

Integration of Marxist Educational Perspectives and Educational Big Data in the Digital Age: Theoretical Logic and Practical Path

Juan Pei

School of Marxism, Xi'an Fanyi University, Xi'an 710000, Shaanxi, China

Corresponding author: Juan Pei (e-mail: peijuan0351@163.com)

ABSTRACT This paper addresses the contradiction between the capital-driven logic of educational big data application and the public and equitable essence of education emphasized in Marxist educational theory. A value-embedded educational data governance architecture is constructed for the digital age. The study generates synthetic data based on differential privacy to prevent uncompensated appropriation of raw student data, uses multidimensional behavioral feature engineering to move beyond score-centered evaluation, and constructs a two-branch adversarial learning model to reduce sensitive-attribute bias. A resource allocation algorithm constrained by minimizing the education Gini coefficient is then used to support compensatory justice. Results show that the average education Gini coefficient after resource allocation is 0.2707. The technical framework can regulate the disorderly expansion of capital logic in educational data use, shift data application from exploitation toward human development, and ensure that technological dividends are distributed more fairly to disadvantaged groups. The study provides a technical paradigm integrating value rationality and instrumental rationality in digital education governance.

INDEX TERMS marxist educational perspective, educational big data, educational equity, differential privacy, algorithmic fairness

I. INTRODUCTION

THE digital age has brought about a significant change in the role of large-scale data in education, much as data-driven precision has revolutionized the weaving and processing techniques of the modern industry. This technological evolution has completely changed the environment of teaching and learning by creating a more interconnected and analytical social fabric, ensuring that educational governance and engineering both benefit from enhanced structural insights. The development of technological applications has increased the capitalistic nature of the use of technology in education. As a result, data has increasingly become a financial commodity, rendering students at risk of being treated as commodities while privacy violations and educational injustice proliferate [1-2]. The public nature of education as well as its fairness are fundamental to Marxist educational theory. Marxist education also stresses the complete development of a person. This creates a substantial conflict between the existing data-based efficiency-first logic and what should be the focus of Marxist education [3-4]. Most existing efforts to improve technology emphasize increasing its efficiency through technological means but do not involve sufficient consideration of the capital logic, through which

value rationality is subordinated to capital rationality [5]. Addressing the contradiction of capital logic and the public aspect of education in the era of the Internet requires an urgent review of how education data should be managed from a theoretical standpoint, guided by Marxist principles.

This paper examines a number of issues related to educational data governance across the full data lifecycle: collecting data, creating features, evaluating models, and allocating resources. At the centre of this issue is the governance of student data, which has two aspects; student data is a technology resource and also the vehicle of subjective rights. The ownership of student data is therefore related to whether capital can own the residual data without payment, creating a risk of privacy breaches and alienation [6-7]. The traditional evaluation system relies on a score-based evaluation, which does not take into account both the learning process and a person's physical and mental state, creating a one-dimensional evaluation of a person's development and thus hindering full development of such person [8-9]. If resources are allocated on the basis of the efficiency principle first, it creates greater inequity for disadvantaged groups and creates an increased disparity between rich and poor in the area of education [10]. Consequently, it is critical to develop a

technical structure that reflects Marists' ideas about how to use technology within education, because this keeps student data safe, ends the problem with only evaluating students by a single score, and helps achieve some measure of fairness [11]. As a result, constructing a technology path that incorporates value concepts lays the foundation for formulating practical technology application strategies. These strategies aim to make technology benefit all people, rather than just those who are capable of affording it; with the help of technology, the education system can be rebuilt according to students' actual abilities, and technological equity and educational equity can be successfully integrated. Various algorithmic models have been proposed by current research as solutions to the identified issues. In the area of academic predictions, the most commonly used ensemble learning method is XGBoost (eXtreme Gradient Boosting), which is intended to achieve maximum accuracy in predictions; however, these models do not have built-in fairness constraints and, therefore, are subject to the historical bias of the data on which they are trained and continue to increase inequities among groups [12]. To facilitate equity, multitask model solutions like FairMTL (Multi-Task Learning) use the concept of aligning group distribution to the distribution of each task but also focus overly on matching distributions, which reduces their ability to represent features effectively and decreases the ability to predict outcomes accurately and makes it hard for them to achieve both efficiency and equity [13]. In relation to privacy protection, although traditional differential privacy techniques can prevent backward calculation, the use of adding noise commonly reduces data utility, which decreases the precision of macro-level decision-making [14-15]. In addition, the current methods primarily passively represent how data are allocated and have no way to actively change allocation decisions, which creates a barrier to making significant progress from formal fairness to substantive fairness. Moreover, the existing tendency to prioritize efficiency as evidenced by the logic of capital has not changed and continues to contribute to algorithmic discrimination and unequal distribution of resources. There is an urgent need for a new technological paradigm that can incorporate value rationality into technological structures in order to resolve the ongoing tension between value rationality as a way of making decisions versus instrumental rationality.

To confront the problematic aspects of current educational data governance involving capital logic dominance, the escalating risk of student alienation and inequality issues, this paper discusses the use of a technological practice approach recognized by Marxist educational philosophy and featuring the embedding of value as its dominant concept. This value-based technology features an entire chain of data governance administration from development, to feature development, to training of machine learning models and allocation of machine learning resources to achieve data governance. This governance framework is defined by four operational parameters: securing student data sovereignty against uncompen-

sated capital appropriation, replacing score-based evaluation with multidimensional developmental profiling, enforcing algorithmic fairness through sensitive attribute decoupling, and redirecting resource allocation toward compensatory justice for disadvantaged groups. In general terms, these include: using synthetic data technology with differential privacy to protect students from having their raw data at the source, protecting their data sovereignty; using a multidimensional behavioral features system that allows for a process and frequently multi-dimensional way to evaluate all aspects of a child's development, rather than just one factor; using an adversarial learning model to develop two branches with decoupled attributes in order to minimize bias in algorithms; placing education perpetuating Gini coefficient can create compensatory justice through disproportionate expenditures of resources in the distribution of educational resources. According to experimental results, the architecture can be considered an effective way to promote group fairness and to improve prediction accuracy by reducing the Gini coefficient for education to 0.2707 after resource allocation. A successful path for limiting the disorderly accumulation of capital involves this architecture as a means of transitioning from a data-exploiting paradigm to a comprehensive, human development model that ensures disadvantaged populations benefit from the technological progress of the industry. By weaving inclusive innovation into the core of engineering, this framework transforms industrial growth into a resilient social fabric that prioritizes equitable advancement and the empowerment of traditional artisanal communities.

II. THEORETICAL LOGIC: VALUE ISOMORPHISM OF MARXIST EDUCATIONAL VIEWS AND BIG DATA TECHNOLOGY

A. TENSION BETWEEN CAPITAL LOGIC AND PUBLICNESS: RISK OF ALIENATION IN THE APPLICATION OF EDUCATIONAL BIG DATA

A critical political economy approach has been adopted to track the entire value flow of data from collection through commercialization, identifying disorderly growth nodes in education data assetization. In establishing educational data ownership of student data, the ability for capital to benefit by appropriating surplus data is interdicted, inhibiting students from being remade into tradable datasets. At the level of technology governance, differential privacy and federated learning architectures sever the direct mapping of individual data to commercial profiles at the data source end; therefore, privacy data cannot, in theory, be used as capital enhancement tools. To resolve fairness inequities due to algorithmic discrimination, an adversarial training method that includes fairness constraints has been developed. Gradient inversion layers enable the decoupling of sensitive attributes; fairness publicness indicators are utilized as components within loss functions. By reducing group differences through optimizing predictions, the model mathematically constrains technological biases and assists in breaking alienation from

performance-based evaluations alone. By implementing an algorithm auditing system that includes ongoing monitoring of the education Gini coefficient for resource allocation strategies can create a continuous feedback loop. It also helps to ensure the direction of technological dividends is more favorable to disadvantaged groups instead of contributing to the Matthew effect. Marxist public values are being embedded in the data governance process through these methods; therefore, capital accumulation logic can be limited to the limits of public service provision. The logical shift that occurs when moving away from data exploitation is to develop individuals holistically rather than just for the benefit of private monopolies. It establishes a synergy of technological justice and educational equity while placing an effective limit on the instrumental rationality of value rationality, thus creating positive results for the entire educational ecosystem.

