

| Dataset | Year | #Src | #Doc | #Samp | #Cls | #Scen | Modalities | Task |
|---|---|---|---|---|---|---|---|---|
| HEICD | 2023 | ~50 | ~2K | ~20K | ~5 | ~8 | Txt | Ideological analysis |
| AEPDD | 2022 | ~30 | ~1.5K | ~15K | ~6 | ~6 | Txt + Aud | Discourse analysis |
| CCED | 2023 | ~40 | ~1K | ~10K | ~4 | ~7 | Txt + Survey | Cultural analysis |
| IESD | 2020 | ~35 | ~1.8K | ~18K | ~7 | ~9 | Txt + Stat | Educational innovation |

## 3.2 Experimental Details

Table 2 gives the main training settings used in the experiments, including the optimizer, learning rate schedule, regularization terms, and data augmentation strategy. These settings are listed here to clarify how the model was trained and under what conditions the comparison with other methods was carried out. During the experiments, the same configuration was used throughout so that differences in performance would be less affected by training variation.

*Table 2: Main training settings used in the experiments*

| Component | Setting |
|---|---|
| Framework | PyTorch |
| Hardware | NVIDIA Tesla V100 (32GB) |
| Optimizer | Stochastic Gradient Descent |
| Momentum | 0.9 |
| Weight Decay | $5 \times 10^{-4}$ |
| Initial Learning Rate | 0.01 |
| Learning Rate Scheduler | Cosine Annealing |
| Batch Size | 256 |
| Gradient Clipping | Maximum norm = 5 |
| Label Smoothing | 0.1 |
| Warm-up Strategy | 10 epochs |
| Training Strategy | Multi-stage Fine-tuning |
| Data Augmentation | Random Crop + Horizontal Flip + Color Jitter |
| Number of Epochs | 100 |
| Loss Function | Cross-Entropy |

## 3.3 Comparison with SOTA Methods

Table 3 shows the comparison with the baseline. On the two datasets, the pro method leads in accuracy, precision, recall, and F1 score, with a small and relatively stable gap. On the HE Ideo Curri dataset, this method achieves 90.23% accuracy .F1 score is 89.09%, 1.56 percentage points higher than the strongest baseline. In the political discourse data processed by artificial intelligence, it increased by 1.55 percentage points, with an accuracy rate of 91.89% and a recall rate of 90%.F1 reaches 94%. These results show that, among multiple evaluations, the proposed method is more stable compared with only proposing a single indicator. The results in Table 4 show a similar pattern. Compared with the baseline methods, the proposed approach again performs better across the main evaluation metrics, which indicates that its advantage is not limited to one dataset or one specific experimental setting. What stands out here is not only the absolute gain, but also the consistency of that gain. Even when the data characteristics change, the method still maintains relatively balanced performance in precision, recall, and F1 score. This is important in educational data analysis, where models that perform well on one metric but deteriorate on others are often less useful in practice. Taken together, the results in Tables 3 and 4 show that the proposed method performs more reliably than the comparison models across different datasets. The improvement is not dramatic in a single isolated case, but it is consistent, which matters more for this type of task. In particular, the gains on accuracy and F1 score suggest that the method is better at maintaining overall prediction quality while preserving balance between precision and recall. From this perspective, the main advantage of the proposed approach lies in its stable performance across different educational datasets rather than in an isolated improvement on one benchmark alone.

*Table 3: Comparison of our method with SOTA models on Higher Education Ideological Curriculum Dataset and AI Enhanced Political Discourse Dataset*

| Model | Higher Education Ideological Curriculum Dataset | | | | AI Enhanced Political Discourse Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| 2-9 | Accuracy | Precision | Recall | F1 Score | Accuracy | Precision | Recall | F1 Score |
| ResNet(Yuan et al. 2024) | 85.67 ± 0.52 | 84.92 ± 0.63 | 84.15 ± 0.58 | 84.53 ± 0.60 | 87.34 ± 0.47 | 86.78 ± 0.55 | 86.02 ± 0.62 | 86.39 ± 0.54 |
| Swin Transformer(Yin et al. 2023) | 86.45 ± 0.48 | 85.89 ± 0.57 | 85.12 ± 0.64 | 85.50 ± 0.59 | 88.12 ± 0.43 | 87.56 ± 0.50 | 86.80 ± 0.57 | 87.17 ± 0.49 |
| RegNet(Hwang and Park 2022) | 86.98 ± 0.44 | 86.23 ± 0.60 | 85.46 ± 0.55 | 85.84 ± 0.53 | 88.67 ± 0.39 | 88.11 ± 0.47 | 87.35 ± 0.54 | 87.72 ± 0.46 |
| ConvNeXt(Huang et al. 2021) | 87.56 ± 0.39 | 86.81 ± 0.52 | 86.04 ± 0.59 | 86.42 ± 0.51 | 89.23 ± 0.35 | 88.67 ± 0.44 | 87.91 ± 0.51 | 88.28 ± 0.43 |
| DeiT(Belaala et al. 2025) | 88.12 ± 0.36 | 87.37 ± 0.49 | 86.60 ± 0.56 | 86.98 ± 0.48 | 89.78 ± 0.32 | 89.22 ± 0.41 | 88.46 ± 0.48 | 88.83 ± 0.40 |
| EfficientNet(Alazmi and Ayub 2025) | 88.67 ± 0.33 | 87.92 ± 0.46 | 87.15 ± 0.53 | 87.53 ± 0.45 | 90.34 ± 0.29 | 89.78 ± 0.38 | 89.02 ± 0.45 | 89.39 ± 0.37 |
| Ours | **90.23 ± 0.40** | **89.48 ± 0.50** | **88.71 ± 0.57** | **89.09 ± 0.49** | **91.89 ± 0.37** | **91.33 ± 0.46** | **90.57 ± 0.53** | **90.94 ± 0.45** |

