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Decomposing and optimizing educational opportunity inequality in china with parametric and robustness testing approaches

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Abstract Education serves as a critical driver for class mobility and human capital accumulation, particularly in countries with pronounced socio-economic stratification. This study investigates the heterogeneity and temporal evolution of educational opportunity inequality in China, focusing on the urban-rural dual structure, gender disparities, and uneven regional development. The study measures how environmental factors, including household registration, income, and regional resource distribution, contribute to educational disparity using micro-level data and a parametric methodology in conjunction with the Shapley value decomposition method. Multiple intelligence theory and discrete inequality indicators, including the Theil index and Gini coefficient, are employed to measure disparities across different education stages. Empirical analysis reveals that although overall educational inequality has declined due to policy interventions, the relative share of inequality stemming from environmental factors has risen since the 1960s. This indicates that exogenous conditions, rather than individual effort, increasingly determine educational outcomes. Additionally, algorithmic optimization and robustness tests enhance the reliability of the measurement framework.

Index Terms educational opportunity inequality, Shapley value decomposition, urban-rural dual structure, vulnerable groups, multiple intelligences theory, algorithmic optimization, data privacy

I. Introduction

It is commonly acknowledged that education is a key factor in socioeconomic growth and a crucial tool for fostering class mobility [1], [2]. It not only fosters human capital accumulation but also serves as a critical lever for breaking the intergenerational transmission of poverty and inequality. In China, the strategic transition from a "demographic dividend" to a "talent dividend" has made educational equity a pivotal policy concern. Ensuring that everyone has equal access to high-quality educational resources, irrespective of socioeconomic background, is essential to the success of this transformation [3]. Disparities in educational attainment exist because of the unequal distribution of educational opportunities among genders, social groups, and geographical areas. These disparities have significant implications for social justice, economic growth, and national competitiveness [4], [5].

The phenomenon of educational inequality in China is shaped by its unique urban-rural dual structure, pronounced regional disparities, and enduring gender-based discrimination in education. Due to the unequal distribution of educational resources, urban pupils now have considerably greater educational opportunities than their rural counterparts [6], [7]. systemic hurdles prevent vulnerable populations, such as migrants and those with disabilities, and economically poor households from receiving educational opportunities. These groups are often marginalized not only in terms of access but also in the quality of education they receive [8].

The presence of these inequalities undermines social cohesion and limits the potential for upward mobility. In the broader context of global development, equitable education is recognized by the United Nations Sustainable Development Goals (SDG 4) as a key target. Therefore, investigating the mechanisms driving educational inequality and identifying effective policy interventions is not only of national but also of international relevance [9], [10].

The study uses datasets on educational funding investment and individual educational attainment across different regions in China. Figure 1 (retrieved from the educational funding dataset) illustrates the disparities in educational input demand across regions in 2021, highlighting the uneven allocation of resources:

Despite substantial reforms in China's educational sector, several challenges remain unresolved: The urban-rural divide continues to restrict the flow of educational resources, with rural schools often lacking qualified teachers, modern facilities, and adequate funding. Income inequality directly affects families' ability to invest in their children's education, reinforcing cycles of poverty. The growing reliance on digital platforms and data-driven educational policies raises concerns about personal information protection. Additionally, data is often siloed, hindering integrated analysis [11], [12]. These challenges underscore the need for new analytical frameworks and methodologies that can address the complexity of educational inequality in a holistic manner [13].

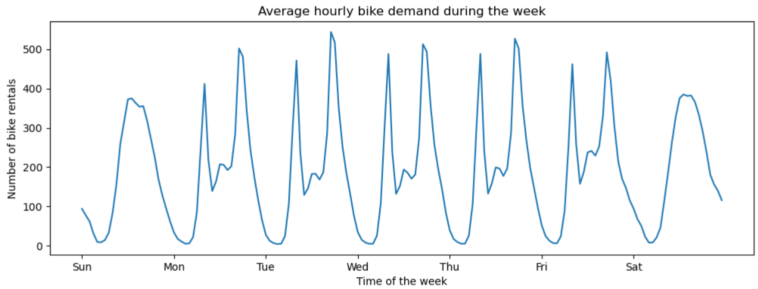

Figure 1: Data retrieval on the education input demand dataset

Numerous studies have explored the measurement and determinants of educational inequality both globally and within China. International research often focuses on socio-economic factors, examining how family background, parental education, and regional policies influence educational outcomes [14], [15]. In the Chinese context, researchers have emphasized the impact of household registration (hukou) and regional development on educational attainment [16], [17]. Classic measurement methods, including index, Theil index, and Gini coefficient, have been widely used to assess disparities. However, these approaches have limitations, particularly in capturing the influence of environmental factors and changes over time.

