



# Cultivating Responsibility and Commitment among University Students through Intelligent Data Analytics: Pathways for Digital Education Management

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**SUMMARY:** *The cultivation of responsibility consciousness in colleges and universities has entered the scene where course learning, collective collaboration, social practice, network behavior and daily education and management work together. Traditional evaluation relies on questionnaires, conversations and stage summaries, which can reflect students' explicit attitudes, but it is difficult to consistently identify the formation process of responsible behaviors. In this paper, we construct a reviewable responsibility awareness data package, build a comprehensive index of responsibility around 1,248 anonymous students, 21 behavioral characteristics, 9,984 weekly intervention records, and 35,944 heterogeneous relational edges, and propose a contextual graphical attention responsibility recognition model. The model incorporates students, course tasks, practical activities, collaborative projects, and educational feedback into the same heterogeneous graph, and identifies student responsibility states through relational attention, temporal smoothing, fairness constraints, and explanatory outputs. The results show that the model in this paper has an AUC of 0.906, an Accuracy of 0.823, a Macro-F1 of 0.831, and an RMSE of 0.294 in responsibility state identification, which are 0.060, 0.062, 0.069 and 0.067 higher and lower than the XGBoost, respectively. The results of the 8-week intervention show that the composite index of responsibility taking of the synergistic intervention group increased from 63.8 to 74.6, the proportion of low concern decreased from 28.4% to 15.9%, and the sustained participation rate increased from 39.4% to 57.6%. The ablation experiment showed that the social practice mapping, reflective text features and temporal attention module contributed the most to the model performance. The study illustrates that the digital cultivation of responsibility awareness needs to shift from single-behavioral statistics to multi-source contextual modeling, and to form a closed loop of educational management through interpretive feedback, hierarchical interventions, and manual review.*

**KEYWORDS:** *intelligent data analytics; college students' sense of responsibility; learning analytics; heterogeneous graphical modeling; digital education management*

## 1 Introduction

The cultivation of college students' sense of responsibility has been embedded in multiple scenarios of the daily operation of colleges and universities. Whether students are able to undertake learning tasks, participate in collective affairs, respond to public needs, and comply with the rules of digital space is usually not only reflected in a questionnaire or a conversation, but also distributed in course platforms, second classrooms, social practices, class collaborations, and counselors' feedback records. The realistic challenge of digital education

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management in higher education lies in the fact that the sense of responsibility is processual and situational, and it is difficult to explain why students show breaks in their responsible behaviors in a single evaluation, or to determine whether certain types of interventions actually change students' sustained actions.

The digitization process of education and the expansion of generative AI have caused more continuous learning and management data to become obtainable for HEIs. The OECD on the Digital Education Outlook 2026 has put emphasis that generative AI only is able to give support to authentic learning when it is restricted by clear pedagogical principles and learning objectives. UNESCO puts forward Guidelines on Educational and research applications; therefore, the guidelines regarding privacy protection, educational relevance and human subject are taken as essential conditions for technology to enter the educational system. The EU guiding documents on the moral employment of AI and data in educational situations also bring transparency, responsibility, justice and data reading ability into the practice framework for teachers and educational institutions[1-3]. These policies and guidelines make clear that the digital education management of higher education cannot stay on the level of technology access, but also needs to respond to how data can serve the goals of education, how models can get explanation, and how results can be utilized to give support to the development of students. The researches which are related have given the methodologic base for the analysis of data in the high education. A meta-systematic summary of Artificial Intelligence within Higher Education indicates that AI has been extensively put into scenarios including learning support, assessment help, teaching feedback, and management decision-making, but ethics, cooperation, and method strictness still are important factors influencing the quality of uses. The study about business intelligence and data analytics on academic management in higher education has indicated that learning analytics, predictive modeling, and educational data mining have already become important instruments for optimization of resource distribution and student assistance in higher education. The research of big data in the educational management of college students has also had attempts which apply data warehousing, clustering and integrated learning to carry out analysis on student behaviors[4-6]. These researches prove that universities on the technical aspect have the equipment to change data from many different sources into management proof.

Learning analytics research has further advanced student state identification. Bergdahl et al. conducted a systematic review of student engagement in learning analytics in higher education, noting that existing studies often capture student engagement states through learning management system logs, discussion behaviors, and learning task records [7]. Johar et al. noted that learning analytics are able to identify behavioral, cognitive, collaborative, and social engagement but that comprehensive measures of multidimensional engagement are still insufficient [8]. Banihashem et al.'s review of learning analytics feedback practices showed that learning analytics can improve feedback mechanisms in technology-mediated environments, but whether feedback translates into self-regulation and sustained action by students still requires a more nuanced intervention design [9]. Pan et al.'s review of learning analytics interventions for LMSs also showed that, while the existing intervention research can provide evidence of design, they focus on academic performance and course participation, and rarely extend to value-based developmental goals such as sense of responsibility [10].

Arroyave et al. suggest that students' commitment to social responsibility can be operationalized into a number of measurable dimensions, which provides a reference for the indexing of college students' sense of responsibility [11], and García-Aracil et al. analyze social commitment from the perspective of strategic planning in higher education institutions, which suggests that the social responsibility of higher education institutions should not be reflected only in the institutional text, but also in the process of students' training. texts, but also into the student training process [12]. Medne et al. study on the development of civic competencies in

HEIs shows that HEI education can influence students' social responsibility and civic competencies through curricula, activities, and public engagement [13]. Valencia-Arias et al.'s case study on the social responsibility strategy of universities also illustrates the need for social responsibility in universities to be realized through projects, community engagement, and organizational mechanisms on the ground [14]. These studies focus on the goals and institutional arrangements of responsibility education, but are less likely to connect responsibility awareness, responsible behavior, and digital management data.

There are still four key shortcomings in the existing studies. First, the data boundary is narrow. Most learning analytics studies rely on course platform logs, which easily equate high-frequency behaviors such as logging in, clicking, and submitting with responsibility status, making it difficult to cover social practices, class collaboration, and tutor feedback. Second, the mapping of indicators is weak. Awareness of responsibility contains cognitive, learning, collective, social and digital responsibilities, and without an intermediate indicator layer, the model is prone to interpret externally apparent behaviors directly as internal awareness. Third, the model is insufficiently explained. Responsibility education in colleges and universities requires counselors, classroom teachers, and classroom teachers to know whether the warning comes from task procrastination, practice disconnection, collaboration marginalization, or digital rule risk. Fourth, intervention closure is inadequate. Models identify low concern students, and in the absence of tiered feedback, practice task undertakings, and manual review, data analytics can only remain at the monitoring level. Hooshyar et al.'s discussion of accountable education AI points out that education AI needs to incorporate domain knowledge, the learning process, stakeholder engagement, and reliable explanations [15]; Morales Tirado et al. also emphasize that learning analytics for colleges and universities systems need to translate transparency, equity and accountability into enforceable systems [16].

