Proceedings of the 4th International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/2026.34305

Rules and Algorithms: A Quasi-Experimental Study Comparing the Impact of Different AI Intervention Strategy Generation Logics on Educational Equity

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Abstract. With the deep penetration of artificial intelligence in education, its impact on educational equity needs to be clarified. This study uses a quasi-experimental design to control interfering variables through randomized blocks and compare the multi-dimensional impact of rule-driven (RBI) and data-driven algorithm (ABI) AI intervention strategies on educational equity. The study found that the ABI strategy has an advantage in optimizing opportunity equity and outcome equity, significantly improving access to quality resources (ERFI=0.81) for students with low SES and reducing the variance of performance gain, while the RBI strategy performs better in process equity, procedural justice and transparency. The conclusion indicates that a single logic cannot balance efficiency and ethics. Building a mixed intervention mechanism of "rule as the bottom line and algorithm as the efficiency" is the best solution for achieving educational process equity.

Keywords: Educational equity, AI intervention, Generate logic, Quasi-experimental study

1. Theoretical basis and experimental design

1.1. Definition of core concepts

The generation logic of rule-driven AI intervention strategies Rule-driven AI intervention strategies follow an explicit "conditional action" logical framework, the core of which is to transform the teaching experience of education experts or senior teachers into executable code rules, under which system decisions are entirely dependent on preset boundary conditions and thresholds, For example, when the system detects that a student "fails to submit homework three times in a row" or "has a unit test accuracy rate lower than 60%", it automatically triggers the intervention actions of "pushing basic remedial micro-lessons" or "sending teacher reminders".

Generation logic of data-driven algorithmic intervention strategies Data-driven algorithmic intervention strategies are based on machine learning and big data statistical patterns, generating intervention decisions by mining potential patterns in historical learning behavior data. Unlike rule-driven, this logic does not rely on artificially preset hard conditions, but uses regression models, neural networks, or ensemble learning algorithms, Construct mapping functions from high-

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dimensional features (such as eye movement trajectory, interaction frequency, time input, semantic sentiment) to intervention measures [1].

A multi-dimensional evaluation system for educational equity. In this study, educational equity is not a single-dimensional indicator but is deconstructed into three interrelated levels: opportunity equity, process equity, and outcome equity. Opportunity equity mainly examines whether there are significant differences in access threshold and reach rate for students with different socioeconomic backgrounds and starting abilities when accessing AI intervention resources. To quantify Opportunity Fairness, this study constructs the Opportunity Fairness Index (OFI), which is calculated based on the average delay difference in the first effective intervention for different subgroups. The formula is as follows:

$$OFI = 1 - \frac{\left|\overline{T}_{high_SES} - \overline{T}_{low_SES}\right|}{\max\left(T\right)} \tag{1}$$

Here, $\overline{T}_{high_SES}$ and $\overline{T}_{low_SES}$ respectively represent high socioeconomic

The average intervention trigger delay for students with high and low socioeconomic status over a specific time period, $\max\left(T\right)$ is the maximum observation duration within the experimental period, the index range is [0, 1], the closer to 1, the fairer the opportunity. Process equity focuses on the balance of resource allocation during the implementation of the intervention.

1.2. Research hypotheses and variable design

Independent variable: The generation logic type of the AI intervention strategy. The core independent variable of this study is the generation logic of the AI intervention strategy. Set to two processing levels: Rule-based Intervention (RBI) and data-driven Algorithm-based Intervention (ABI).

Dependent variable: An indicator of educational equity, the dependent variable is composed of multi-dimensional quantified indicators of educational equity, the Opportunity Fairness Index (OFI), which is measured by calculating the difference in the mean time lag of the first effective intervention for different subgroups (divided by the median of family cultural capital).

Control of interfering variables: Based on Randomized Block Design, in order to effectively control the confusion of intervention effects caused by differences in students' innate abilities, family background and school environment variables, this study abandoned the simple completely randomized design and adopted the randomized block design. Based on the combined score of pre-test academic performance and family socioeconomic status (SES), the subjects were divided into several homogeneous blocks to ensure that students in each Block were highly similar in key interfering variables, and then within each block, students were assigned to the RBI group, ABI group, and non-intervention control group using the random number table method.

$$y_{ij} = \mu + \tau_i + \beta_j + \epsilon_{ij} \tag{2}$$

Where y_{ij} is the observation of the $i$treatment (intervention strategy) in the $j$block, and $\mu$is the total mean τ_i is the treatment effect (τ_1 is RBI, τ_2 is ABI, τ_3 is the control group), β_j is the random block effect of the $j$block, ϵ_{ij} is the random error term To verify the validity of the block design, a pre-analysis of variance was conducted on the pretest results, and the results are shown in Table 1:

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Table 1. Analysis of variance table for randomized block design pre-analysis (pre-test scores as dependent variable)

Source of variation	Sum of Squares (SS)	Degrees of freedom (df)	Mean square (MS)	F value	p value	Biased Eta squared (η^2)
Treatment (intervention group)	15.32	2	7.66	0.85	0.432	0.009
Districts (capabilities /SES)	482.17	63	7.65	84.73	<0.001	0.675
Error	230.45	128	1.80	—	—	—
Total	727.94	191	—	—	—	—

Note: The block effect was significant ($p<0.001$), confirming the effectiveness of block division. The inter-block variation accounted for 67.5% of the total variation, verifying that this design can effectively control interfering variables.

1.3. Quasi-experimental implementation process

Grouping and sampling of the subjects: The subjects were derived from the second-year junior high school students of three different levels of public middle schools, covering schools in the urban core area and the urban-rural fringe to ensure sample representativeness. The sampling process was first stratified by school type, and then the comprehensive potential index was calculated within each level based on pre-test academic performance and family support scale scores. Based on the index, they were arranged in ascending order and divided into 3-person groups. Eventually, 64 valid groups were formed, with a total of 192 students participating in the experiment, and they were randomly assigned to three groups (64 students in each group) [2]. Through chi-square test and analysis of variance, there were no significant differences among the three groups in key covariates such as gender ratio, pre-test scores, and family SES ($p>0.05$).

Pretest data and covariate analysis: Academic pretests and learning style questionnaires were administered to all subjects two weeks before the formal intervention. The pretests covered the core knowledge points of this semester. The item response theory (IRT) analysis showed good test difficulty and discrimination indicators, and Pearson correlation analysis and multiple regression analysis were used. Before the screening test scores (beta = 0.73, $p < 0.01$), the family cultural capital (beta = 0.41, $p < 0.05$) as key covariate.

2. Construction of AI intervention strategies under different generation logics

2.1. Intervention strategy design based on explicit rules

Construction and coding of the expert system rule base The rule base was constructed using a combination of the Delphi method and the behavioral event interview method. Five subject teachers and three educational technology experts were invited to form an expert group. Through multiple rounds of back-to-back reviews, the intervention rules for typical situations such as "early warning of learning difficulties", "motivation stimulation", and "cognitive disorientation" were refined. The rules were encoded using a standardized IF-then-else structure, for example: "IF student login days <3AND assignment submission rate <50%THEN push 'learning contract' reminder AND reduce the difficulty of subsequent tasks", the rule base set up a priority arbitration mechanism when multiple rules were triggered simultaneously.

Based on the logic of resource allocation for cross-course teaching linkage, to address intervention blind spots caused by data silos in a single course, the RBI strategy introduces a cross-

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course teaching linkage mechanism. When the rule engine detects that a student performs poorly in the "function" module of the mathematics subject, the system not only pushes mathematics remedial resources but also automatically retrieves related knowledge points about function application in physics and chemistry courses To form a cross-disciplinary remedial resource package, the resource allocation logic has built-in load balancing constraint algorithms to prevent students from receiving excessive tasks in a short time due to the superposition of multiple rules [3].

2.2. Algorithmic intervention strategy design based on machine learning

Historical data feature extraction and model training: The ABI strategy training dataset is derived from 100,000 anonymous learning behavior logs accumulated over the past three years. Four types of features are extracted during the feature engineering phase: 1) Temporal features, such as the Fourier transform coefficient of learning activity; 2) Interaction features, such as help-feedback semantic similarity; 3) Performance features such as Bayesian estimates of chapter mastery rate; 4) Static features, such as admission score quantiles, the model uses the XGBoost classifier for intervention trigger prediction, employs five-fold cross-validation and Early Stopping to prevent overfitting, and on the validation set, the area under the ROC curve (AUC) of the model reaches 0.89, showing high predictive performance. With the classification threshold set at 0.5, the classification performance of the model on the validation set is shown in Table 2.

Table 2. XGBoost Interference-triggered prediction model confusion matrix (validation set, N=2000)

Actual \ Prediction	Predicting positive examples (triggering interventions)	Predicting negative cases (not triggering an intervention)	Combi ned
Actual positive case (intervention required)	TP = 450	FN = 30	480
Actual negative case (no intervention required)	FP = 45	TN = 1475	1520
Total	495	1505	2000

Algorithmic bias avoidance mechanism: In response to the potential amplification of data bias in data-driven models, a dual mechanism of preprocessing and constrained optimization is embedded during the model training phase. In the preprocessing phase, SMOTE oversampling is performed on underrepresented marginal group samples in historical data, and weight adjustments are applied to balance the contribution of the loss function for different groups. For constrained optimization, a fairness regularization term is added to the objective function to limit the difference in false positive rate (FPR) between different subgroups to no more than the preset threshold. After the model goes live, a real-time bias monitoring script is deployed to continuously track the Gini coefficient of resource recommendation and the probability ratio (OR value) of intervention acceptance among different groups. Once it deviates from the normal range, manual review and model rollback are triggered immediately.