Recent advances have introduced more sophisticated techniques such as regression-based decomposition and ex-ante/post-event methods to analyze inequality of opportunity [18]. Moreover, the application of Shapley value decomposition has provided a more comprehensive framework for quantifying the contributions of various factors to overall inequality. Nevertheless, existing studies remain largely macro-empirical and rely on cross-sectional data, longitudinal trends or micro-level mechanisms [19].

Current research predominantly follows a three-step paradigm: selecting cross-sectional data, applying inequality indices, and offering policy recommendations. While this approach has yielded valuable findings, it fails to fully address the dynamic nature of educational inequality. Moreover, there is a lack of integration between quantitative modeling and algorithmic optimization, which the precision of measurements. Another significant gap is the insufficient focus on privacy-preserving techniques in educational data analysis, an increasingly critical issue in the digital age [20].

Furthermore, most studies do not differentiate between inequalities arising from individual effort and those stemming from external environmental factors. This distinction is crucial for designing targeted interventions that promote fairness without discouraging personal initiative.

To address these gaps, this study adopts an integrated methodological framework that combines parametric modeling, Shapley value decomposition, and algorithmic optimization. Specifically, we: Measure educational inequality using both traditional indicators (Theil index, Gini coefficient) and advanced methods that incorporate multiple intelligences theory and discrete variable indicators [21], [22]. Decompose the contributions of environmental factors (e.g., region, household registration, income level) to inequality through Shapley value analysis. Analyze temporal trends by dividing the sample into cohorts based on birth years (1930–1989), enabling a longitudinal perspective on the evolution of educational disparities. These visualizations reinforce the importance of considering both structural and temporal dimensions when analyzing inequality.

This paper makes the following contributions:

Methodological Innovation: By combining Shapley value decomposition with multiple intelligences theory and algorithmic optimization, we provide a more comprehensive measurement of educational inequality.

Policy-Relevant Insights: Our findings identify key factors contributing to inequality, offering evidence-based recommendations for targeted interventions.

Temporal Perspective: The longitudinal analysis reveals how reforms have influenced educational inequality over time, highlighting persistent challenges.

II. Research objective

Vulnerable groups in the educational environment are not unique to China, they exist in any society, and the duration and form of expression are different due to the joint influence of the state and society. In this paper, from the perspective of rural areas, through data collection and comparison, this paper studies the causes, influencing factors, hazards and countermeasures of disadvantaged in educational environment. To discuss the importance of education for disadvantaged groups such as rural areas, so as to attract the attention and support of the state and society to this group, and truly realize the fairness and justice of the environmental rights and interests of the whole society, which belong to the attributes of human rights [23], [24].

II. A. Factor recursion of educational imbalance

my country's large population, coupled with the influence of the long-term, makes education policies also divided according to the structure. This leads to inequity in education in remote areas such as rural areas. The education is not broad enough, the level is not high, the scope is not complete, and the resources are not enough. As a result, it is difficult for rural groups to adapt to the rapidly developing new type of rural areas. The recursive graph of its education factor is shown in Figure 2.