Based on the above issues, this paper focuses on “how intelligent data analytics can serve the cultivation of college students' sense of responsibility”. The work of this paper includes three points: first, constructing a locked data package for responsibility awareness, which organizes student portraits, behavioral characteristics, responsibility scores, weekly interventions, and heterogeneous relationship edges into a reviewable data structure; second, proposing a contextual graphical attention to responsibility recognition model, which incorporates multiple types of relationships between students and course tasks, practical activities, collaborative projects, and educational feedback into the modeling; third, establishing a digital education management pathway to shift the cultivation of responsibility awareness from staged evaluation to continuous support through responsibility portraiture, interpretive clues, layered interventions, and manual review.

## 2 Methods

### 2.1 Data Package Construction, Sample Organization and Responsibility Indicator Mapping

The data package this paper uses is a locked synthetic verification data package, whose goal is to verify the computable property, drawing repeatability, and digital management path implementation ability of the Responsibility Consciousness Intelligent Analysis Model. This data package structurally takes the student management situation of a comprehensive university in the academic year 2023-2024 as reference, but it does not include any real student personal identities, mobile phone numbers, IP addresses, equipment numbers, or original text materials. Our sample's quantity is 1,248 nameless students which cover four grades, five kinds of special fields of study, and two kinds of habitation status. The data are layered according to

responsibility condition and then are parted into training, validation and test groups with 70%, 15% and 15%. The data package is composed of five kinds of objects. The first kind is student profile objects, which record grade level, major type, living situation, starting responsibility status, and intervention group.

The second kind is the behavioral profile object, which is made of 21 variables, including login stability, task timeliness, discussion amount, depth of resource visiting, expansion rate, volunteer time, practice finishing rate, practice continuity, service feedback, group attendance, peer contribution, group positions, peer peer evaluation, conversation number, warning number, reflection quality, finishing rate of correction action, online manners, platform rules, and AI use announcement. The third kind is the responsibility score object, which includes pre-test and post-test scores on five aspects: responsibility cognition, study responsibility, group responsibility, society responsibility, and digital responsibility. The fourth classification is the every week intervention target, which records the changes of the Responsibility to Take Charge composite index, task timeliness, practice continuity, and reflection quality in an 8-week time length. The fifth kind is heterogeneous relation things which connect students with course assignments, social activities, cooperation items, teaching replies and thinking notes.

Data generation does not use a single random number to fill in the table. Five-dimensional responsibility latent variables were first set up and correlations between perceptions of responsibility, academic responsibility, collective responsibility, social responsibility, and numerical responsibility were controlled for through a correlation matrix. Subsequently, slight group effects were added by grade level, major category, and residential status, resulting in slightly higher continuity of social practice among upperclassmen, slightly higher scores on timeliness of academic tasks and numerical rules among engineering students, and slightly lower stability of collective participation among commuter students. Behavioral characteristics were then generated driven by the corresponding responsibility dimensions. For example, task timeliness is primarily influenced by learning responsibility, practice continuity is primarily influenced by social responsibility, peer contribution is primarily influenced by collective responsibility, and netiquette and AI disclosure scores are primarily influenced by digital responsibility. The design allows the data package to retain the logic of the variables in the educational scenarios rather than splicing the results with completely independent random numbers, as shown in equation (1).

$$u_i = \mu_{g_i} + L\epsilon_i + \eta_i \quad (1)$$

where  $u_i$  denotes the five-dimensional responsibility latent variable for student  $i$ ,  $\mu_{g_i}$  denotes the group mean corresponding to his/her grade, major, and accommodation combination,  $L$  denotes the result of Cholesky decomposition of the latent variable correlation matrix,  $\eta_i$  denotes a standard normal random perturbation, and  $\epsilon_i$  denotes slight noise at the individual level. This formula is used to ensure that the five dimensions of responsibility are reasonably correlated with each other and not cut off from each other.

The Responsibility Composite Index is calculated based on a five-dimensional responsibility score. The five dimensions are responsibility perception, learning responsibility, collective responsibility, social responsibility and digital responsibility. Learning responsibility and social responsibility have slightly higher weights due to the fact that the two have a higher differentiation of responsibility status in the data package, and also correspond more directly to the learning fulfillment of responsibility and public participation in the day-to-day education and management of colleges and universities, as shown in equation (2).

$$RCI_i = \sum_{k=1}^5 \alpha_k z_{ik}, \quad \sum_{k=1}^5 \alpha_k = 1, \quad 0 \leq \alpha_k \leq 1 \quad (2)$$

where  $RCI_i$  denotes the comprehensive index of responsibility taking of the  $i$ th student,  $z_{ik}$  denotes the standardized score of the  $i$ th student on the  $k$ th responsibility dimension, and  $\alpha_k$  denotes the weight of the  $k$ th responsibility dimension. In this paper, we set  $\alpha_k$  as 0.20, 0.24, 0.18, 0.22 and 0.16, corresponding to responsibility cognition, learning responsibility, collective responsibility, social responsibility and digital responsibility, respectively.

$$z_{ik} = \frac{s_{ik} - \min(s_k)}{\max(s_k) - \min(s_k) + \varepsilon} \quad (3)$$

where  $s_{ik}$  denotes the raw score of the  $i$ th student on the  $k$ th dimension,  $\min(s_k)$  and  $\max(s_k)$  denote the minimum and maximum values of the  $k$ th dimension in the sample, respectively, and  $\varepsilon$  denotes the smoothing term. This treatment compresses variables with different scales into the same numerical interval, so as to avoid that variables such as the length of volunteering, the number of discussions and the quality of reflection affect the composite index due to unit differences. The mapping of responsibility awareness dimensions and behavioral characteristics is shown in Table 1.

