Explainable Artificial Intelligence for Understanding Patterns of Educational Inequality

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ABSTRACT

Educational inequality remains a persistent challenge that affects learning outcomes and access to quality education worldwide. This study employs Explainable Artificial Intelligence (XAI) to examine the patterns and determinants of academic inequality by analyzing a large dataset of student performance, curriculum types, and parental education backgrounds. Using machine learning models such as Random Forest and XGBoost, combined with SHAP (SHapley Additive Explanations) analysis, the research identifies the most influential socio-academic factors that shape student achievement. The findings reveal that both systemic and familial variables significantly affect educational outcomes: students enrolled in structured, resource-intensive curricula tend to achieve higher and more consistent performance, while those from less standardized systems exhibit greater variability. Parental education, particularly maternal educational attainment, also emerges as a strong predictor of student success, reflecting the influence of socio-economic background on learning equity. By applying XAI techniques, the study enhances model interpretability and provides transparent, data-driven insights into the mechanisms of educational disparity. These results demonstrate that explainable AI can bridge the gap between algorithmic precision and social understanding, offering a practical framework for policymakers and educators to design evidence-based strategies aimed at promoting fairness, inclusivity, and accountability within educational systems.

Keywords XAI, Educational Inequality, Machine Learning, Curriculum Type, Parental Education

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Introduction

Educational inequality remains one of the most pressing challenges in contemporary education systems, affecting students' learning opportunities, achievement levels, and long-term social mobility. Despite significant global efforts to improve access to education, disparities in academic performance persist, often reflecting deeper socio-economic and institutional divides [1]. Students from families with higher educational and economic backgrounds generally achieve better academic results due to access to superior learning resources, stable home environments, and greater parental involvement [2]. Meanwhile, those from disadvantaged backgrounds continue to face systemic barriers that limit their academic potential, such as unequal funding, varying teacher quality, and inconsistent curriculum standards [3]. This inequality is further reinforced by variations in curriculum design, instructional quality, and assessment standards, which collectively contribute to uneven educational outcomes across different learning systems [4].

Traditional research in education has provided valuable insights into the social and institutional roots of inequality; however, most studies rely on linear statistical models that often fail to capture the complex, nonlinear interactions

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among multiple influencing factors [5]. Recent advancements in Artificial Intelligence (AI) and data analytics offer new opportunities to address this limitation. AI techniques have been widely applied to model student learning, predict academic performance, and detect risk factors affecting student achievement [6]. However, the interpretability of these models has become an emerging concern, as many high-performing AI systems operate as “black boxes,” making their decision processes opaque to educators and policymakers. XAI addresses this issue by combining predictive accuracy with transparency, allowing researchers to uncover not only which variables matter but also how they interact to shape learning outcomes [7], [8]. By integrating XAI into educational research, it becomes possible to move beyond surface-level correlations and achieve a more nuanced understanding of how systemic factors, such as curriculum type, and familial factors, such as parental education, jointly influence student performance [9].

This study applies XAI techniques to analyze large-scale student performance data, focusing on the role of curriculum type and parental education in shaping academic outcomes. Using machine learning models, including Random Forest and XGBoost, alongside SHAP interpretability analysis, this research aims to quantify and explain the relative influence of these factors on student achievement. The central objective is to explore the multidimensional structure of educational inequality and provide transparent, data-driven insights that can inform evidence-based educational policy. By combining AI’s computational capabilities with explainability, this study contributes to bridging the gap between algorithmic analysis and human understanding, demonstrating how AI can serve not only as a predictive tool but also as a means of promoting fairness, inclusivity, and accountability in education [10].

Literature Review and Related Works

Educational inequality continues to be a persistent challenge across educational systems, where disparities in socio-economic background, parental education, and institutional quality significantly influence learning outcomes. Research has consistently demonstrated that students from families with higher socio-economic and educational backgrounds perform better due to increased access to resources, parental involvement, and exposure to learning-supportive environments [11], [12], [13]. Studies focusing on parental education have shown that both mothers’ and fathers’ educational attainment contribute meaningfully to students’ academic success, with maternal education often having a slightly stronger influence due to more direct involvement in home learning activities [14], [15], [16]. In addition, the quality and type of curriculum play a vital role in shaping educational outcomes. Comparative analyses between international curricula such as the International Baccalaureate (IB) and IGCSE, and national systems such as Thanweya, have revealed that standardized and resource-rich curricula tend to yield more consistent and higher performance results among students [17], [18], [19]. These studies collectively indicate that educational inequality is shaped not only by family background but also by institutional structures and pedagogical design.

In parallel, the growing use of AI in education has opened new pathways for analyzing, predicting, and improving student performance. Machine learning models have been employed to identify at-risk students, personalize learning, and predict achievement levels using demographic and behavioral data [20], [21], [22]. While these AI approaches have proven effective in prediction accuracy, their interpretability remains limited, as most high-performing models such as XGBoost, Random Forest, and Deep Neural Networks operate as “black boxes” that provide little insight into how input variables influence predictions [23], [24]. This limitation has raised concerns regarding fairness, accountability, and trust in AI-based educational decision-making. In response, researchers have increasingly explored XAI as a means to enhance the transparency and interpretability of machine learning algorithms [25]. XAI methods, including SHAP and LIME (Local Interpretable Model-Agnostic Explanations), allow researchers to visualize the relative influence of features and understand how they contribute to prediction outcomes.