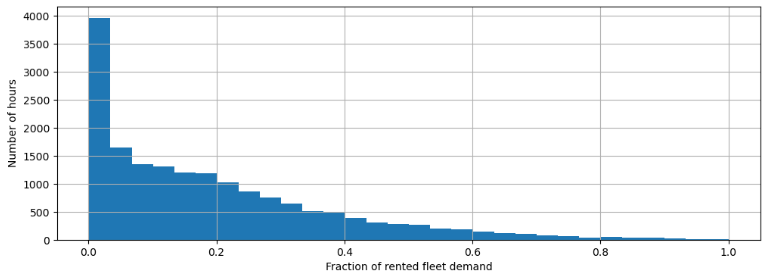

Figure 2: Recursive graph of education factor

On the one hand, education in most provinces and regions is based on the admission rate of the pays little attention to the comprehensive quality education of students. Especially in underdeveloped and underdeveloped areas, the philosophy of both schools and families is that students have only one way out for further education, which creates a mental set for this group of people. That is, apart from education, nothing else matters. They do not have a sense of protection for the severity of the environmental problems in the living area, and do not care about the damage. Therefore, these groups can easily become environmentally disadvantaged groups, unless they have really acquired relevant environmental knowledge through further education, otherwise. To a large extent, they have become potentially vulnerable groups in the environment; on the other hand, the urban-rural division of school-running system has also blocked rural education and made nearly 80% of students miss the college entrance examination. In this regard, it can be said that rural groups are cut from other educational opportunities other than local educational resources. Many researchers have pointed out that the current system of regional division is largely due to the remnants of the idea of "city priority" under the planned economic system. In addition, urban resources are more abundant and sound than rural educational resources. Even if some wealthy rural residents send their children to urban schools, they rarely care about what their children gain and what they lose. Development is not based on the level of commodity prices, it needs to be evaluated based on the combination of various groups of people and their education, quality and morality. Strictly speaking, the most essential reason why a country or region is backward, aside from other objective reasons, is the low quality of people. The inequality of education is undoubtedly an important reason for the low quality of and thus the low quality of the nation. The low proportion of educated people and the low quality of citizens further exacerbate the possibility of rural groups becoming environmentally disadvantaged.

II. B. Optimization and robustness test of multivariate algorithm

A combination of theory and evidence. At the theoretical level, the relevant research methods in the field of opportunity inequality are introduced, Including ex-ante method, post-event method, random dominant method, parametric method, non-parametric method, etc. Based on the relevant theoretical models and the research content of this paper, a more appropriate parametric method is selected. Based on this, we quantify the disparity in educational possibilities in my nation using micro-level statistics. Utilizing parametric analysis techniques that are normative in the field of inequality of opportunity research, mixed OLS, binary Probit, and sorted Probit models are used simultaneously to measure the inequality of opportunities in my nation at the empirical level. In addition, the disparity in educational chances in my nation is measured and objectively examined using the Theil index, the dissimilarity index, and the modified dissimilarity index. Test the validity of the conclusions reached using a range of robustness testing techniques. Additionally, the contribution of many environmental elements to the inequality of educational chances in my nation is measured using the Shapley value decomposition approach based on regression equation, which is a more rational and thorough measure. To prepare for policy suggestions, the primary influencing elements are examined and the chronological trend of each influencing factor is empirically tested. Figure 3 below depicts the waterfall model.

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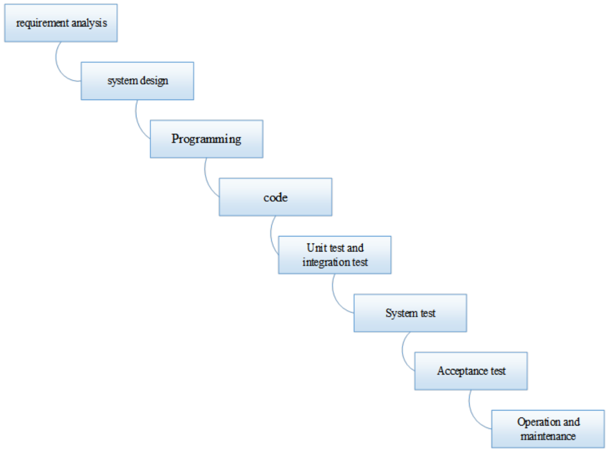

Figure 3: Waterfall development model

III. Methods

The intelligent evaluation and algorithm optimization is to provide users with a fair experience of education closely related to real life. It is only a tool for teachers and students, and it has a certain reference value. But it is not an absolute tool for identifying high and low intelligence. The system mainly includes a large number of test questions designed for different types of intelligence, and test randomly gives the test questions to ensure the validity of the results. Before entering the test, testers mr and log in to enter the interface for testing and managing their own information. After the test, there will be feedback information about the relevant results.