Table 1: Mapping of Responsibility Awareness Dimensions to Behavioral Characteristics

Responsibility Dimension	Behavioral Features	Data Table	Explanation Scope
Responsibility Awareness	Reflection quality, correction completion rate, feedback acceptance	BehaviorFeatures, WeeklyIntervention	Whether students can transform educational feedback into self-understanding and subsequent plans
Learning Responsibility	Login stability, task completion rate, resource access depth, delay rate	BehaviorFeatures, WeeklyIntervention	Whether students continuously take on course tasks and learning schedules
Collective Responsibility	Group attendance, peer contribution, group roles, peer evaluation	BehaviorFeatures, HeterogeneousEdges	Whether students assume collaborative responsibilities in class, groups, and organizational activities
Social Responsibility	Volunteer service duration, practical completion rate, continuity of practice, service feedback	BehaviorFeatures, WeeklyIntervention	Whether students consistently participate in public service and social practice
Digital Responsibility	Online etiquette, platform rules, AI usage disclosure, academic integrity risks	BehaviorFeatures	Whether students adhere to digital space rules and academic ethics

The multi-source data is organized by student portrait, behavioral characteristics, responsibility score, weekly intervention and heterogeneous relationship edge to form the responsibility awareness modeling object, as shown in Figure 1.

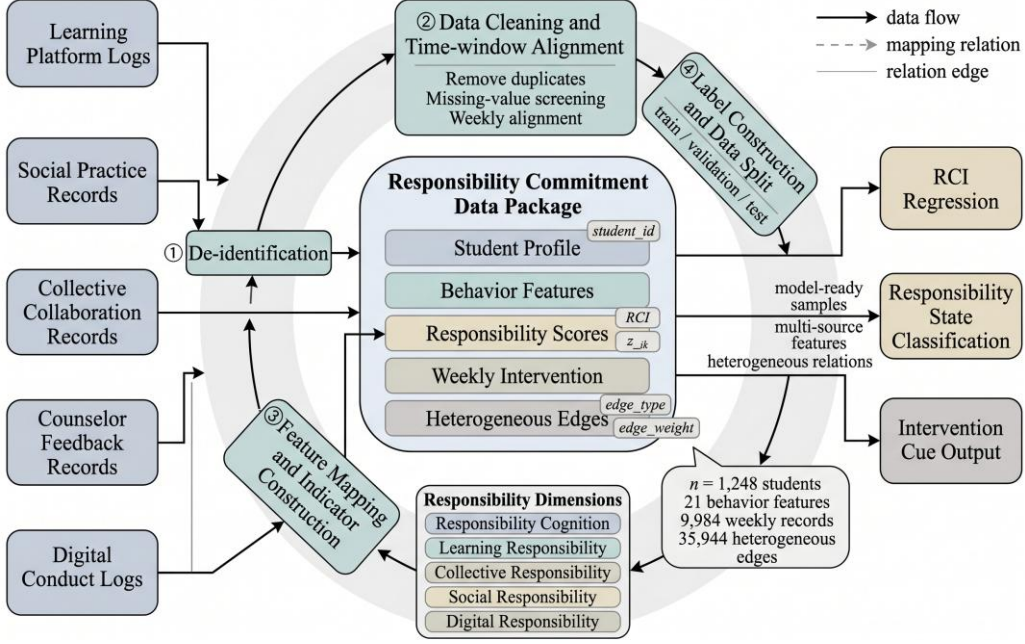


Figure 1: Responsibility awareness data organization and sample construction mechanism.

## 2.2 Contextual Graph Attention Responsibility Recognition Modeling

Awareness of responsibility is not suitable to be categorized only by students' personal characteristics. There are multiple types of relationships between students and course tasks, social practices, collaborative projects, educational feedback, and reflective records that influence the formation of responsibility states. In this paper, we organize responsibility awareness data into a heterogeneous graph with nodes including student nodes, course task nodes, practice activity nodes, collaborative project nodes, feedback nodes, and reflection nodes; and edge types including completing a task, participating in a practice, joining a collaboration, receiving feedback, and submitting a reflection. Edge weights come from task completion quality, practice continuity, peer contribution, feedback intensity and reflection quality.

This paper proposes a contextual graph attention responsibility recognition model. The inputs of the model are student behavioral characteristics and heterogeneous relationship edges, and the outputs are three types of responsibility states and continuous responsibility taking index. The three types of states are low attention, stable development and high responsibility taking. The model structure contains an input representation layer, a heterogeneous relationship coding layer, a time smoothing layer, a fairness constraint layer, and an interpretation output layer. The input representation layer deals with 21 behavioral characteristics and five-dimensional responsibility pre-test scores; the heterogeneous relationship coding layer learns the effects of different relationship types on the responsibility status; the temporal smoothing layer reduces the perturbation of episodic behaviors on the status judgments; the fairness constraints layer controls the recognition differences among grades, majors, and residential statuses; and the explanatory output layer gives the key variables affecting the responsibility statuses.

$$h_i^{(l+1)} = \sigma\left(\sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_r(i)} \beta_{ij}^{r,l} W_r^l h_j^l\right) \quad (3)$$

where  $h_i^{(l+1)}$  denotes the representation of node  $i$  in layer  $l+1$ ,  $\mathcal{R}$  denotes the set of heterogeneous relation types,  $\mathcal{N}_r(i)$  denotes the set of neighbors connected to node  $i$  under

relation  $r$ ,  $\beta_{ij}^{r,l}$  denotes the attention weight of the relation of node  $j$  to node  $i$  in layer  $l$ ,  $W_r^l$  denotes the corresponding transformation matrix of relation  $r$ ,  $h_j^l$  denotes the representation of node  $j$  in layer  $l$  and  $\sigma$  denotes the nonlinear activation function. This formulation enables the model to distinguish between the different contributions of course tasks, social practices, collaborative projects and educational feedback to the responsibility state.

$$\beta_{ij}^{r,l} = \frac{\exp(q_r^{lT} [W_r^l h_i^l \| W_r^l h_j^l \| e_{ij}^r])}{\sum_{u \in \mathcal{N}_r(i)} \exp(q_r^{lT} [W_r^l h_i^l \| W_r^l h_u^l \| e_{iu}^r])} \quad (4)$$

where  $q_r^l$  denotes the attention vector of relation  $r$  at layer  $l$ ,  $\|$  denotes vector splicing,  $e_{ij}^r$  denotes the edge feature between node  $i$  and node  $j$ , and  $u$  denotes any neighboring node of node  $i$  under relation  $r$ . This weight is used to identify sources of liability risk. For example, the postponement of successive tasks, interruption of practical activities, insufficient peer contribution and failure to rectify after feedback, although they may all enter the low attention judgment, correspond to completely different educational interventions.