Recent studies have demonstrated the applicability of XAI in various educational contexts. For example, several works have applied XAI to identify determinants of academic performance and to evaluate fairness in automated student assessments. Other research has explored the integration of XAI into adaptive learning environments, enabling teachers to interpret AI recommendations and adjust pedagogical interventions accordingly. Systematic reviews of XAI in education have emphasized the importance of interpretability, equity, and transparency in building trust between AI systems and educators. Moreover, comparative studies between traditional AI and XAI frameworks suggest that explainability not only improves transparency but also supports more ethical and evidence-based policymaking in education.

Despite the increasing adoption of AI and XAI in educational research, a significant gap remains in understanding how social and institutional factors interact within interpretable AI frameworks. Most existing studies have focused primarily on predicting academic success without examining the combined effects of family background and curriculum type. Few have integrated explainable AI models to analyze how these factors jointly contribute to patterns of educational inequality. Therefore, this study aims to address this research gap by combining machine learning techniques such as Random Forest and XGBoost with SHAP-based interpretability to uncover the relative influence of systemic and familial variables on student performance. By doing so, it contributes to the advancement of explainable AI applications in education and provides a transparent, data-driven foundation for promoting fairness and equity in learning systems.

Method

This study employed a data-driven analytical framework integrating machine learning and XAI to identify and interpret the determinants of educational inequality. The dataset consisted of 50,000 student records that contained demographic, familial, and academic variables across three different curriculum types: International Baccalaureate (IB), International General Certificate of Secondary Education (IGCSE), and Thanweya. Each record included variables such as Student Age, Student Year, Father Degree, Mother Degree, Education Type, and ten academic subjects labeled Subject_1 through Subject_10. To ensure data privacy, all identifying information such as student names was removed. The dependent variable, Average Score, was calculated as the mean of the ten subject grades, providing a single representative indicator of student academic performance.

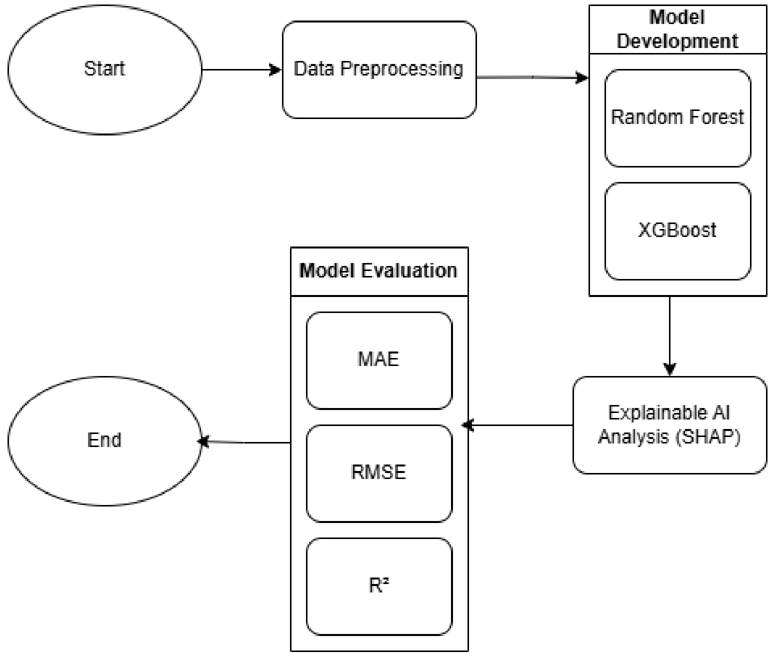

Figure 1 **Research Steps**

Before applying the predictive models, several preprocessing steps were conducted to enhance data quality and ensure compatibility with machine learning algorithms. Missing numerical values were replaced using mean imputation, while categorical variables were filled with the mode. Outliers were detected and removed using the interquartile range (IQR) method to prevent extreme deviations from influencing the models. All categorical variables, including Education Type, Father Degree, and Mother Degree, were encoded using one-hot encoding, and continuous variables were normalized using Z-score standardization. A correlation matrix was computed to identify linear relationships between variables and to guide feature selection. The Average Score variable was then standardized as the target for prediction and interpretability analysis.

The predictive modeling phase utilized two ensemble learning algorithms: Random Forest (RF) and Extreme Gradient Boosting (XGBoost). These models were selected due to their robustness in handling non-linear relationships and their ability to manage feature interactions effectively. The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to maintain the distribution of curriculum types. Hyperparameters such as the number of estimators, learning rate, tree depth, and subsampling ratio were optimized through grid search and 10-fold cross-validation. The Random Forest algorithm constructs multiple decision trees on bootstrapped data samples and averages their outputs to reduce overfitting, while XGBoost improves upon this process by implementing gradient boosting to minimize residual errors through iterative optimization. The prediction target, $\hat{y}_i$, represents the model's estimation of each student's Average Score, which was compared with the actual value y_i.