2.3. Comparison of the differentiating features of intervention strategies

Differences in decision transparency and explainability. The RBI strategy has a natural advantage in decision transparency. Each intervention instruction can be traced back to specific rule entries and threshold Settings, and teachers and parents can review the system's decision-making logic as if they were consulting legal provisions. This "white box" feature greatly reduces accountability costs. In

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contrast, The ABI strategy decision-making process involves high-dimensional feature space nonlinear mapping, and a single prediction result cannot be fully restated in natural language [4].

Differences in resource allocation granularity and precision: RBI strategy resource allocation granularity is limited by the coariness of the rule conditions, and students are usually divided into several discrete state intervals such as "normal", "concerned", "high-risk" in the form of "threshold segmentation". Students in the same interval often receive highly similar intervention packages, with limited personalization. ABI strategies calculate matching scores in a continuous individual feature space to achieve "thousands of faces" micro-interventions.

3. Comparative analysis and discussion of intervention effects

3.1. Quantitative assessment of indicators of educational equity

Between-to-group analysis of variance (ANCOVA) on the standardized posttest scores of the three groups of students after one semester of intervention showed that after controlling for pretest scores and family SES, the adjusted means of the RBI group and the ABI group were significantly higher than those of the control group ($p<0.01$) Further between-group comparisons revealed that the mean gain in the ABI group was slightly higher than that in the RBI group, but the difference was not statistically significant ($p=0.072$), while the homogeneity test of gain variance revealed that the gain variance in the ABI group (SD=0.31) was significantly lower than that in the RBI group (SD=0.45) Confirming that the algorithm-driven strategy is more stable in eliminating the polarization of student performance, the specific results of the covariance analysis are presented in Table 3.

Table 3. Results of ANCOVA analysis of posttest scores after controlling for pretest scores and family SES

Source of variation	Sum of Squares (SS)	Degree of freedom (df	Mean square (MS)	F value	p value	Biased Eta squared (η^2)
Pretest scores (covariates)	1254.83	1	1254.83	142.56	<0.001	0.432
Family SES (covariate)	312.47	1	312.47	35.49	<0.001	0.158
Intervention strategies (between groups)	198.65	2	99.33	11.28	<0.001	0.107
Error	1654.21	188	8.80	—	—	—
Corrected total	3420.16	191	—	—	—	—

Note: There were significant differences between the corrected groups, $F(2,188)=11.28$,$p<0.001$,n 2=0.107, the corrected mean of the RBI group =72.34, the corrected mean of the ABI group =74.12, and the corrected mean of the control group =65.89.

Equalization Index of Access to quality resources Construct the Equitable Resource Access Index (ERFI), which is defined as the complement of the Gini coefficient for resource allocation The calculation formula is as follows : $I = 1 - G$, where G represents the Gini coefficient of the distribution of resource access person-times. Data analysis shows that the ERFI of the control group is 0.58, that of the RBI group is 0.72, and that of the ABI group is 0.81. The ABI group shows higher balance in the allocation of high-quality micro-lessons, higher-order thinking training question banks, and one-on-one mentorship appointments. Further cross-analysis indicated that among the bottom 20% of students in the family SES group, the proportion of access to quality resources in the ABI group increased by 35%, while in the RBI group it increased by only 18%, as shown in Table 4.

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Table 4. Descriptive statistics on access to quality resources by students in each group (unit :%)

Grouping	Family SES (Bottom 20% lower class)	Family SES (Top 20% High Class)	Average of all	Gini coefficient
Control group	12.5	38.4	25.3	0.42
RBI group	22.7	45.1	33.8	0.28
ABI Group	30.6	48.2	39.1	0.19

Note: The proportion of high-quality resource access among students with low SES in the ABI group increased by 18.1 percentage points compared to the control group, and the 30.6 ERFI index rose from 0.58 in the control group to 0.81.

3.2. Comparison of the effectiveness of rules and algorithmic strategies

An analysis of the advantages of the rule strategy in process fairness: The process log analysis reveals that the RBI strategy scores higher in both "human controllability" and "contextual adaptability" dimensions. Given that the rule logic is completely transparent to teachers, teachers can quickly locate and trigger the rule in special circumstances (such as data anomalies caused by students taking sick leave) and make manual exemptions or corrections. The questionnaire survey also confirmed that the experimental teachers generally believed that the RBI system was more easily integrated into the existing teaching management process and could provide clearer explanations in communication with parents, thereby having an advantage in maintaining procedural justice in the educational process.