The model draws on the ideas of graph attention networks and heterogeneous graph Transformer's treatment of relation weights [17, 18], and uses XGBoost as a non-graph structured strong baseline model [19]. Interpretation of the output synthesizes the ideas of feature attribution and gradient attribution with reference to the interpretation principles of SHAP and Integrated Gradients [20, 21]. Fairness checking references the idea of equal opportunity in supervised learning, focusing on monitoring Macro-F1 differences across grades, specialty categories, and residential status [22]. Learning analytics dashboard design references learning analytics visualization and student-oriented dashboard research to avoid showing students only negative risk labels [23, 24]. The intervention feedback design further references motivation theory-oriented learning analytics dashboard studies to enable feedback content to be translated into self-monitoring and action plans [25].

$$\mathcal{L} = \mathcal{L}_{ce} + \lambda_1 \mathcal{L}_{mse} + \lambda_2 \mathcal{L}_{fair} + \lambda_3 \mathcal{L}_{temp} \quad (5)$$

In the formula,  $\mathcal{L}$  denotes the total loss function,  $\mathcal{L}_{ce}$  denotes the classification loss of responsibility state,  $\mathcal{L}_{mse}$  denotes the regression loss of responsibility bearing index,  $\mathcal{L}_{fair}$  denotes the loss of group fairness constraint,  $\mathcal{L}_{temp}$  denotes the loss of time smoothing constraint,  $\lambda_1$  and  $\lambda_2$  and  $\lambda_3$  denote the corresponding loss term weights. The classification loss ensures that the model can identify three types of responsibility states, the regression loss ensures that the model can predict the continuous RCI, the fairness constraint is used to reduce the group misjudgment difference, and the time smoothing constraint is used to reduce the short-term episodic behavior caused by the state jump. The liability identification model consists of input representation, heterogeneous relationship coding, time smoothing, fairness constraints, and interpreted outputs together, as shown in Figure 2.

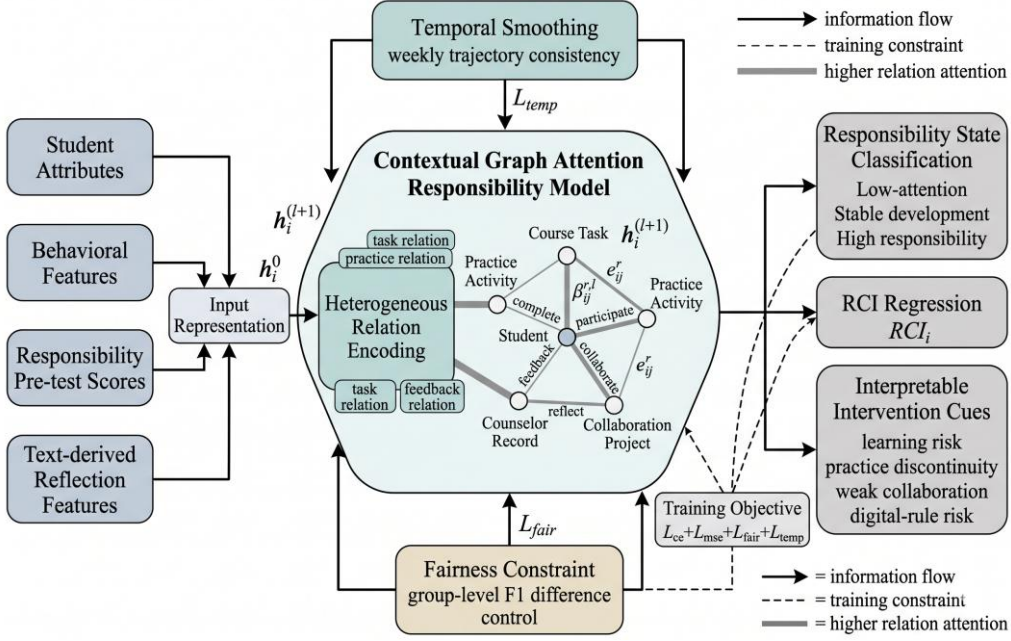


Figure 2: Responsibility Context Map Attention Responsibility Recognition Model Structure.

### 2.3 Experiment protocol, evaluation metrics and digital management tasks

The experiment includes five types of tasks: recognition performance, intervention effectiveness, module contribution, deployment efficiency and error sources. The recognition performance compares six types of models: logistic regression, Random Forest, XGBoost, LSTM, Heterogeneous GNN and the model in this paper. The evaluation indexes include AUC, Accuracy, Macro-F1 and RMSE. AUC is used to judge the ability of the model to distinguish the responsible states, Accuracy is used for the overall classification accuracy, Macro-F1 is used to check whether the recognition of the three types of states is balanced or not, and RMSE is used to evaluate the continuous prediction error of RCI.

We have carried out the arrangement of the intervention effect experiment, which possesses three groups. The contrast group obtained conventional handling, keeping merely term feedback and common prompts. The group of the dashboard obtained the RCI, five-dimension responsibility scores, and the reminding for behaviors. The group that receives co-intervention added counselor talks, practice task introductions, partner mutual help supports, and every week thought feedback to the display platform. The cycle of intervention was an 8-week length. The matching work among different groups was carried out on the basis of grade level, major category, residential status, baseline RCI, and baseline responsibility status, hence thus to prevent initial differences from directly influencing the results of intervention.

The digital management tasks were set into four categories. The first category was responsibility status identification, which was used to identify low-concern students and high-responsibility taking-charge demonstration subjects. The second category is Interpretation Output, which is used to determine whether the risk of responsibility comes from academic responsibility, social responsibility, collective responsibility, or digital responsibility. The third category is Intervention Recommendation, which is used to match curricular support, hands-on tasks, peer collaboration, and rules education. The fourth category is review evaluation, which is used to compare the RCI, sustained engagement rate, task timeliness rate, and low concern percentage before and after the intervention. The experimental protocol and digital management evaluation mechanism are shown in Figure 3.