B. HOLISTIC VIEW OF HUMAN DEVELOPMENT: FROM SINGLE-SCORE EVALUATION TO MULTI-DIMENSIONAL BEHAVIORAL FEATURE MAPPING

To address the problem of using only scores to measure student performance, this research develops a multidimensional mapping mechanism for student behavior to change the evaluation of a student's performance from just static outcomes to also include dynamic behavioral processes, and to provide an overall perspective on development through the use of technology. The research improves on previously published research by using high granularity temporal behavior mining to collect continuity of the overall learning experience; rather than aggregating scores to evaluate learning, they use a longitudinal collection of end-to-end interaction logs. Three types of feature spaces are defined from the original response sequences, which are classified during conversation level by average duration and the number of items completed in a week; the question level is classified by maximum length between consecutive correct responses and the number of error bursts in the latest three questions; and classification of temporal patterns is determined by the amount of learning occurring between 10 PM and 6 AM. The use of deep learning formalizes the process of understanding how to process temporal dependencies using unstructured behaviors that eventually get converted into 18-dimensional vectors, which then become the basis for establishing a mapping between behaviour and state. By applying normalization to remove dimensional differences, evaluation indicators become comparable. Other aspects of the methodology also move from the evaluation of "what was learnt" to "how was learned", thereby creating dynamic depictions of individuals' development potential through the capture of their effort, thinking style and both the physical and mental states they are in while learning. Therefore, the technical model no longer produces only a single scalar ranking but rather produces a multi-dimensional development profile that ensures evaluation indicators are reflective of cognitive, emotional and behavioral dimensions. Conse-

quently, this methodology supports a holistic understanding of human development based on the logic of data while preventing technological rationality from alienating students into datasets/objects. Furthermore, it ensures that the purpose of evaluation is individual growth rather than selection of capital, thus accomplishing a fundamental shift of the evaluation paradigm from selection to development. Finally, the technical evaluation ontology that is constructed aligns with Marxist principles of education, thus ensuring that how data represents individuals is indicative of subjective development rather than a means of efficient capital accumulation.

C. EDUCATIONAL EQUITY AND TECHNOLOGICAL JUSTICE: ALGORITHMIC CONSTRAINTS AS A MEANS TO ACHIEVE COMPENSATORY JUSTICE

In this research paper, a mathematical optimization problem is created using algorithms and constraints to transform compensatory justice into a computable form. During its construction, an MLP (multilayer perceptron) with two branches uses gradient reversal to establish an adversarial branch that creates an adversarially trained MLP using the principle of backpropagation. The primary branch attempts to minimize prediction errors, while the adversarial branch attempts to maximize the amount of difficulty identifying sensitive attributes in its outputs. The overall loss function consists of two types of losses: prediction loss and adversarial loss, each of which is calculated based on how closely they correspond to one another. Once this has been established, backpropagation provides an opportunity for the model to decouple sensitive features from the ability to evaluate abilities, thus preventing algorithmically-based discrimination based upon the weight update operations being performed on the inputs. Lastly, during the resource allocation phase, a linear programming model is constructed with the intent of minimizing the Gini Coefficient associated with educational attainment. The personalized algorithm for resource allocation is the solution to two constraints: total resource conservation and minimum guarantee for the resource allocation process. The algorithm uses data to automatically identify the low development index groups of students so that targeted resource supply is given to address the lack of academic success by presenting algorithmic bias in disadvantaged populations. This algorithmically-based compensation provides for a more accurate means of measuring the difference in the two groups and dynamically adjusting the weights of the groups to divide opportunities more equitably and predictively. This means that rather than just reflecting the distribution of the data, there is active intervention by the algorithm in the allocation logic. The algorithm uses mathematical constraints to counter the long history of inequity in the education system, ensuring that the distributive effect of technology benefits the disadvantaged and transitions from the concept of formal fairness to that of substantial fairness and makes the algorithm the means of carrying out compensatory justice. Ultimately, the algo-

rhythm operates to correct and repair educational inequities through the technological architecture so that technological rationality produces the highest value to the public and creates a virtuous circle for the continued reconstruction of the educational ecosystem.

D. INTEGRATION FRAMEWORK: TECHNICAL APPROACH TO DATA GOVERNANCE GUIDED BY MARXIST VALUES

The present research develops an innovative technical methodology for database governance that includes both an embedment of value systems into the data and a means to provide a full chain of control through specifying an algorithmic constraint to satisfy the attributes of a public good. As a result of this methodology, a number of issues related to protecting students' data are identified, including how CTGAN (Conditional Tabular Generative Adversarial Network) is used to transform the data received, and how to integrate the protection of raw /actual data sources and the integrity of the data from these sources that protect the data from capture by those without the appropriate entitlement to do so. In feature representation, a single score classification is replaced by using 18-dimensional temporal behavioral features extracted at the level of conversation, question and knowledge point. Multidimensional mapping technology is used to recreate the learning process and state, enabling a holistic evaluation of human development and addressing the limitations of evaluating by score alone, as well as the problem of evaluating one dimension. In the model-training stage, a dual-branch MLP architecture is implemented with the addition of a gradient inversion layer to create an adversarial loss function to force the model to decouple gender and urban/rural sensitivity attributes from its optimization of prediction accuracy at the mathematical level, thereby eliminating algorithmic bias and ensuring equal access to opportunity and reducing group bias.

The theoretical principles outlined above—data sovereignty protection, multidimensional evaluation, algorithmic bias elimination, and compensatory resource allocation—require operationalization through a coherent technical architecture. This architecture translates each theoretical component into a corresponding technical module: differential privacy mechanisms secure data sovereignty, behavioral feature engineering enables multidimensional evaluation, adversarial learning enforces algorithmic fairness, and education Gini coefficient optimization implements compensatory resource allocation. The following section details the implementation of these four modules and their integration into a unified governance framework.

III. PRACTICAL PATH: VALUE-RATIONAL EDUCATIONAL BIG DATA TECHNOLOGY ARCHITECTURE

A. DIFFERENTIAL PRIVACY EDUCATIONAL SYNTHETIC DATA GENERATION

This study constructs a differential privacy-preserving synthetic data generation pipeline based on the original interaction sequences of the Junyi Academy Online Learning Activity Dataset, blocking the uncompensated appropriation of original student data by capital from the source. First, the original interaction data is cleaned and standardized, and user ID, question ID, timestamp, and answer result are extracted as basic feature vectors. CTGAN is used as the core generation model, and the data distribution fitting ability is optimized through the game between generator G and discriminator D [16-17]. To prevent privacy leakage during training, a differential privacy stochastic gradient descent algorithm is introduced in the gradient update stage [18-19]. Specifically, in each iteration, the gradient of each sample is truncated according to the norm, and Gaussian noise is added to ensure that the influence of a single sample on the model parameters is limited [20]. The realization of this protective function requires a formal mechanism that bounds the influence of any single student record on the generated synthetic data, thereby preventing the reconstruction of individual-level information while preserving aggregate distributional properties. This mechanism is implemented through a differentially private stochastic gradient descent algorithm, whose gradient update operation is formally expressed as follows:

$$\tilde{g}_t = \frac{1}{L} \sum_{i=1}^L \text{clip}_C(\nabla_{\theta} \mathcal{L}(x_i, \theta_t)) + N(0, \sigma^2 C^2 I) \quad (1)$$

In Formula (1), $\tilde{g}_t$ represents the noise gradient of the t -th iteration; L is the batch size; clip_C represents the gradient norm clipping operation; C is the clipping threshold; $\nabla_{\theta} \mathcal{L}$ is the gradient of the loss function with respect to parameter θ ; N is the Gaussian noise distribution; σ is the noise standard deviation; I is the identity matrix. The privacy budget ϵ is set to 2.0 to seek a balance between data availability and privacy protection, preventing excessive noise from causing data utility loss.