1. System objective

The system aims to provide individuals in the educational process with a fair and real-life relevant learning experience through intelligent evaluation E and algorithm optimization O:

$$SystemGoal : max(F(E, O))s.t.F \to Fairness, Relevance. \tag{1}$$

Here, E denotes the intelligent evaluation module, and O denotes the algorithm optimization module. Both are jointly optimized through the function F.

2. User set and role classification

Let the total user set be U, composed of three disjoint subsets:

$$U = A \cup T \cup S, \tag{2}$$

where, A: Set of Administrators; T: Set of Teachers; S: Set of Students.

The user roles are mutually exclusive:

$$A \cap T = T \cap S = A \cap S = \phi. \tag{3}$$

Each user group has its own functional set $\mathcal{F}_i$, where: $\mathcal{F}_A = \{f_1, f_2, f_3\}$: System management, question bank maintenance, permission control; $\mathcal{F}_T = \{f_4, f_5\}$: Student monitoring, results viewing and feedback; $\mathcal{F}_S = \{f_6, f_7\}$: Test participation, personal feedback access.

3. Evaluation structure modeling

Let the question bank be$Q = \{q_1, q_2, \ldots, q_n\}$. Each test is a random sampling process from Q:

$$Q_{test} \subset Q, \quad where\ |Q_{test}| = k, \quad k < n. \tag{4}$$

The result of user $s_i \in S$is expressed as a vector:

$$R(s_i) = [r_1, r_2, \ldots, r_m], \quad r_j \in \mathbb{R}, \tag{5}$$

where mmm represents the number of intelligence dimensions (e.g., logical, linguistic, spatial). The results are mapped to the corresponding teacher through the function:

$$F_T : S \to T, \quad such, that\, T_j\, can, view. \tag{6}$$

4. Registration and login mechanism

Users must first register$Reg(u)$, and then log in using the function$Login(u, p)$:

$$Login(u, p) = \begin{cases} True, & if(u, p) \in D, \\ False, & otherwise. \end{cases} \tag{7}$$

Here, D is the set of valid user credentials, u is the username, and p is the password.
5. Feedback mechanism
After completing the test, the system generates feedback based on the user's results using:

$$Feedback(s_i) = f(R(s_i)). \tag{8}$$

Feedback may include text analysis, graphical reports, or learning recommendations. It is displayed to both teacher and student via:

$$View(T_j, R(s_i)) \quad and \quad View(s_i, R(s_i)). \tag{9}$$

At present, the main users of this system are students and teachers. Students are managed by teachers. Individual results and all results will be viewed by teach help. To sum up, according to the different functions of users, they are divided into three users: administrators, teachers, and students.The descriptions are shown in Table 1.

Table 1: User function table of educational equity software

User category	Function description	explain
administrators	Add teacher user Add student user delete user View user information Edit user information	Have the highest authority of the system
teacher	Modify personal password Change student password View individual test results View all user test results	System registered user
student	Conduct tests View test results Personal information maintenance Modify personal password	System registered user

III. A. System structure design

The joint verification task is a model, presentation, console and web application based on the joint verification task model, which can be easily implemented with multiple controllers. When creating the console, the navigation page setting is relatively unstable. Through the web application search based on the joint audit panel structure, we can understand the execution differences, develop online software based on these differences, adjust the communication according to the joint audit pature, and use the external strategic configuration file to display the differences. This intelligent method can change the file settings, making the network software a development platform for developers. The previous software was based on the structure of the joint Verification Mission, which developers could implement.Its design structure is shown in Figure 4.