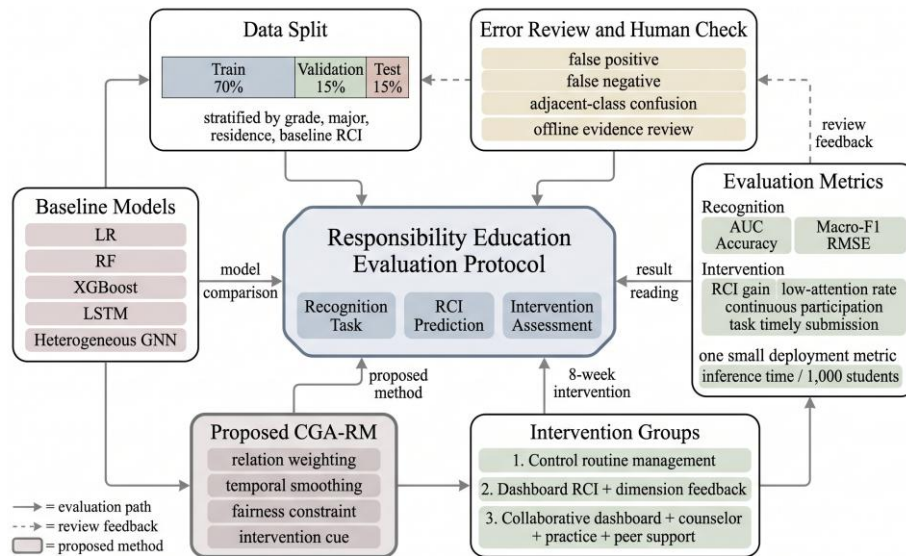


Figure 3: Experimental protocol and evaluation mechanism for digital management.

### 3 Results and Discussion

#### 3.1 Responsibility State Recognition Performance and Key Feature Contribution

This section answers the question of whether the model can stably recognize the responsibility status of college students. Responsibility awareness recognition is different from common course alerts, and the model needs to handle learning tasks, social practices, collaborative contributions, feedback and corrective actions, and digital rules at the same time. If the model only relies on course platform activity, it is easy to misclassify high-frequency login as high responsibility. Based on the test set results, the recognition performance of different models is shown in Table 2.

Table 2: Comparison of the performance of different models in the recognition task of responsibility awareness

Model	AUC	Accuracy	Macro-F1	RMSE
Logistic Regression	0.781	0.692	0.704	0.418
Random Forest	0.813	0.724	0.738	0.386
XGBoost	0.846	0.751	0.762	0.361
LSTM	0.858	0.764	0.776	0.349
Heterogeneous GNN	0.872	0.781	0.791	0.333
Proposed CGA-RM	0.906	0.823	0.831	0.294

In Table 2, the model of this paper has an AUC of 0.906, Accuracy of 0.823, Macro-F1 of 0.831, and RMSE of 0.294. Compared with XGBoost, the AUC improves by 0.060, Accuracy improves by 0.062, Macro-F1 improves by 0.069, and RMSE decreases by 0.067. Compared with the Heterogeneous GNN, AUC improves by 0.034, Accuracy improves by 0.042, Macro-F1 improves by 0.040, and RMSE decreases by 0.039. This result suggests that the recognition of sense of responsibility requires the simultaneous utilization of structural relationships, temporal variations, and explanatory constraints. XGBoost is able to deal with nonlinear features, but it is difficult to express the multiple types of relationships between students and

practical activities, collaborative projects and feedback records; LSTM is able to handle time series but under-expresses educational contextual relationships; Heterogeneous GNN improves its performance by adding relational structures, but the balanced recognition of the three types of responsibility states is still insufficient when time smoothing and fairness constraints are missing. In order to observe the recognition stability under different thresholds, the responsibility state recognition ROC and PR curves are plotted, as shown in Figure 4.

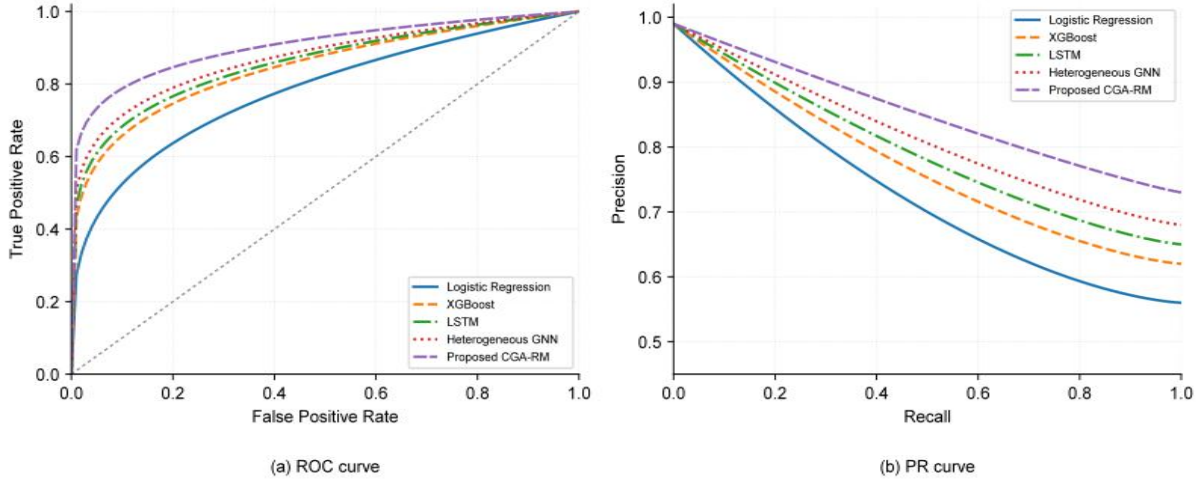


Figure 4: Responsibility state recognition ROC vs. PR curve.

In Figure 4, the model of this paper maintains a higher curve position in both ROC and PR curves. When FPR is 0.10, the TPR of this paper's model is 0.74, which is higher than the 0.66 of Heterogeneous GNN and the 0.59 of XGBoost; when Recall is 0.70, the Precision of this paper's model is 0.82, which is higher than the 0.77 of Heterogeneous GNN and the 0.73 of LSTM. Dai et al.'s study on learning to analyze early risk identification and feedback intervention illustrates that early warning models have practical intervention value only if they maintain recall ability at lower levels of false alarms [26]. The better performance of the model in this paper in the low false alarm interval implies that tutors do not need to deal with too many false alarm targets and are able to focus their management efforts on students with more pronounced breaks in responsible behavior. The key feature contributions further explain why the model is effective. The responsibility state identification key feature contributions are shown in Figure 5.