Based on this, high-fidelity synthetic interactive records are generated. To break through the sole reliance on scores and retain evaluation references, a linear mapping mechanism is constructed to convert the correct answer rate into a synthetic score label. The calculation formula is as follows:

$$S_{syn} = \left\lfloor 100 \times \frac{\sum_{j=1}^M I(r_{ij} = 1)}{M} \right\rfloor \quad (2)$$

In Formula (2), S_{syn} is the synthetic score label; M is the total number of questions answered by student i ; r_{ij} is the answer result of question j (1 for correct, 0 for incorrect); $I(\cdot)$ is the indicator function; $\lfloor \cdot \rfloor$ is the floor function. This label only reflects the relative ability distribution and is not associated with real identity, thus preventing scores from becoming the sole criterion for capital screening. As shown

in Figure 1, the original educational data and the differential privacy-protected synthetic data exhibit a high degree of similarity.

Their overall distribution patterns are similar, but the specific data point locations show offsets. Replacing the original data with synthetic data prevents the alienation of student data. The similarity in distribution shown in the figure proves that this substitution does not affect data utility. In the digital age, technology can be a tool for implementing Marxist educational values, not a tool for capital accumulation; public value and technological innovation can achieve a dialectical unity.

To address potential group biases caused by capitalist logic, balanced sensitive attribute labels are forcibly injected. A gender ratio of 1:1 and an urban-rural ratio of 6.7:3.3 are set. The use of a conditional input vector generator allows for an exact control over synthetic data's distribution within sensitive dimensional subspaces. The ratio of urban to rural is specified via the National Bureau of Statistics of China's most recent longitudinal statistical yearbooks, mirroring this actual structure and guarding against the extension of discrimination by sample bias under the guidance of this algorithm. This provides a means to ensure no uncompensated appropriation of original student data occurs by capital prior to the issuance of synthetic data, as the original data is housed in a controlled environment, and only the privacy-protected synthetic data is released. Differential privacy ensures that at data subjects are not abused through the use of their data, while the synthetic data preserves the utility-relevant statistical properties necessary for subsequent model training and policy simulation. This preservation is constrained to the distributional patterns that inform algorithmic predictions, whereas the direct mapping between individual student identities and their behavioral records is severed through noise injection, and the distribution of sensitive attributes is explicitly controlled through conditional generation, thereby preventing the synthetic data from inheriting the exploitable structures—such as the capacity to identify and prioritize students based on commercial value—that characterize the original data as a capital asset. Furthermore, controlling the distribution of sensitive attributes prevents algorithms from inheriting structural injustices from historical data and provides a clean foundation for future fairness-conscious model development. This research achieves a balance between data utility and privacy security, builds a data governance principle that prioritizes the public good, and ensures that technology is used for the continuing advancement of man, not the financial interests of capitalism.

B. PURE QUESTION-ANSWERING BEHAVIOR FEATURE ENGINEERING

This study revisits large-scale cross-of-record interaction data based on synthetic interactions and creates an entirely new feature engineering pipeline based on pure

question/answer behavior rather than result-oriented score labels. The overall outcome is a new multi-dimensional state characteristic or process-oriented representation of all people's development that uses technology as a process facilitator. The process begins by completely preprocessing the original date/time series, defining the abnormal noise points with density-based clustering, and establishing a new conversation start point based on intervals between responses to successive questions that exceed 30 minutes [21–22]. From this, by using sliding window and sequence labeling methods, four feature spaces; conversation level, question level, knowledge point level, and temporal pattern, have been rebuilt from the original question answering sequence, resulting in the total extraction of 18-dimensional temporal feature vectors.

The number of conversations per week and the average length of time that subjects spend on conversations represent ways to determine how engaged subjects are in learning; in other words, they reflect their persistence and willpower during the learning process. Determining the error outbreak ratio provides a gauge of how cognitively stable and resilient the subject has been. The error outbreak ratio refers to the percentage of times a participant answers three or more questions incorrectly while experiencing cognitive interruptions and emotional fluctuations during the learning process. The following formula is used to calculate this coordinate point:

$$R_{burst} = \frac{\sum_{k=1}^K I(L_k \geq 3)}{N_{seq}} \quad (3)$$

In Formula (3), R_{burst} represents the error burst rate; K is the total number of consecutive error sequences; L_k is the length of the k -th consecutive error sequence; $I(\cdot)$ is the indicator function; and N_{seq} is the total number of conversation sequences. At the same time, the average number of seconds it takes to answer and the maximum number of correct answers that can be given in succession are calculated as measures of mental agility and strength of mastery of knowledge, respectively.

With respect to knowledge-point-level characteristics, statistics are calculated for coverage rates of the weak knowledge points, and knowledge graphs are used to identify cognitive silent spaces in subjects. In relation to temporal-pattern characteristics, the proportion of learning at night is calculated in order to measure how learning load and sleeping patterns affect development physically and mentally. These indicators serve as metrics of development intensity during abnormally timed sleeping patterns, providing a measurement of risk to physical and mental health. The following formula determines the value of this indicator:

$$R_{night} = \frac{\sum_{j=1}^M I(22 \leq h_j < 6)}{M} \quad (4)$$

In Formula (4), R_{night} is the proportion of nighttime learning; M is the total number of questions answered;

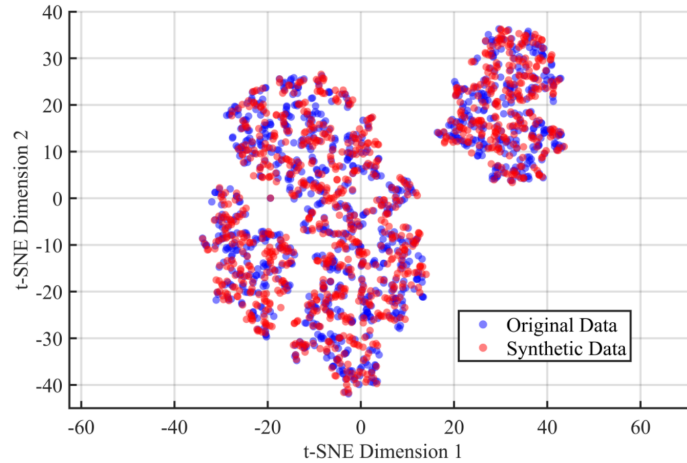


FIGURE 1. Comparison of t-SNE dimensionality reduction between original data and differential privacy synthetic data

and h_j is the number of hours at which the j -th question is answered. This indicator strictly defines the proportion of questions answered between 22:00 and 6:00 to prevent excessive exploitation of students' rest time.