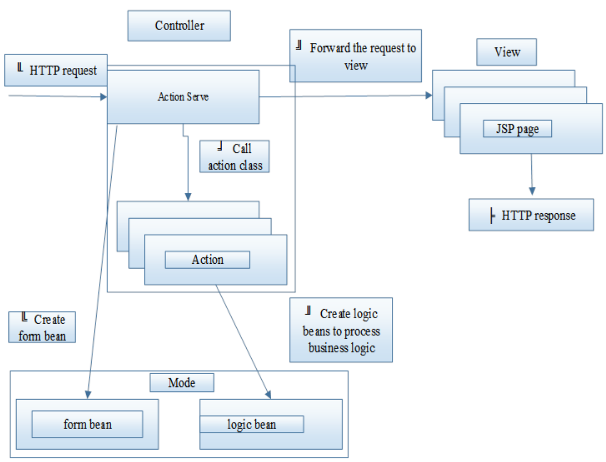

Figure 4: MVC system design structure diagram

III. B. Algorithm optimization

Based on the intelligent evaluation system, this research systematically optimizes the MPV (Multi-Process Value) model to enhance system consistency, performance efficiency, and role-based access control.

III. B. 1) MPV model optimization objective

Let the original MPV model be represented as a multi-function structure:

$$MPV = \{M_1, M_2, \ldots, M_k\}. \tag{10}$$

Each sub-module M_i corresponds to a specific process such as: M_1: Evaluation engine; M_2: Feedback generator; M_3: Data synchronization; M_4: Role-based access handler.

The optimization objective is to improve the overall utility U of the MPV model under constraints C:

$$\max_{\theta} U(MPV_\theta) \quad s.t. \quad C = \{C_1, C_2, \ldots, C_m\}, \tag{11}$$

where, θ represents the parameter set of the model; C includes constraints on consistency, latency, user permissions, and data integrity.

III. B. 2) System administrator responsibilities and role definition

Let $A \in U$denote a system administrator. The administrator has the authority over:

$$\mathcal{F}_A = \{f_{acc}, f_{auth}, f_{sync}\}, \tag{12}$$

where, f_{acc}: Manage user accounts (T,S); f_{auth}: Authorize login credential; f_{sync}: Ensure cross-module data consistency.

Define the user sets again as:

$$T = \{t_1, t_2, \ldots, t_n\}, \quad S = \{s_1, s_2, \ldots, s_m\}. \tag{13}$$

The administrator performs mappings:

$$f_{acc} : A \to (T \cup S). \tag{14}$$

This implies, Consistency Constraint: $\bigcap_{i=1}^{k} D_i = D$, where D is the unified consistent data view across all modules.

III. B. 3) Role activation and dependency rule

A core principle of the MPV optimization is that power must be used to be effective. Define the available permission set P, and the activation function:

$$P = \{p_1, p_2, \ldots, p_q\}, \quad Activate(p_j) \Rightarrow Enable(f_i). \tag{15}$$

If a permission $p_j \in P$is not activated by A, the corresponding function $f_i \in \mathcal{F}_A$ is disabled:

$$Activate(p_j) \Rightarrow f_i = \phi. \tag{16}$$

Thus, only when the administrator uses the existing permissions can the intended system functions be fully executed. The administrator interface Figure 5 is as follows:

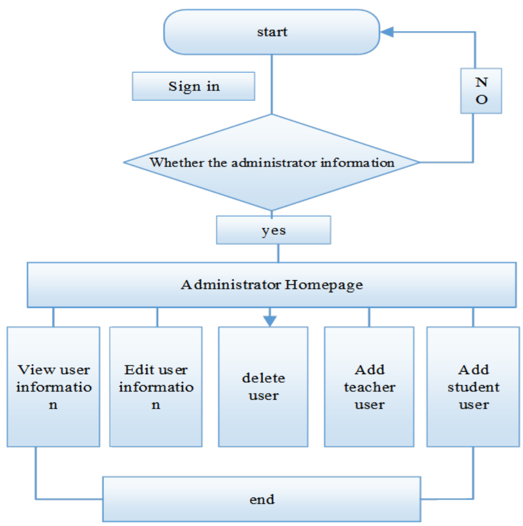

Figure 5: Optimized flow chart of the administrator interface to add student users

In short, while maintaining their own information, civil servants have the greatest power to restrict and restrict teachers and student staff from engaging in specific businesses. In addition, teachers can manage students within a certain range, and teachers can protect students’ privnderstanding students. In addition to using their own work permits, students will not affect other users, but they are the main users of the system and other users of the process. Its PBL flow chart is shown in Figure 6.