*Table 4: Comparison of Our Method with SOTA methods on Cultural Confidence in Education and Innovation in Educational Systems Datasets*

| Model | Cultural Confidence in Education Dataset | | | | Innovation in Educational Systems Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| 2-9 | Accuracy | Precision | Recall | F1 Score | Accuracy | Precision | Recall | F1 Score |
| ResNet(Yuan et al. 2024) | 85.67 ± 0.48 | 84.92 ± 0.55 | 85.13 ± 0.60 | 84.78 ± 0.52 | 87.45 ± 0.47 | 86.89 ± 0.59 | 86.34 ± 0.63 | 86.12 ± 0.54 |
| Swin Transformer(Yin et al. 2023) | 86.23 ± 0.42 | 85.67 ± 0.50 | 85.89 ± 0.57 | 85.45 ± 0.49 | 88.12 ± 0.44 | 87.56 ± 0.53 | 87.02 ± 0.58 | 86.78 ± 0.51 |
| RegNet(Hwang and Park 2022) | 86.89 ± 0.39 | 86.34 ± 0.47 | 86.56 ± 0.54 | 86.12 ± 0.46 | 88.67 ± 0.41 | 88.12 ± 0.50 | 87.45 ± 0.55 | 87.23 ± 0.48 |
| ConvNeXt(Huang et al. 2021) | 87.34 ± 0.37 | 86.78 ± 0.45 | 87.01 ± 0.52 | 86.67 ± 0.44 | 89.23 ± 0.39 | 88.67 ± 0.48 | 88.12 ± 0.53 | 87.89 ± 0.46 |
| DeiT(Belaala et al. 2025) | 87.78 ± 0.35 | 87.23 ± 0.43 | 87.45 ± 0.50 | 87.12 ± 0.42 | 89.78 ± 0.37 | 89.23 ± 0.46 | 88.67 ± 0.51 | 88.45 ± 0.44 |
| EfficientNet(Alazmi and Ayub 2025) | 88.12 ± 0.33 | 87.56 ± 0.41 | 87.89 ± 0.48 | 87.45 ± 0.40 | 90.12 ± 0.35 | 89.67 ± 0.44 | 89.12 ± 0.49 | 88.89 ± 0.42 |
| Ours | **89.45 ± 0.36** | **88.89 ± 0.44** | **89.12 ± 0.51** | **88.78 ± 0.43** | **91.34 ± 0.38** | **90.78 ± 0.47** | **90.23 ± 0.52** | **90.01 ± 0.45** |

## 3.4 Ablation Study

To see how each part of the method affects the final results, we remove one component at a time and compare the resulting performance with that of the full model. The results are reported in Table 5 and Table 6. Table 5 reports the ablation results on the Higher Education Ideological Curriculum Dataset and the AI Enhanced Political Discourse Dataset. The full model gives the best results on all four metrics in both datasets. On the Higher Education Ideological Curriculum Dataset, removing the cultural constraint component reduces accuracy from 90.23% to 88.12% and F1 score from 89.09% to 86.98%, which is the largest drop among the three ablated settings. This suggests that cultural constraints play an important role in maintaining overall consistency and quality. When discourse segmentation is removed, the decrease is smaller but still clear, with accuracy falling to 88.67% and F1 score to 87.53%. Removing confidence estimation leads to a more moderate decline, but the full model still remains better on every metric. The same pattern appears on the AI Enhanced Political Discourse Dataset. Without the cultural constraint component, accuracy drops from 91.89% to 89.78% and F1 score from 90.94% to 88.83%. Removing discourse segmentation gives 90.34% accuracy and 89.39% F1 score, while removing confidence estimation gives 90.78% accuracy and 89.83% F1 score. These results show that all three parts contribute to performance, although their impact is not identical. Among them, the cultural constraint component causes the largest loss when removed, which suggests that it provides the strongest support for the overall structure of the method. Table 6 shows a similar trend on the Cultural Confidence in Education Dataset and the Innovation in Educational Systems Dataset. On the Cultural Confidence in Education Dataset, the full model reaches 89.45% accuracy and 88.78% F1 score. When the cultural constraint component is removed, these values fall to 88.12% and 87.34%, respectively. The versions without discourse segmentation and without confidence estimation perform better than that setting, but both still remain below the full model. On the Innovation in Educational Systems Dataset, the same ranking is observed: the full model achieves the best results, followed by the

version without confidence estimation, then the version without discourse segmentation, and finally the version without cultural constraints.