All original features are normalized using Z-Score normalization $z = (x - \mu)/\sigma$, allowing to have equal weight across all dimensions, thereby preventing any one high-frequency feature from dominating the model training process [23-24]. The resulting features are then combined into an 18-dimensional tensor that is fed into the next evaluation model. This approach alters the analysis from “what was learned” to “how was learned” through fine granularities of behavior mining. Error burst rate shows intellectual resilience; night time percentage shows condition (physical and mental) and conversation frequency shows engagement. Multi-dimensional feature mapping breaks down the one-dimensionality of individual growth (as reflected in one score) and allows the technical model to capture effort put forth, type of thinking and measure of potential risks. By blocking the path of capital using single-score feature engineering to select students, this method provides data ontology support for a holistic development perspective—compared to an evaluation system based on performance allocation, it focuses more on individual growth diagnosis; by constructing an educational data representation system that focuses on process, state, and potential, it ensures that data features reflect subjective development rather than capital appreciation efficiency, while providing rich semantic forms for subsequent fairness algorithms. This paradigm allows technological rationality to return to the value-driven essence of education.

C. STUDENT DEVELOPMENT ASSESSMENT MODEL

The two-part multilayer perceptron evaluation is performed by creating a model for evaluation using an adversarial learning architecture that divides sensitive attributes apart from each other (achieving technological equality of opportunity). The input for this model is comprised of

an 18-dimensional behavioral feature vector. The primary branch uses regression to forecast a development index, while the adversarial branch uses classification to discover which sensitive attributes exist. A gradient reversal layer is embedded between the feature extraction layer and the adversarial branch. Forward propagation maintains the signal unchanged, while backward propagation flips the gradient sign, forcing the feature representation to exclude sensitive information. The adversarial branch consists of two MLP layers to enhance discriminative power and ensure that the feature extractor faces sufficiently strong adversarial pressure [25-26].

The overall optimization objective is defined as the weighted sum of the prediction loss and the adversarial loss. The dual-branch architecture operationalizes the trade-off between prediction accuracy and fairness through a joint optimization objective. The primary branch minimizes the discrepancy between predicted and actual development indices, while the adversarial branch maximizes the difficulty of sensitive attribute classification based on the learned feature representation. The gradient reversal layer transforms this two-player game into a unified minimization problem, where the total loss combines both objectives with adjustable weights. The formula is as follows:

$$\mathcal{L}_{total} = \lambda_p \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 + \lambda_a \frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K -z_{ik} \log(\hat{z}_{ik}) \quad (5)$$

In Formula (5), $\mathcal{L}_{total}$ is the total loss; N is the batch sample size; y_i , $\hat{y}_i$ are the true and predicted development indices, respectively; λ_p and λ_a are the weight coefficients; K is the number of sensitive attribute categories; z_{ik} is the true attribute label; and $\hat{z}_{ik}$ is the adversarial branch prediction probability. The loss function curve is shown in Figure 2.

As shown in Figure 2, the prediction loss decreases rapidly in the early stage and tends to stabilize in the later

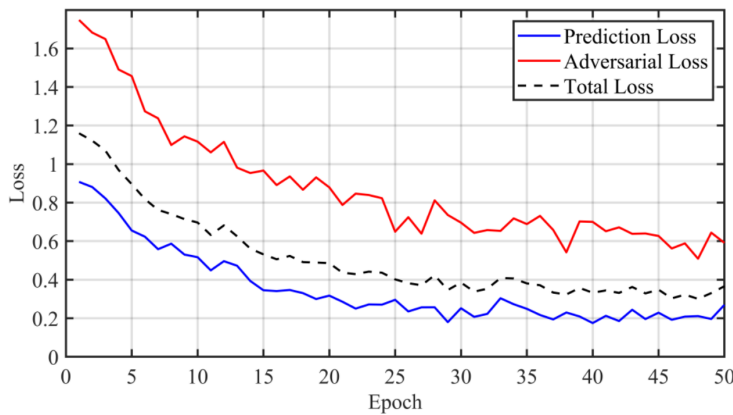


FIGURE 2. Loss function curve

stage. The adversarial loss also decreases with the increase of epochs. The early feature representation still contains a lot of sensitive information, and the adversarial branch can be easily identified, resulting in a faster decrease in loss. In the middle and late stages, the identification difficulty increases, and the decrease in loss slows down. The operation of the gradient reversal layer is defined as:

$$R(x) = x, \quad \frac{dR}{dx} = -\alpha I \quad (6)$$

In Formula (6), R is the reversal function; x is the input feature; α is the reversal coefficient; and I is the identity matrix. During training, the main branch minimizes the prediction error; the adversarial branch minimizes the attribute identification error; the feature extractor maximizes the adversarial branch error through

gradient reversal. This minimax game forces the model to learn feature representations orthogonal to the sensitive attributes.

The optimization method employs Adam as the optimizer with a learning rate of $1e-3$. The model uses the coefficient adjustments to achieve a balance between prediction accuracy and fairness constraints [27-28]. The utilization of a very high adversarial loss weight decreases the model's ability to represent its features leading to prediction failure. Conversely, the use of a low adversarial loss weight enables the model to not be able to remove bias effectively. This approach removes algorithmic bias at a mathematical level, thereby stopping historical biases from being passed onto the final outcome of the decision via data distributions. Previously, the model relies heavily on sensitive attributes as a quick way to reduce loss. The new design has made a major shift away from this methodology to instead use the intrinsic relationship between behavior and the index as referenced development. Through these dimensions of similarity, all disadvantaged persons are not structurally undervalued based on their identity labels; hence, algorithms are the instruments of implementing compensatory justice, transitioning from purely formal fairness to substantive fairness and allowing for the public nature of educational

assessment not to become degraded through the application of classification and selection based upon the logic of capital or an industry model. The index produced as a result of this output development phase allows for resource distribution for what occurs throughout the entire rest of the cycle. Therefore, the processes that followed rely on fair and valid assessments of each previous stage, providing closure for a cycle of technological evaluation based on value-rationality.

D. RESOURCE ALLOCATION ALGORITHM FOR OPTIMIZING THE EDUCATION GINI COEFFICIENT

This study constructs a resource allocation algorithm for optimizing the education Gini coefficient. It solves for personalized resource vectors using linear programming to achieve compensatory justice [29-30]. The input is the student development index D_i output by the evaluation model. The resource allocation vector is set as r_i , representing the amount of specialized practice allocated to the i -th student. The relationship between resource input and development index improvement follows a pattern of diminishing marginal returns, wherein each additional unit of resource yields a progressively smaller gain. The model employs a linear approximation of this relationship within a localized operating range, treating the coefficient γ as an empirically calibrated estimate of the average marginal benefit rather than a fixed linear rate. The development index after allocation is defined as $D'_i = D_i + \gamma r_i$. The optimization objective is to minimize the degree of inequality in the group after allocation, i.e., the education Gini coefficient. Due to the nonlinearity of the absolute value function, an auxiliary variable u_{ij} is introduced for linearization, transforming the nonlinear programming into a standard linear programming problem, ensuring solution efficiency and global optimality. The minimization of the education Gini coefficient constitutes a non-linear optimization problem due to the absolute value operations in the coefficient calculation. To render this problem computationally tractable and guarantee convergence to a globally optimal solution, the absolute value terms are linearized through the introduction of auxiliary variables that represent

pairwise development index differences, transforming the objective into a standard linear programming formulation. The objective function and constraints are:

$$\begin{aligned} \min \quad & \frac{\sum_{i=1}^n \sum_{j=1}^n u_{ij}}{2n^2 \mu'}, \quad s.t. \quad -u_{ij} \leq D'_i - D'_j \leq u_{ij}, \\ & \sum_{i=1}^n r_i = R_{total}, \\ & r_i \geq 0.1 \times \bar{r} \end{aligned} \quad (7)$$

In Formula (7), n is the total number of students; u_{ij} is an auxiliary variable representing the absolute value of the difference in development index; μ' is the average development index after allocation; R_{total} is the total amount of resources; and $\bar{r}$ is the average resource per capita. μ' is dynamically updated to $\frac{1}{n} \sum_{i=1}^n (D_i + \gamma r_i)$ to ensure that the denominator of the objective function is adjusted in real time during the allocation process, reflecting the changes in the overall development level.