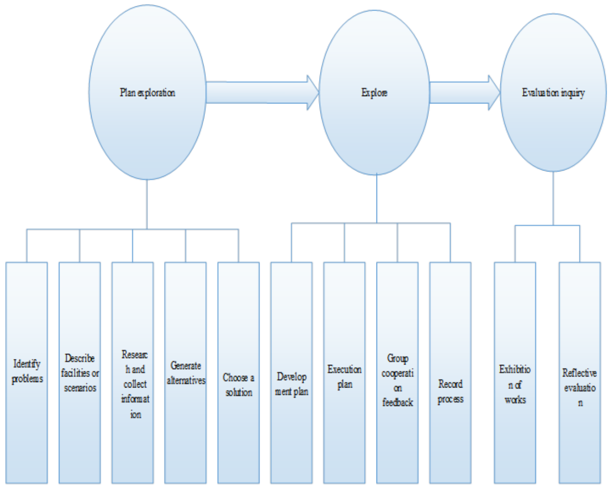

Figure 6: PBL flow chart

IV. Experiment

To quantify the disparity in educational possibilities in my nation and its historical trajectory, We first consider the environmental factors Mixed OLS regression was performed on the educational level of individuals, and then the overall sample was divided into1930-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989 six subgroups were mixed OLS regression. The regression heatmap is shown in Figure 7.

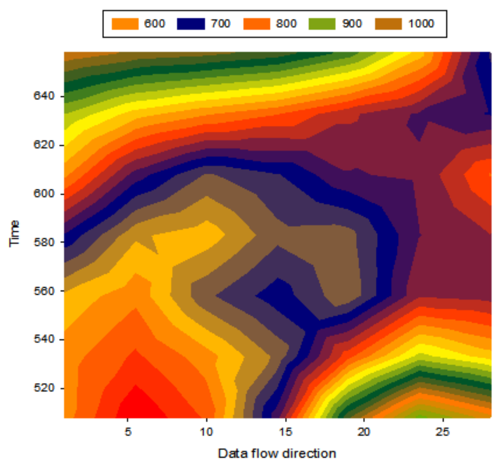

Figure 7: Regression heat map of inequality of educational opportunity

From this, it can be found that for social background factors, including region and household registration type. The coefficients of dummy variables in each province are significantly negative. The reference group is Beijing, and the place of birth has a significant impact on the educational level of individuals. Beijing is still an area with relatively high educational level and cultural level in China. In general, individuals with urban hukou have higher educational attainment than rural individuals, The household registration factor is still an important factor restricting the fairness of educational opportunities in my country, and factors such as differences in access to educational resources between urban and rural areas make it impossible for urban and rural individuals to have the same education rights.

IV. A. Staged inspection optimization improvement

Based on the above regression results, the educational inequality and educational opportunity inequality in my country are calculated as shown in Table 2 below.

Among them, the inequality index selects the Theil index of education, and lists the results of the Gini coefficient and the average logarithmic deviation as a comparison. Absolute value and relative contribution degree are two aspects of opportunity disparity. The degree to which the sample's actual overall educational inequality may be explained by the disparity in educational opportunities is known as the relative contribution degree. Both direct and indirect methods are used to present the results. Among them, the overall educational inequality has maintained a downward trend, which reflects the overall effect of my country's various educational reform policies and measures, and the per capita education gap is narrowing. Although the relative to overall educational inequality showed a trend of first declining and then growing, the absolute value of educational opportunity inequality also dropped year over year. After the 1960s, the upward tendency accelerated considerably. We decompose educational inequality into unequal educational opportunity and unequal educational effort, Among them, the inequality of educational opportunities is the unreasonable inequality originating from the exogenous environment of individuals, and the inequality of educational effort is the reasonable inequality caused by the degree of individual effort. Consequently, a more asure is definitely the relative level of educational opportunity disparity. As the proportional degree of educational opportunity inequality rises, irrational returns to "environment" rather than reasonable returns to "effort" are increasingly the cause of educational success inequality among individuals. Figure 8 below provides a more user-friendly representation of the findings of the calculation of educational opportunity inequality as expressed by the direct technique.