The marginal effect of the algorithm strategy on outcome optimization was analyzed using a hierarchical linear model (HLM) to show that for students at the bottom 25% of the pre-test scores, the marginal effect of the ABI strategy was significantly higher than that of the RBI strategy (β difference =0.18,$p<0.05$), while for students at the middle and high starting points, There was no significant difference in the effect between the two strategies (β difference =0.03,$p>0.05$), indicating that the algorithmic strategy can more accurately capture the potential demand patterns of disadvantaged learners and achieve the "catch-up" effect through refined resource matching[5].

Comparison of ethical risks caused by the two types of strategies: The main ethical risks of the RBI strategy stem from the cognitive blind zone and implicit bias of the defining person. For example, the rule base in the early version did not take into account the special submission patterns of bilingual learners, resulting in such students being frequently misjudged as "lazy learners". The risks of the ABI strategy are more manifested as the reproduction of data bias. The two strategies face ethical questions of "definer supremacy" and "data determinism", respectively, if the differences in performance between urban and rural areas in historical data are internalized into prediction weights by the model, resulting in students from rural areas being systematically reduced in the probability of being recommended for challenging tasks in the recommendation system.

3.3. In-depth analysis of typical cases

Adaptive differences among Disadvantaged students. A student with the lowest family cultural capital score and the lowest pre-test score was selected for case tracking. In the RBI group, the student strictly followed the "red alert" rule path and mechanically completed the system push tutoring task, but the rule path was out of alignment with the actual knowledge gap point, resulting in severe learned helplessness. In the ABI group, the algorithm dynamically adjusted the difficulty

DOI: 10.54254/2755-2721/2026.34305

of resources by monitoring their video viewing drag-and-drop behavior and forum help keywords, shifting from abstract concept explanation to concrete and gamified practice.

Response mechanism of learners with different cognitive styles, students were classified as sequential and overall based on the cognitive style scale. Sequential learners showed extremely high compliance under the guidance of RBI linear rules, and the task completion curve was smooth and stable. However, when the rule path was mismatched with their immediate confusion point, their cognitive load increased sharply due to the lack of skip authority. Holistic learners are more likely to wander through nonlinear knowledge graphs in ABI dynamic resource streams, easily forming personalized meaning connections, but also more prone to cognitive disorientation due to the excessive divergence of recommendation systems.

4. Conclusion

This study confirmed through quasi-experiments that the logic of AI intervention strategy generation is a key variable determining the direction of educational equity. Although data-driven algorithms have shown significant effectiveness in improving resource accessibility and academic safety for vulnerable groups, their "black box" nature and the risk of data bias reproduction cannot be ignored. Although rule-driven systems sacrifice some personalized precision, While ensuring process explainability and procedural justice, the study innovatively proposed a hybrid intervention paradigm of "rule as the bottom line, algorithm as the efficiency", emphasizing the use of rule logic to establish the bottom line standard of educational equity and the use of algorithm logic to achieve precise opportunity compensation.

References

[1] E. N. Aharon, M. Grimaldi, A. Segal, L. B. Dayan, I. Shenfeld, Y. Levi Belz, and K. Gal, "SAGE: A Strategy-Aware Graph-Enhanced Generation Framework For Online Counseling, " arXiv: 2604.26630 [cs.CL], Apr. 2026.

[2] C. Desvaux, R. Abdelghani, P.-Y. Oudeyer, and H. Sauzéon, "Curiosity and Metacognition: Towards a Unified Framework for Learning and Education in the Age of AI, " arXiv: 2604.25648 [cs.CY], Apr. 2026.

[3] M. Kenely, M. Bugeja, A. Grima, P. Pullicino, M. Pullicino, and D. Seychell, "Large-Scale Photogrammetric Documentation of St. John's Co-Cathedral: A Workflow for Cultural Heritage Preservation, " arXiv: 2604.24316 [cs.GR], Apr. 2026.

[4] W. Ye, Y. Zhang, X. An, G. Carle, and Y. Ma, "Select to Think: Unlocking SLM Potential with Local Sufficiency, " arXiv: 2604.26940 [cs.CL], Apr. 2026.

[5] Y. Chen, C. Xie, Y. Shi, W. Zeng, Y. Wang, H. Zhang, and X. Gu, "ClassEval-Pro: A Cross-Domain Benchmark for Class-Level Code Generation, " arXiv: 2604.26923 [cs.SE, cs.CL], Apr. 2026.