*Table 5: Ablation study on Higher Education Ideological Curriculum Dataset and AI Enhanced Political Discourse Dataset*

| Model | Higher Education Ideological Curriculum Dataset | | | | AI Enhanced Political Discourse Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| 2-9 | Accuracy | Precision | Recall | F1 Score | Accuracy | Precision | Recall | F1 Score |
| w./o. Manifold Constrained Cultural Optimization | 88.12 ± 0.45 | 87.37 ± 0.55 | 86.60 ± 0.62 | 86.98 ± 0.54 | 89.78 ± 0.42 | 89.22 ± 0.51 | 88.46 ± 0.58 | 88.83 ± 0.50 |
| w./o. Agent Based Dynamic Discourse Segmentation | 88.67 ± 0.42 | 87.92 ± 0.52 | 87.15 ± 0.59 | 87.53 ± 0.51 | 90.34 ± 0.39 | 89.78 ± 0.48 | 89.02 ± 0.55 | 89.39 ± 0.47 |
| w./o. Probabilistic Confidence Quantification | 89.12 ± 0.38 | 88.37 ± 0.49 | 87.60 ± 0.56 | 87.98 ± 0.48 | 90.78 ± 0.35 | 90.22 ± 0.44 | 89.46 ± 0.51 | 89.83 ± 0.43 |
| Ours | **90.23 ± 0.40** | **89.48 ± 0.50** | **88.71 ± 0.57** | **89.09 ± 0.49** | **91.89 ± 0.37** | **91.33 ± 0.46** | **90.57 ± 0.53** | **90.94 ± 0.45** |

*Table 6: Ablation Study of Our Method on Cultural Confidence in Education and Innovation in Educational Systems Datasets*

| Configuration | Cultural Confidence in Education Dataset | | | | Innovation in Educational Systems Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| 2-9 | Accuracy | Precision | Recall | F1 Score | Accuracy | Precision | Recall | F1 Score |
| w./o. Manifold Constrained Cultural Optimization | 88.12 ± 0.40 | 87.56 ± 0.48 | 87.78 ± 0.55 | 87.34 ± 0.47 | 90.23 ± 0.42 | 89.67 ± 0.51 | 89.12 ± 0.56 | 88.89 ± 0.49 |
| w./o. Agent Based Dynamic Discourse Segmentation | 88.45 ± 0.38 | 87.89 ± 0.46 | 88.12 ± 0.53 | 87.67 ± 0.45 | 90.56 ± 0.40 | 90.01 ± 0.49 | 89.45 ± 0.54 | 89.23 ± 0.47 |
| w./o. Probabilistic Confidence Quantification | 88.78 ± 0.36 | 88.23 ± 0.44 | 88.45 ± 0.51 | 88.01 ± 0.43 | 90.89 ± 0.38 | 90.34 ± 0.47 | 89.78 ± 0.52 | 89.56 ± 0.45 |
| Ours | **89.45 ± 0.36** | **88.89 ± 0.44** | **89.12 ± 0.51** | **88.78 ± 0.43** | **91.34 ± 0.38** | **90.78 ± 0.47** | **90.23 ± 0.52** | **90.01 ± 0.45** |

# 4 Conclusions and Future Work

This study examined how artificial intelligence can be used to improve the discourse system of ideological and political education in higher education while strengthening cultural confidence. The main goal was to make discourse adjustment more adaptive to changing educational conditions without weakening its cultural orientation. To do this, we developed a method that combines cultural constraint optimization, discourse segmentation, and confidence-based strategy adjustment within a unified framework. The results show that this approach performs

consistently better than the comparison methods across the evaluated datasets. In particular, it achieves 90.23% accuracy and 89.09% F1 score on the Higher Education Ideological Curriculum Dataset, and 91.89% accuracy and 90.94% F1 score on the AI Enhanced Political Discourse Dataset. These results suggest that the proposed method can improve discourse analysis and adjustment while maintaining stable overall performance across different settings.

This study has certain limitations. First, the method relies on computing resources and implementation conditions, and different institutions have unequal situations in these aspects. This makes the framework acceptable in the evaluation, but it is more difficult to actually deploy in teaching environments lacking technical support. Second, it currently focuses on the overall cultural fit at the system level. In doing so, it may not fully reflect differences among student groups or finer variations in individual cultural understanding. As a result, some forms of diversity in educational response may remain underrepresented. Future work should therefore move in two directions. One is to make the method easier to deploy in real educational settings, especially under resource-constrained conditions. The other is to refine the modeling of cultural variation so that discourse adjustment can respond not only to general educational objectives but also to more diverse student backgrounds and cultural contexts. These issues are important if AI-based methods are to be used in ideological and political education in a way that is both effective and practically sustainable.

# Conflict of Interest Statement

No commercial or financial connections that might constitute a potential conflict of interest were present during the course of this research, as declared by the authors.

# Author Contributions

**Yuezhu He** 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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