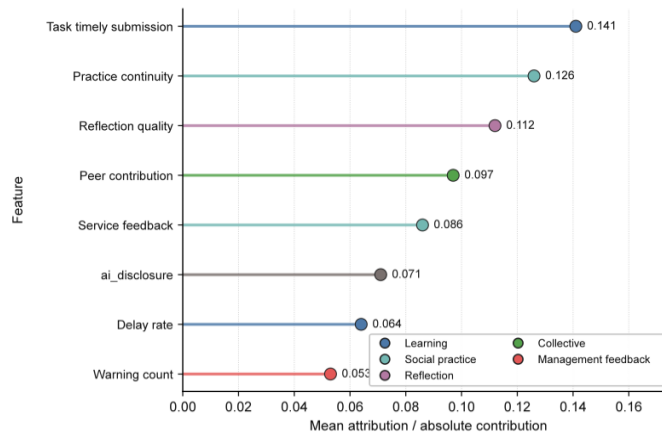


Figure 5: Responsibility Status Identification Key Feature Contributions.

In Figure 5, task timeliness has the highest average attribution value of 0.141, practice continuity of 0.126, reflection quality of 0.112, peer contribution of 0.097, and service feedback of 0.086. the digital responsibility-related AI usage disclosure score is 0.071, and the extension rate and number of warnings are 0.064 and 0.053, respectively. this result suggests the model does not reduce responsibility taking awareness as a simplification of learning platform activity, but rather incorporates learning to take responsibility, public engagement, collaborative contribution, and feedback uptake into the same judgment. Drugova et al.'s review on learning analytics-driven improvement in learning design states that learning analytics needs to embed data interpretation into the learning design and feedback design if it is to truly improve the educational process [27]. The results of the feature contributions in this paper also suggest that accountability awareness identification can only generate actionable management cues if it enters specific educational dimensions.

### 3.2 Stratified intervention effects and three-dimensional response relationships

The identification model can only serve the cultivation of responsibility taking awareness if it enters the intervention process. This section compares the three types of modalities of routine management, dashboard feedback and collaborative intervention, focusing on observing the changes in students' RCI, low concern percentage, sustained engagement rate and task timeliness rate. The effects of the three types of intervention modalities are shown in Table 3.

*Table 3: Effects of Three Types of Intervention Approaches on Responsibility Consciousness and Behavioral Indicators*

Group	RCI Pre-test	RCI Post-test	RCI Increment	Low Attention Ratio Change	Continuous Participation Rate Change	Task Timeliness Rate Change
Control	63.5	65.1	+1.6	27.8%→25.9%	38.7%→41.2%	70.4%→72.1%
Dashboard	63.2	70.4	+7.2	28.1%→19.7%	39.1%→49.8%	69.8%→78.6%
Collaborative	63.8	74.6	+10.8	28.4%→15.9%	39.4%→57.6%	70.1%→83.5%

In Table 3, the control group RCI increased only 1.6 and the proportion of low attention decreased 1.9 percentage points. The dashboard group's RCI improved by 7.2 and the proportion of low attention decreased by 8.4 percentage points, suggesting that dimensional feedback and behavioral reminders promote student self-monitoring. The RCI of the collaborative intervention group increased by 10.8, the percentage of low attention decreased by 12.5 percentage points, the rate of sustained engagement increased by 18.2 percentage points, and the rate of task timeliness increased by 13.4 percentage points. This result shows that responsibility awareness cultivation cannot rely only on automatic reminders. After students see their responsibility portraits, they also need counselor explanations, practice task undertakings, and peer collaboration opportunities in order to transform cognitive feedback into sustained behaviors. The changes in the five-dimensional responsibility indicators in different intervention groups are shown in Figure 6.



Figure 6: Heatmap of changes in five-dimensional responsibility indicators.

In Figure 6, the synergistic intervention group had the highest increment on the social responsibility dimension at +12.4; learning responsibility at +10.9, responsibility perception at +8.6, collective responsibility at +8.3, and digital responsibility at +7.2. The dashboard group's increment on learning responsibility was +8.4, which was higher than its increment on social, collective, and digital responsibility. The control group's increment for all five dimensions was lower than +2.0. This result suggests that the dashboard is more likely to promote task management and learning self-regulation, while social and collective responsibility need to be scenario-specific to carry them. The collaborative intervention provides students with responsible behavioral scenarios that can be completed, fed back, and reviewed through practice project recommendations and peer collaboration tasks. To further analyze the relationship between intervention intensity, participation continuity, and posttest RCI, a three-dimensional response surface was plotted, as shown in Figure 7.

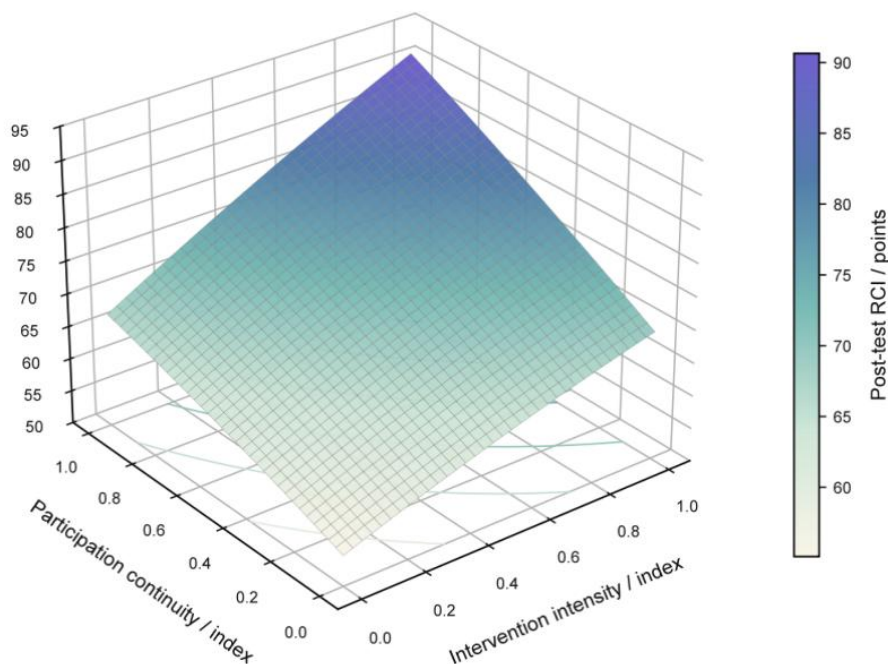


Figure 7: Three-dimensional response surface of intervention intensity, engagement continuity and posttest RCI.