The solution process employs an interior-point optimization algorithm. First, a resource vector is initialized, and the initial education Gini coefficient is calculated. Then, an iterative search is performed within the feasible region, with the gradient descent direction preferentially pointing towards groups with lower D_i [31-32]. The constraint $\sum r_i = R_{total}$ ensures resource conservation and prevents unlimited investment. The constraint $r_i \geq 0.1 \times \bar{r}$ sets a minimum guarantee line for individuals, preventing the algorithm from completely ignoring extremely disadvantaged groups in pursuit of overall optimality, reflecting basic fairness. The parameter γ is calibrated through historical data regression to ensure accurate assessment of the effectiveness of resource investment. If γ is too high, the model may over-allocate; if it is too low, the regulatory effect is not significant. The algorithm outputs personalized resource vectors. For students with development indices below average, their resource weight value r_i is set higher to compensate for limitations imposed by the natural environment by tilting resource allocation towards these individuals. This approach creates a correction to the technology-

based efficiency first philosophy that aligns with the capitalist ideal. Historically, algorithms place resources with the greatest potential and, therefore, produce a greater quantity of output, while this algorithm forces the minimization of the difference in the amount of output generated by less privileged students by providing them with additional assistance. To determine the presence of a regulatory effect, the education Gini index ΔG before and after completing the redistribution is calculated. Positive ΔG indicates a reduction in inequity. This pathway turns Marxist equitable economic phenomena into enforceable mathematical constraints and causes technological dividends to be skewed toward disadvantaged groups rather than widening the gap between the wealthy and poor in educational attainment. This pathway accomplishes a transition from formal eq-

uity to substantive equity. Therefore, this pathway builds an allocation system for public education resources that emphasizes the comprehensive development of all learners and not just the selection of a few elite learners and creates a virtuous cycle for the educational ecosystem while maximizing the creation of public value through educational attainment.

E. DIFFERENTIAL PRIVACY RELEASE OF AGGREGATED STATISTICS

A differentially private mechanism for releasing aggregate statistics is implemented for the regional student development index to balance the needs of data openness with the requirement of protecting the privacy of individuals within the data using a public governance model. Figure 3 shows how the release of statistical indicators for regional education statistics is accomplished.

First, a query function $f(D)$ for the regional average development index is defined, where D represents the student development index data within the region. To prevent the inference of individual privacy through aggregated statistics, a Laplace mechanism is used to add noise to the query results. The noise scale is determined by both global sensitivity and privacy budget. Global sensitivity Δf is defined as the maximum impact of a change in a single data item on the query results. In the standardized scenario of this study, the development index is normalized to the interval 0 to 1, and the sensitivity is simplified to $\Delta f = 1/n$, where n is the total number of students in the region. This calculation ensures that the noise level is inversely proportional to the data size; large-scale groups have less statistical noise, while small-scale groups have more noise, which conforms to the distribution law of privacy risks.

Subsequently, noise following a Laplace distribution is generated and injected into the statistical results [33-34]. The formula for publication is expressed as:

$$\tilde{f}(D) = f(D) + \eta, \quad \eta \sim \text{Lap}\left(\frac{\Delta f}{\epsilon}\right) \quad (8)$$

In Formula (8), $\tilde{f}(D)$ is the noisy statistical value after publication; η is the random noise variable; $\text{Lap}(\cdot)$ represents the Laplace noise distribution; ϵ is the privacy budget. $\epsilon \in [0.5, 2.0]$ is set, and the privacy protection strength and data availability are controlled by adjusting ϵ . When ϵ approaches 0.5, the noise scale increases, privacy protection is enhanced but statistical error increases; when ϵ approaches 2.0, the noise scale decreases, data availability is improved but privacy risk increases. The system dynamically adjusts ϵ according to the regional data sensitivity, using a low budget for high-risk areas and a high budget for low-risk areas, achieving fine-grained control of privacy protection. Noise generation adopts the inverse transformation sampling method to ensure that the random number distribution strictly conforms to the theoretical definition and prevents the pseudo-random number generator from

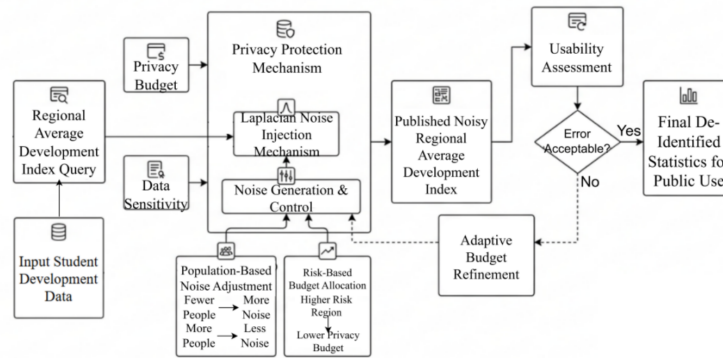


FIGURE 3. Flowchart for publishing regional educational statistical indicators based on differential privacy

introducing additional bias [35]. To achieve the accuracy of macro-educational decision-making, a mechanism for evaluating the availability of regional statistical indicators under privacy protection is established. Based on 100 region query simulations, the average relative error is calculated to quantify the impact of noise on decision-making. The formula is as follows:

$$RE = \frac{1}{K} \sum_{k=1}^K \frac{|\tilde{f}_k(D) - f_k(D)|}{|f_k(D)| + \delta} \quad (9)$$

In Formula (9), RE is the average relative error; K is the number of queries; $\tilde{f}_k(D)$ is the noisy statistical value of the k -th query; $f_k(D)$ is the true statistical value; and δ is a smoothing factor to prevent the denominator from being zero.

IV. EXPERIMENT AND VERIFICATION

A. EXPERIMENTAL DESIGN

The goal of this experiment is to systematically test the effectiveness, robustness, and generalizability of the technical architecture of value rationality. At the data level, the primary dataset used is journeys of students' interactions (synthetic) and it is divided into three datasets - training, validation and testing - in a 7:2:1 ratio. The training set is for updating model parameter gradients; the validation set is used for tuning hyperparameters and early stopping strategies; the test set is only used for final performance evaluation.

To consider baseline models for selection of control objects to effectively evaluate model performance, there are two classes of control objects established as sources of comparative performance. Firstly, the control object of XGBoost serves as a measurement of technical efficiency (without fairness constraints) via optimization of the accuracy loss function. An example of pursuing the technical path of maximizing efficiency under capital logic is demonstrated by XGBoost, which represents a conventional benchmark for technical model performance. The second class of control object is represented by FairMTL, which is considered the best benchmark available for fairness algorithms. FairMTL uses a multi-task learning architecture to mitigate issues

of fairness and represents the best possible capability of currently available technology to achieve fairness in prediction. Through performance comparison, the performance of the proposed two-branch adversarial structure and Gini coefficient education optimization algorithm on the removal of certain education biases, particularly the actual impact of the compensatory justice mechanism with regard to urban-rural and gender disparities, are demonstrated, evidencing the advancement of the technical methodology utilized.