Table 2: Recursive factors of inequality of educational opportunity

		Full sample	30-39	40-49	50-59	60-69	70-79	80-89
Overall education inequality	GE(1)	0.1507	0.4018	0.2341	0.1931	0.1037	0.0791	0.0512
	GE(0)	0.2384	0.4845	0.3357	0.2962	0.1564	0.1073	0.0624
	GINI	0.2811	0.4765	0.3504	0.3138	0.2264	0.2055	0.1709
Unequal opportunities	direct method	0.0548	0.1419	0.0674	0.0551	0.0301	0.0301	0.0210
absolute value	indirect method	0.0763	0.1299	0.0931	0.082	0.0422	0.0368	0.0239
Unequal opportunities	direct method	0.3634	0.3532	0.2868	0.2855	0.2902	0.3805	0.4099
Relative value	indirect method	0.5061	0.3233	0.3978	0.4244	0.4065	0.4661	0.4663
sample size	N	34748	1992	4123	6559	7726	7104	5086

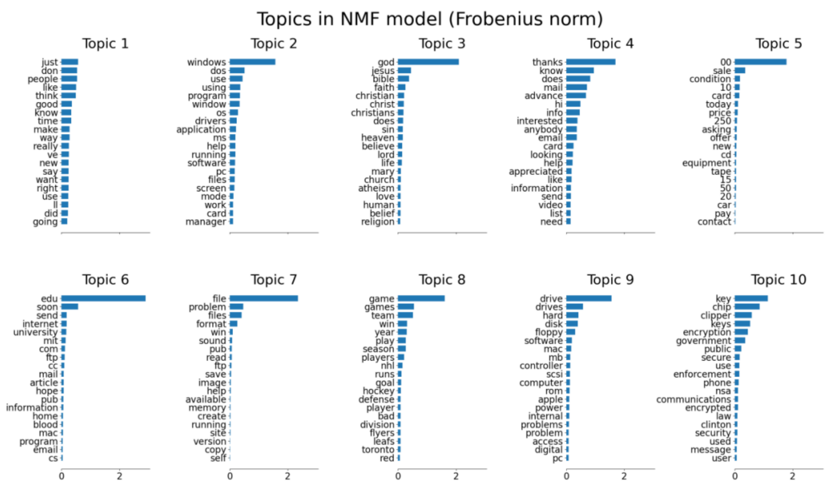

Figure 8: Topic modeling results revealing latent factors relevant to educational inequality and environmental influences

The topic modeling results shown in Figure 8 illustrate ten distinct themes extracted from a corpus, covering areas such as technology and software (Topic 2, Topic 9), online education and information exchange (Topic 6), commerce and pricing (Topic 5), cultural and religious discourse (Topic 3), entertainment (Topic 7, Topic 8), and cybersecurity/privacy (Topic 10). These topics align closely with the dimensions discussed in this study on educational opportunity inequality. Specifically, technological access and digital literacy gaps reflected in Topics 2, 6, and 9 correspond to the digital divide that limits rural students' educational opportunities; economic aspects highlighted in Topic 5 resonate with disparitnal investment and resource allocation; cultural factors in Topic 3 influence gender roles and participation in education; and privacy/security concerns in Topic 10 reflect the necessity of safeguarding personal information in data-driven educational analytics. This visualization demonstrates how algorithmic approaches, such as topic mcover latent factors driving educational disparities, supporting the integration of advanced data analysis methods into the framework of inequality measurement and policy evaluation proposed in this research.