In Figure 7, the post-test RCI increases synchronously with the intervention intensity and participation continuity. When the intervention intensity is lower than 0.30 and the participation continuity is lower than 0.45, the post-test RCI is mainly concentrated in the range of 60-67; when the intervention intensity is increased to about 0.55 and the participation continuity is increased to about 0.50, the RCI rises to about 70; when the intervention intensity reaches 0.90 and the participation continuity is close to 0.58, the RCI reaches 74.6. The larger slope from the middle to the upper-right region of the surface indicates that the increase in sense of responsibility does not only come from the increase in the number of interventions, but also relies on whether or not students continue to enter into the process of practice, collaboration, and reflection. Papageorgiou et al.'s study on the dynamics of participation in learning platforms pointed out that student participation has a time-transferring characteristic, and that short-term activity is difficult to represent stable participation [28]. The three-dimensional results of this paper are consistent with this judgment that responsibility awareness enhancement requires stable participation rather than one-time high-intensity reminders. The intervention trajectory of typical students is shown in Figure 8.

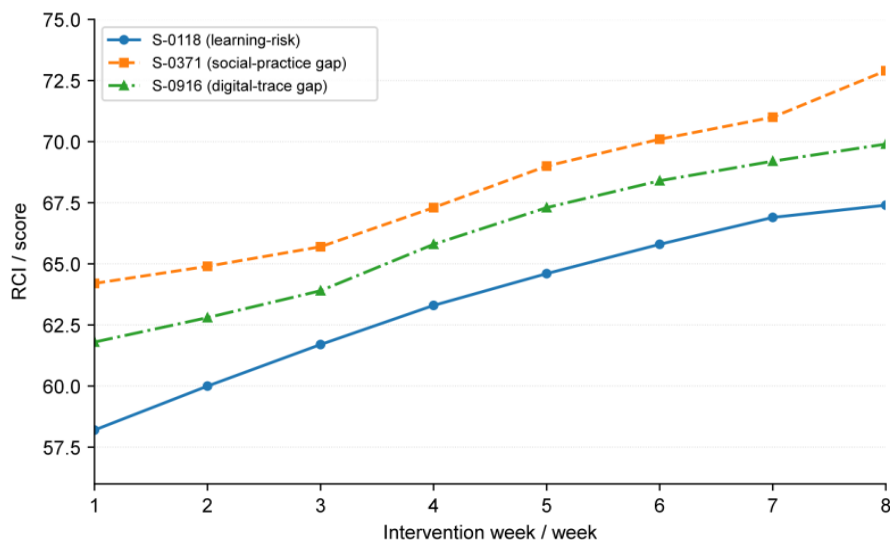


Figure 8: Typical students' tiered intervention trajectories.

In Figure 8, S-0118 belongs to the learning responsibility risk type, with an initial RCI of 58.2, and after task planning, submission reminder, and course feedback, the RCI increased to 67.4 in week 8. S-0371 belongs to the social practice disconnection type, with an initial RCI of 64.2, and after practice task recommendation and service feedback, the RCI increased to 72.9 in week 8. S-0916 belongs to the digital insufficient trace type, with more stable offline activities but weak platform records, after evidence supplementation and reflective feedback, the RCI improved to 69.9 in week 8. The three cases illustrate that the same students identified by the system as needing attention do not have the same intervention focus. The value of digital education management is in giving a structure of risk, rather than replacing educational judgment with a generalized label.

### 3.3 Ablation Experiments, Deployment Efficiency, and Error Review

The results of the previous two sections illustrate that the model can identify liability states and that tiered interventions can improve liability behavior. This section further analyzes the model module contribution, deployment efficiency, and error sources. The results of the ablation experiment and deployment efficiency are shown in Table 4.

Table 4: Ablation Experiment and Deployment Efficiency Results

Model Configuration	AUC	Macro-F1	RMSE	Group F1 Difference	Inference Time per Thousand
Full model	0.906	0.831	0.294	0.031	0.42 s
w/o social-practice graph	0.873	0.798	0.324	0.036	0.38 s
w/o reflection text	0.881	0.805	0.317	0.034	0.39 s
w/o temporal attention	0.865	0.789	0.336	0.039	0.34 s
w/o fairness constraint	0.902	0.825	0.299	0.074	0.42 s
w/o counselor feedback	0.889	0.811	0.309	0.033	0.40 s

In Table 4, the AUC decreased from 0.906 to 0.865, the Macro-F1 decreased from 0.831 to 0.789, and the RMSE increased from 0.294 to 0.336 after removing the temporal attention module, indicating that there is a significant temporal continuity in the responsibility status. The AUC decreased to 0.873 and Macro-F1 decreased to 0.798 after removing the social practice mapping, indicating that social responsibility and public participation have a key role in the recognition of responsibility taking awareness. The RMSE increased to 0.317 after removing the reflective text feature, indicating that the quality of reflection can help the model to determine whether students transform external reminders into self-understanding. The AUC only decreased by 0.004 after removing the fairness constraints, but the group F1 difference widened from 0.031 to 0.074, suggesting that the overall accuracy may mask the recognition bias of different student groups. The coupling between the model module and deployment efficiency is shown in Figure 9.

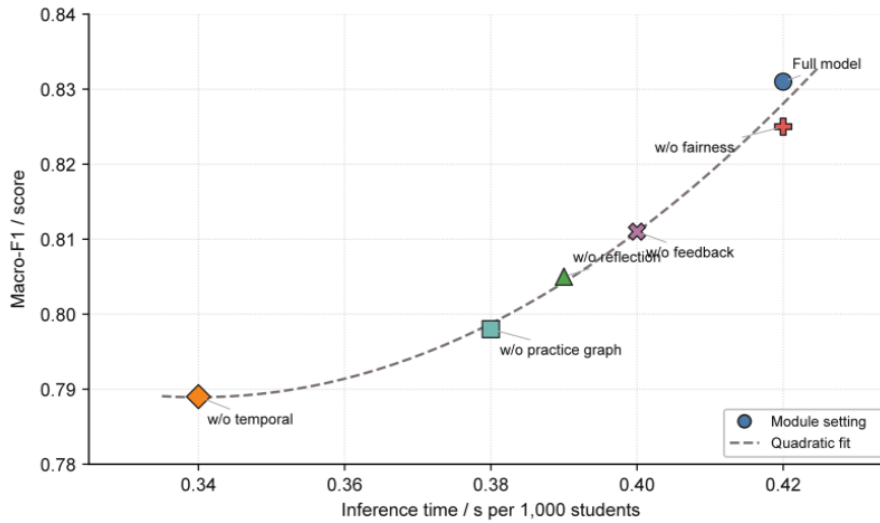


Figure 9: Coupling of Ablation Module to Deployment Efficiency.