B. ACCURACY VERIFICATION OF ACADEMIC PREDICTION TASKS

The goal of this research is to assess whether the introduction of fairness constraints to the model reduces levels of accuracy in predicting academic performance and makes educational metrics less effective due to excessive reliance on value-based reasoning, rather than limiting the practical value of the design because of ethical objectives. In assessing prediction capability, there are three key performance measures used to quantify prediction capability: root mean squared error (RMSE), mean absolute error (MAE), and determination coefficient. RMSE is calculated as the square root of the sum of the squared differences between predicted and actual synthetic grades, emphasizing larger error penalties and indicating how well the model has controlled for extreme bias (which can severely affect the evaluation of an individual student and result in an unfair distribution of resources to students). MAE is calculated as the mean of the absolute values of discrepancies between the predicted value and the actual value, which is an indicator of how much error exists at the mean, and that is being used for aggregate analysis to avoid creating inaccurate macro-level actions from systematic error. The coefficient of determination (COD) is calculated as the ratio of the sum of squared residuals to the total sum of squares. It measures the model's explanatory power for performance variability; a value closer to 1 indicates a better fit. This verifies the representative power of behavioral characteristics on the development index and confirms that multidimensional process data can adequately replace single scores. Ten rounds of testing are conducted to avoid the randomness of a single

experiment. The proposed two-branch adversarial model is compared with the XGBoost model without fairness constraints and the current best fairness algorithm, FairMTL. By comparing the three indicators, the efficiency loss caused by fairness constraints is quantified; the space and boundaries for technological improvement are clarified; the feasibility of the technological path guided by Marxist educational philosophy is verified. The accuracy data for each indicator is shown in Figure 4.

Figure 4(a) illustrates the RMSE validation results. The RMSE of the Proposed Method in ten rounds of testing remains stable between 3.0141 and 3.0595, with a mean of approximately 3.0413. This is very close to the mean of 3.0328 of the XGBoost model, which aims to maximize efficiency. The mean RMSE of the FairMTL model, however, reaches 3.5010, higher than both of the former two, indicating a significant deficiency in extreme bias control. Figure 4(b) shows the MAE validation. The mean absolute error of the Proposed Method fluctuates between 2.3289 and 2.3584, with a mean of 2.3408. There is a small difference in RMSE from the mean of 2.3319 for XGBoost; however, with a mean RMSE of 2.7981 for the FairMTL model, the error is significantly larger and indicates greater bias in overall prediction. As shown in Figure 4(c), the R^2 validation results show that the determination coefficient for the Proposed Method ranges from 0.8697 to 0.8760, with an average of 0.8734. This number is almost equal to the mean R^2 of XGBoost, 0.8759, while the FairMTL determination coefficient is 0.8199. By combining all three measures, the Proposed Method meets the standards of predictive accuracy consistent with both the efficient-first criterion established by XGBoost and that of FairMTL, thus demonstrating that instrumental rationality within value rationality lies within an adequate range. The RMSE standard deviation can be found in Table 1.

TABLE 1. RMSE standard deviation

Test Round	Proposed Method	XGBoost	FairMTL
1	0.0142	0.0155	0.0213
2	0.0138	0.0161	0.0228
3	0.0145	0.0172	0.0205
4	0.0133	0.0158	0.0219
5	0.0129	0.0149	0.0234
6	0.0136	0.0153	0.0211
7	0.0125	0.0146	0.0225
8	0.0141	0.0165	0.0217
9	0.0139	0.0159	0.0241
10	0.0144	0.0151	0.0230

Table 1 shows the comparison of RMSE standard deviations for the three models over 10 rounds of cross-validation. Proposed Method's RMSE standard deviation is very consistent between 0.0125 and 0.0145, averaging about 0.0137 throughout 10 cycles. Therefore, the Proposed Method has the least amount of fluctuation in RMSE standard deviation compared to XGBoost and FairMTL (XGBoost's RMSE standard deviations range from 0.0146-

0.0172, with an average about 0.0157; FairMTL's RMSE standard deviations fluctuate from 0.0205-0.0241, with an average of about 0.0222). Generally speaking, this data supports that the Proposed Method is more robust than either of the other two algorithms as the RMSE standard deviation is lower than both XGBoost and FairMTL, indicating that the Proposed Method maintains similar prediction accuracy across a variety of rounds of experiments.

C. QUANTIFICATION OF DIFFERENCES IN GROUP OPPORTUNITY FAIRNESS

This research employs the opportunity equality difference index as a measure for assessing the predictive fairness of the model explored across the demographic sub-groups represented by the sample employed in this study, and provides empirical data that supports the proposition that effective algorithmic constraints help to reduce or eliminate discrimination.

To assess how successful the model is at identifying students who have a high potential based on different dimensions of gender and rural/urban classification, the true probability for each group is calculated. True Probability Ratio - The true probability ratio is defined as the ratio between the number of high-potential students correctly classified by model predictions and the total number of high-potential students in that group. The true probability ratio is computed separately for female and male students and for both urban and rural students. The calculation process is strictly limited to the test set to prevent training data leakage that could lead to evaluation distortion and to ensure that the results reflect the model's generalization fairness on unknown data.

The opportunity equality difference index is defined as the absolute value of the difference between the true probability ratios of the two groups. For gender fairness, the absolute value of the difference between the true probability ratios of female and male groups is calculated; for urban-rural fairness, the absolute value of the difference between the true probability ratios of rural and urban groups is calculated. This index ranges from zero to one; the closer the value is to zero, the more equal the opportunities between the groups; the larger the value, the more severe the discrimination. A comparison of group opportunity equality differences is shown in Figure 5.

Figure 5 illustrates the comparison results of group opportunity equity differences. Figure 5(a) illustrates the performance of opportunity equality differences in different models under the gender dimension, while Figure 5(b) presents the fairness comparison in the urban-rural dimension. In the gender dimension, the median opportunity equality difference of the Proposed Method is only 0.0474, significantly lower than 0.1877 of the XGBoost model and 0.0982 of the FairMTL model. Its fluctuation range between the minimum (0.036) and maximum (0.065) is also narrower than other baseline models, indicating that this method has high stability in eliminating gender bias. In terms of urban

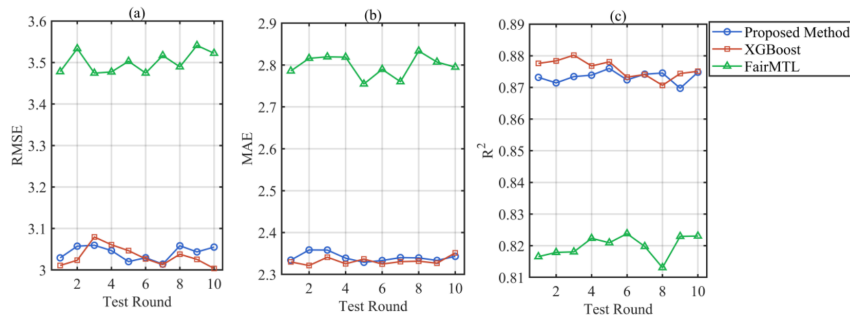


FIGURE 4. Validation of accuracy indicators: (a) RMSE validation; (b) MAE validation; (c) R^2 validation

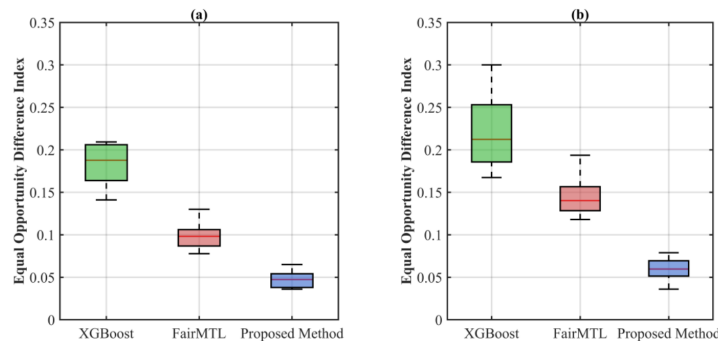


FIGURE 5. Comparison of group opportunity equity differences: (a) Comparison of fairness in the gender dimension; (b) Comparison of fairness in the urban-rural dimension

and rural dimensions, the median of the Proposed Method is 0.0597, significantly better than XGBoost's 0.2123 and FairMTL's 0.1402. Notably, its maximum value of 0.0789 is lower than FairMTL's minimum value of 0.118, indicating that the model maintains high group equity even under the most unfavorable scenario.