IV. B. Data situation optimization

The scatter plots in Figure 9 depict the relationships between the dependent variable y and three explanatory variables (x_1, x_2, x_3) assessed using both F-test and Mutual Information (MI). The first plot shows a strong linear correlation ($F{-}test = 1.00, M_I = 0.36$), indicating that $x_1$significantly explains variations in y. The second plot exhibits a clear nonlinear relationship ($F{-}test = 0.28, M_I = 1.00$), demonstrating that traditional linear models may underestimate factors with complex influences, which are better captured by MI. The third plot reveals no meaningful association ($F{-}test = 0.00, M_I = 0.00$), suggesting $x_3$is irrelevant to y. Within this research context, the Figure exemplifies how different environmental or socioeconomic variables impact educational outcomes in varying ways: some factors (analogous tox_1) exert straightforward linear effects, others (x_2) have hidden nonlinear impacts often overlooked by classical statistical approaches, and some (x_3) contribute negligibly. This supports the study's methodological framework, where combining parametric (F-test) and non-parametric (MI) analyses with Shapley value decomposition provides a more comprehensive understanding of the heterogeneous drivers behind educational opportunity inequality.

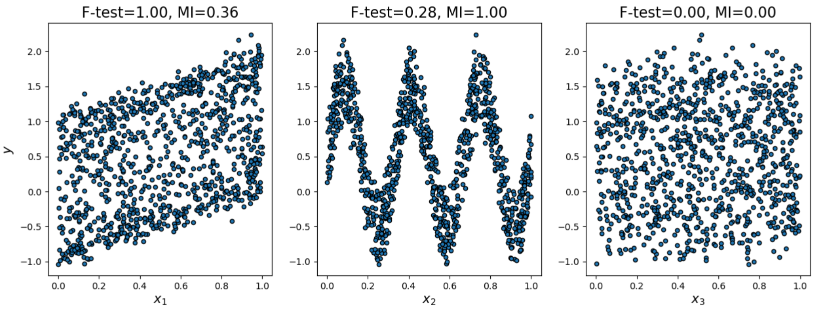

Figure 9: Feature relevance analysis using F-test and Mutual Information, reflecting linear, nonlinear, and negligible effects of environmental factors on educational outcomes

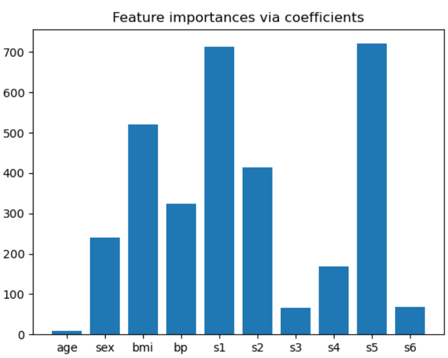

Figure 10: Feature importance derived from model coefficients, reflecting the disproportionate influence of key factors on educational outcomes

The bar chart in Figure 10 shows the relative importance of different features (ageage, sexsex, bmibmi, bpbp,s_1–s_6) based on model coefficients, where $s_1$and $s_5$have the highest contributions, followed by bmibmi ands_2, while ageage, s_3, and $s_6$exhibit minimal influence. This distribution highlights how certain variables dominate the prediction of outcomes, whereas others have negligible effects. Within the framework of this research on educational opportunity inequality, this experiment mirrors the analysis of environmental and socioeconomic factors, where key determinants such as household registration, regional resource allocation, and economic status exert the greatest impact on inequality, whiher factors play only a minor role. The visualization reinforces the methodological approach of the study, emphasizing the integration of coefficient-based feature weighting with Shapley value decomposition and other statistical measures to identify and prioritize the most influential variables for targeted policy interventions.

V. Conclusion

This research provides a comprehensive quantitative assessment of educational opportunity inequality in China, revealing significant heterogeneity across regions, genders, and social groups. Through Shapley value decomposition, it is shown that household registration and regional resource disparities remain the dominant contributors to unequal opportunities. The results demonstrate that while educational reforms have narrowed absolute disparities, the relative inequality associated with environmental factors has persisted or even intensified. The integration of multiple intelligence theory aization enhances the precision of inequality measurement, offering novel methodological insights. Moreover, the study emphasizes that achieving educational fairness requires not only increased investment but also targeted policies that address structural barriers and protect the rights of disadvantaged populations. In the context of digital transformation, ensuring personal data privacy during educational data analysis is crucial for sustainable policy design.

Data availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of interest

The authors declared that they have no conflicts of interest regarding this work.

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