In Figure 9, the full model lies in the higher Macro-F1 and acceptable inference elapsed time intervals. The reasoning elapsed time after removing the temporal attention module decreases from 0.42 s to 0.34 s, but the Macro-F1 decreases by 0.042, and the performance loss exceeds the efficiency gain. Reasoning elapsed time after removing the social practice mapping drops by only 0.04 s, but Macro-F1 drops by 0.033, which is also not a practical substitute. Removing the fairness constraint barely changes the reasoning elapsed time but significantly widens the group F1 variance. Mukred's study on the adoption of learning analytics tools in higher education points out that the entry of learning analytics tools into college management requires simultaneous consideration of decision value, acceptability, and implementation

conditions [29]. The results of this paper show that retaining the explanation, time, and ping-pong constraints under the condition that 1,000 inference takes 0.42 s is deployment-justified. The error review uses the confusion matrix and error source records and the results are shown in Figure 10.

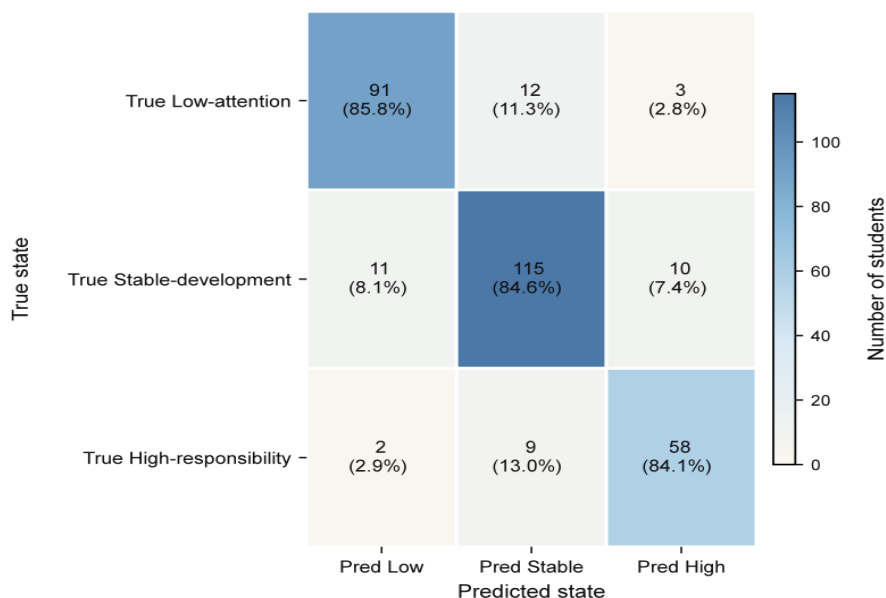


Figure 10: Confusion Matrix for Responsibility Status Identification.

In Figure 10, 91 of the Low Concern students were correctly identified as Low Concern, 12 as Stable Development, and 3 as High Responsibility; 115 of the Stable Development students were correctly identified as Low Concern, 11 as Low Concern, and 10 as High Responsibility; and 58 of the High Responsibility students were correctly identified as Stable Development, 9 as Stable Development, and 2 as Low Concern. Misclassification is mainly concentrated between adjacent categories, indicating that the model controls extreme misclassification better, but there is still a boundary ambiguity between stable development and high responsibility taking.

The sources of error are further categorized into three categories. The first category is false positives, totaling 43 cases or 41.3%, which are mainly characterized by high-frequency participation but low-quality responsibility performance. Students in this category had a high number of logins, discussions and activities, but weak quality of peer contributions, service feedback and reflections. The second category is False Negative, with 37 cases (35.6%), which is mainly characterized by more stable offline performance of responsibilities but insufficient digital traces. Students in this category have actual contributions to class affairs and offline volunteer activities, but platform records and electronic feedback are incomplete. The third category is the confusion of adjacent categories, with a total of 24 cases, accounting for 23.1%, which mainly occurs between stable development and high responsibility taking, because the difference between the two categories of students in academic responsibility and digital responsibility is smaller, and the difference comes more from the depth of social practice and public affairs initiative.

The above errors suggest that the responsibility awareness analysis system should be positioned as an educational evidence generation tool and cannot replace the situational judgment of counselors and teachers. The digital management platform should retain a manual review portal that allows for supplemental offline practice evidence, class affairs records, and

student special case descriptions. For the student side, the system should display dimensional feedback and action suggestions without directly displaying negative labels. For the management side, the system should give sources of risk, key variables and suggested ways to intervene. In this way, intelligent data analysis can be transformed into a tool for cultivating a sense of responsibility, rather than forming a simple monitoring.

## 4 Conclusion

This paper focuses on the cultivation of college students' sense of responsibility and digital education management path, and constructs a locked data package, a comprehensive index of responsibility, a context map attention responsibility recognition model and a tiered intervention mechanism. Based on 1248 anonymous students, 21 behavioral characteristics, 9984 weekly records and 35944 heterogeneous relationship edges, the study verifies the feasibility of applying multi-source data analysis in the cultivation of responsibility consciousness.

(1) In this paper, the sense of taking responsibility is divided into five dimensions: responsibility cognition, learning responsibility, collective responsibility, social responsibility and digital responsibility, and course learning, social practice, collective collaboration, educational feedback and digital behavior are included in the same data structure. This treatment transforms responsibility awareness from a stage evaluation object to a sustainably observable educational object.

(2) The AUC of this paper's model in the responsibility status recognition task is 0.906, the Macro-F1 is 0.831, and the RMSE is 0.294; the RCI of the collaborative intervention group increases by 10.8, and the proportion of low concern decreases by 12.5 percentage points. The ablation results suggest that social practice mapping, reflective text and temporal attention modules are important supports for responsibility status identification, and fairness constraints are necessary to reduce group identification differences.

(3) The results of this paper are based on the locked synthetic validation data package, which cannot directly replace the empirical findings of real colleges and universities. Subsequent research should access real on-campus data based on ethical approval, data authorization and desensitization governance, expand the multi-campus sample, and further test the long-term effect of responsibility awareness cultivation, the ability of model cross-campus generalization, and the acceptability of feedback from the student side.

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