D. PREDICTION ERROR OF VULNERABLE GROUP SUBSETS

This paper entails performing an analysis on prediction error from subgroups of at-risk populations, in order to investigate patterns in algorithmic bias occurring with respect to distinct populations; in this case, rural students, as well as ensuring the technical infrastructure does not mistakenly under-estimate the developmental capability of at-risk populations due to imbalances in data distributions. Initially, all test set samples are divided into separate rural and urban sample subsets based on their urban/rural label that is established by virtue of the overall dataset consisting of artificial data. The rural subset consists of all student records identified by having a rural house registration, and the urban subset consists of all student records identified by having an urban house registration with no overlap between the two subsets of samples, thus allowing for total test sample coverage while avoiding analytical bias caused by labels being confused due to sample mismeasurement.

The root mean squared error between the two subsets is determined independently following the same method of calculation; first, by traversing through all rural students,

by calculating the squared difference between the predicted index and the true index of synthetic performance for rural students, taking the mean of all squared errors, and forcing the mean into a square root to create a prediction error index for the rural population. The same set of calculations is employed for the urban population in the same manner as to resolve differences in performance measurement standards. The prediction error of this index provides insight on the model's predictive accuracy for a specific population; a low number for the prediction error index indicates a more accurate prediction, whereas a high number indicates a higher degree of bias in the model's prediction error. Calculating an error by subsets independently prevents the overall prediction error index from masking the differences in performance between these groups, thereby allowing for the determination of the source of algorithmic bias.

To ascertain the degree of bias present, a relative error difference index is computed. This measure is derived from the difference between the rural subset's root mean squared error and the urban subset root mean squared error, normalized with respect to the urban subset root mean squared error. The order of calculations is first determining the difference, and then normalizing the calculations to permit comparable results. A positive, large relative error difference signifies that the prediction error for rural students is significantly greater than that of urban students, suggesting systemic as well as potential underestimation. Conversely, a value close to zero or negative represents that the model has performed relatively similarly between

both groups, thereby descriptive of having not introduced a structural bias from the historic dataset. The prediction errors for the disadvantage population subset can be found in Figure 6.

A comparison of the error predictions from the three models (XGBoost, FairMTL, and Proposed Method) with respect to urban and rural student subsets is shown in Figure 6. Figure 6(a) provides the distribution of errors as predicted by the XGBoost model. The average prediction error for the urban student subset is 0.177, and the standard deviation is 0.0177. In contrast, the rural student subset has an average error of 0.3194 and a standard deviation of 0.0332, a significant difference between the two subsets, and the rural student subset has larger error fluctuations, indicating that the predictions of efficiency-first models without fairness constraints are significantly more sensitive to structural biases that exist in the training dataset. Figure 6(b) shows how well the FairMTL model fares in relation to its error, due to its better multi-task learning design. The average errors for the urban and rural subsets are 0.2021 and 0.2727, respectively, and the standard deviations decrease to 0.0192 and 0.0246, respectively. The gap between groups has narrowed but has not been completely eliminated. Figure 6(c) shows the most balanced performance of the Proposed Method, with an average error of 0.211 for the urban subset and 0.2309 for the rural subset, with standard deviations controlled at 0.0164 and 0.0181 respectively. This is superior to XGBoost and FairMTL. Furthermore, the maximum error of 0.2695 for the rural subset is lower than XGBoost's 0.38, indicating that this model effectively suppresses the systematic underestimation of disadvantaged groups while ensuring overall prediction accuracy, achieving equalization of assessment quality among groups.

E. IMPROVEMENT IN RESOURCE ALLOCATION BALANCE

This study quantifies the moderating effect of resource allocation algorithms on educational inequality by using the education Gini coefficient, verifying the actual effectiveness of the compensatory justice mechanism. First, the student development index output by the assessment model is extracted as the initial state before resource allocation, and the initial education Gini coefficient is calculated. The calculation process uses the pairwise difference accumulation method: iterates through all student pairwise combinations, calculates the absolute value of the difference in development indices and accumulates them, then divides by twice the product of the square of the total sample size and the mean to obtain a normalized inequality measure. The Gini coefficient for education ranges from zero to one. A value closer to 1 indicates a greater disparity, while a value closer to zero indicates a more balanced distribution. Figure 7 shows a comparison of the education Gini coefficients.

Figure 7 shows the comparison of the education Gini coefficients of the Proposed Method, FairMTL, and XGBoost across 10 rounds of experiments. The data clearly

demonstrates that the Proposed Method has a significant advantage in promoting the equitable distribution of resources. In terms of average value, the education Gini coefficient of the Proposed Method is 0.2707, lower than FairMTL's 0.415 and XGBoost's 0.626. Throughout all 10 rounds of experiments, the Gini coefficient of the Proposed Method remains consistently low, ranging from 0.218 to 0.342, with manageable fluctuations. In contrast, XGBoost's coefficient ranges from 0.568 to 0.712, reflecting its allocation results being significantly affected by data distribution and lacking stability. A Gini coefficient closer to zero indicates a smaller development gap between groups. The algorithm consistently maintains a low coefficient level, empirically verifying its technical effectiveness in narrowing the educational gap between the rich and poor and achieving compensatory justice. This provides quantifiable data support for the public and equitable nature emphasized in Marxist educational theory. The standard deviation of the education Gini coefficient is shown in Table 2.

TABLE 2. Standard deviation of the Gini coefficient for education

Test Round	Proposed Method	FairMTL	XGBoost
1	0.012	0.024	0.045
2	0.009	0.021	0.038
3	0.011	0.026	0.051
4	0.008	0.019	0.042
5	0.010	0.023	0.056
6	0.007	0.018	0.044
7	0.009	0.022	0.047
8	0.006	0.017	0.062
9	0.008	0.020	0.049
10	0.005	0.016	0.068

Table 2 shows the comparative data of the standard deviation of the education Gini coefficient for the three models in 10 rounds of cross-validation. The standard deviation of the Proposed Method remains consistently low, ranging from 0.005 to 0.012, with a mean of approximately 0.0085 over 10 rounds, reaching as low as 0.005 in the 10th round, demonstrating strong stability. The standard deviation of FairMTL ranges from 0.016 to 0.026, while the standard deviation of XGBoost ranges from 0.038 to 0.068, indicating that its allocation results are influenced by the randomness of data partitioning and have weak control over balance.

F. AVAILABILITY OF REGIONAL STATISTICAL INDICATORS UNDER PRIVACY PROTECTION

The present study employs the Mean Relative Error (MRE) metric to assess how implementing differential privacy safeguards at an aggregate level can inhibit the availability of data required for making high-level educational policy decisions while still providing a data-supported decision making process for these types of policies. As part of this, a query of regional-type data is created to simulate the regional statistics used by educational administration agencies to determine the average educational development of a region. From this, multiple regional subsets are cre-

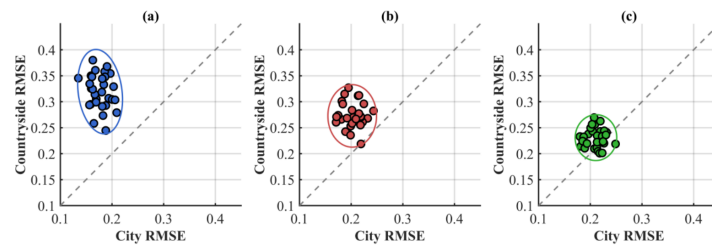


FIGURE 6. Prediction errors of disadvantaged subsets: (a) XGBoost prediction error; (b) FairMTL prediction error; (c) Proposed Method prediction error

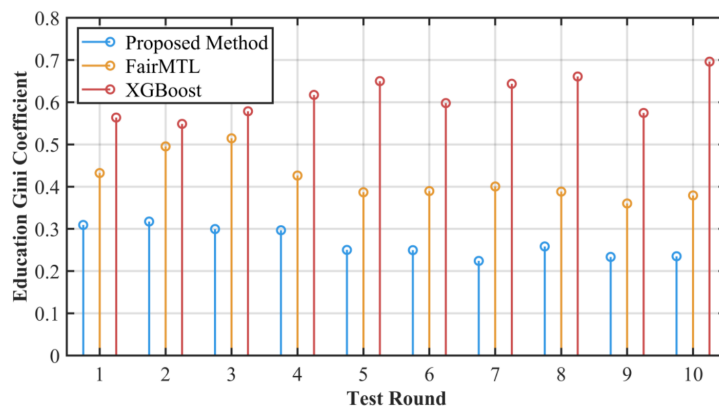


FIGURE 7. Comparison of education Gini coefficient

ated, using administrative area labels, to form a sample of students from various ranges in size, thus containing a representative sample of students from counties through provinces represented by government levels while also allowing for the applicability of the evaluation results for use in real-time policy decisions made in the given regional area.

Next, a method for adding Laplace noise to the data is applied. The true regional population average development index is determined, and that index becomes the baseline for calculating noise. From that point, a padded privacy budget parameter is used to compute a noise scale for each regional subset, and the noise is generated from a Laplace distribution. The noisy published value is calculated by taking the true statistical value and adding the noise into it after it's all calculated out. A random number generator, which is encrypted, is used to generate the noise. This prevents anyone from reproducing the noise by averaging it from multiple queries and deters an attack by preventing averaging of noise from multiple queries. All regions are tested on multiple privacy budget tiers to determine if a correlation exists between privacy budget tier selection and data quality, from very strong privacy protection to high levels of data access.

To determine how noisy an interference is, an average relative error index is formed. This is done by taking the

absolute value of the difference between the noisy and true statistical value using a total of 100 independent regional queries. The absolute value of the true statistical value is taken and divided by the absolute value of the noise value with smoothing to avoid dividing by zero. This gives the relative error for each query. The relative errors resulting from all 100 queries are then averaged to create a usability metric for working with this privacy budget. The relative error metric is indicative of noise impacting the accuracy of statistics; as a result, the lower the mean relative error value, the higher the usability of data; conversely, the higher the mean relative error value, the greater the risk to a decision maker. The mean relative error data is depicted in Figure 8

Figure 8 illustrates the distribution of the mean relative error of regional education statistics under the differential privacy protection mechanism. When the sample size is only 50, the mean relative error reaches 8.3% with a privacy budget of 0.5. However, as the privacy budget increases to 2.0, the error rapidly decreases to 0.6%, reflecting the significant impact of privacy protection strength on data usability in small sample scenarios. When the sample size expands to 500, the error corresponding to a privacy budget of 0.5 is 3.1%, decreasing to 0.8% with a privacy budget of 1.0, and further stabilizing at 0.5% with a privacy budget of 2.0, indicating that a medium sample size can effectively buffer noise interference. When the sample size reaches

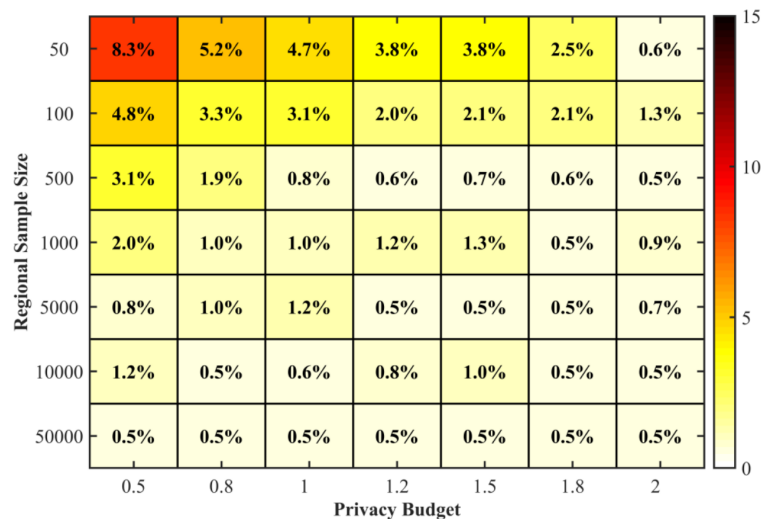


FIGURE 8. Mean relative error

5000 or more, regardless of the privacy budget adjustment, the error generally converges to the range of 0.5% to 1.2%. Especially with a sample size of 50,000, the error at all privacy budget levels stabilizes at 0.5%, demonstrating the dilution effect of large samples on Laplace noise. A horizontal comparison shows that when the privacy budget increases from 0.5 to 2.0, the error for a sample size of 100 decreases from 4.8% to 1.3%, and for a sample size of 1000 decreases from 2.0% to 0.9%. However, the error remains constant at 0.5% for a sample size of 50,000. This indicates that sample size is the dominant factor determining data usability, and the moderating role of the privacy budget is even more crucial in small-sample scenarios.

V. CONCLUSION

This research examines the conflict between the expanding influence of capital and the common good of education within the digital application of big data, mirroring the structural tension between mass industrial output and the preservation of traditional craftsmanship in the industry. By analyzing these parallel shifts, the study reveals how the data-driven transformation of both pedagogy and engineering must be navigated to ensure that technological advancement reinforces, rather than unravels, the collective social fabric. It develops a governance framework for technology based on Marxist educational principles. As a result, it provides an effective barrier to the unremunerated acquisition by capital of student data, using a synthetic data-generating method that preserves differential privacy. Additionally, it transforms the evaluation process from a focus on a single numeric score to one based on the process of learning and an individual's mental and physical state through the use of engineering techniques to generate multi-dimensional temporal behavioral feature representations. Moreover, it provides data-based, representation-based support for the holistic development of a person. A two-branch adversarial

learning model is developed to segregate sensitive features from one another. When classifying sensitive features, one can use the Gini Coefficient of education as a constraint for minimization in order to produce a mathematically computable objective function that combines compensatory justice into an algorithmic bias and resource allocation for the benefit of the disadvantaged. The results indicate that after the resources are allocated, the Gini Coefficient of education falls to 0.2707, demonstrating success in helping to reduce the educational gap between poor people and wealthy individuals. This enables the governance of education in the digital age to effectively merge value and instrumental rationality, mirroring the precision and structural integrity required in engineering to produce an advancement from spurious to substantive equity. By weaving ethical considerations into the very fiber of data-driven systems, this approach ensures that the digital social fabric supports the genuine empowerment of all learners through the same meticulous interlacing of technology and human-centric design.

AUTHOR CONTRIBUTIONS

Pei Juan designed, collected and analyzed the data, and drafted the manuscript. Pei Juan conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Pei Juan participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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