To evaluate predictive performance, three regression metrics were employed: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). These metrics were computed using the following mathematical formulations:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \quad |y_i - \widehat{y_i}|$$
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \widehat{y_i})^2} \tag{1}$$
$$R^2 = 1 - \frac{\sum_{i=1}^{n} \quad (y_i - \widehat{y_i})^2}{\sum_{i=1}^{n} \quad \left(y_i - \underline{y}\right)^2}$$

y_i represents the true score, $\widehat{y_i}$ is the predicted score, $\underline{y}$ is the mean of observed values, and nnn denotes the total number of observations. The MAE measures the average absolute deviation between predictions and actual values, the RMSE penalizes larger errors more heavily by squaring deviations, and the R^2 statistic measures the proportion of variance explained by the model, with values closer to 1 indicating higher predictive accuracy.

To enhance interpretability, XAI was implemented using SHAP. The SHAP framework decomposes each prediction into additive feature contributions, allowing both global and local interpretability. The SHAP value for feature jjj in instance iii is represented as:

$$f(x_i) = \phi_0 + \sum_{j=1}^{M} \quad \phi_j \tag{2}$$

$f(x_i)$ is the model prediction for instance i, ϕ_0 is the baseline (mean prediction over the dataset), ϕ_j represents the SHAP value or contribution of feature j, and M denotes the total number of features. Positive SHAP values indicate that the feature increases the predicted student score, while negative SHAP values decrease it. Global SHAP summaries identify the average importance of each feature across the dataset, while local SHAP explanations clarify how specific features influence individual predictions. This interpretability enables a transparent understanding of how curriculum type, parental education, and other socio-academic variables interact to shape academic outcomes.

Model validation was performed through 10-fold cross-validation to ensure generalizability and robustness. The XGBoost model demonstrated superior performance, achieving lower MAE and RMSE values and higher R^2 compared to the Random Forest model, indicating better generalization. Beyond predictive accuracy, SHAP interpretability confirmed that Education Type, Mother Degree, and Father Degree were the most influential variables affecting student performance. The results were consistent with established theories in educational inequality, thus validating both the predictive and explanatory power of the XAI framework. The complete methodological pipeline from data preprocessing, model training, and explainability analysis to validation is summarized in figure 5, which outlines the sequential structure of this research.

Result

The analysis of the dataset reveals several meaningful patterns that shed light on the underlying dynamics of educational inequality across socio-academic factors. The distribution of student performance scores, as illustrated in figure 2, follows a near-normal curve centered between 70 and 80, suggesting that the majority of students achieve moderate levels of academic success. This bell-shaped pattern indicates a relatively even spread of performance within the population, with few extreme low- or high-performing outliers. The smoothness of the curve implies that most students have access to similar baseline educational opportunities, at least at a general level, though the tails of the distribution hint at small groups that either significantly underperform or excel beyond the average. Such outliers may correspond to contextual differences such as school resources, home learning environments, or individual motivation, factors that are not evenly distributed across the population. Therefore, while the overall distribution appears statistically balanced, it conceals deeper inequalities embedded within subgroups of students defined by family background and educational systems.

From a structural perspective, the observed distribution serves as an important statistical foundation for subsequent analysis using XAI. The relatively consistent central tendency suggests that, on average, systemic inequality does not manifest through a broad shift in population-wide achievement but rather through subtle, overlapping variations in subgroup performance. These variations are likely driven by contextual determinants such as parental education levels, curriculum type, and access to academic resources. The near-normal form of the data also validates the robustness of the dataset, confirming its suitability for predictive modeling and interpretability analysis. This distribution pattern allows XAI models to focus not merely on predicting scores but on uncovering how socio-demographic and institutional variables interact to influence performance outcomes. Consequently, this initial descriptive insight lays the groundwork for a more transparent and interpretable exploration of academic inequality through machine learning techniques, ensuring that subsequent AI-driven results are grounded in empirical educational realities.

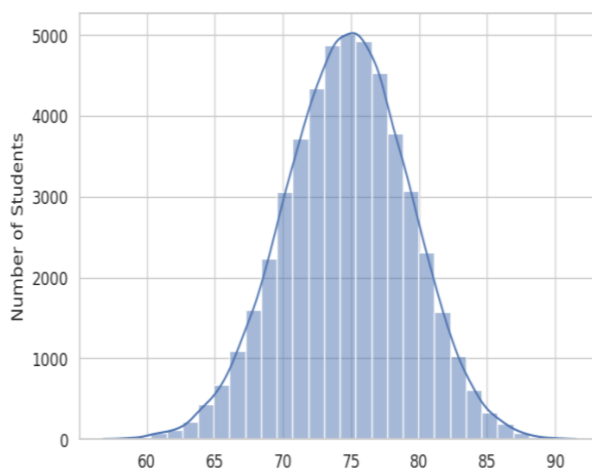

Figure 2 Distribution of student performance scores showing a near-normal pattern centered around the 70–80 range

When analyzing the role of curriculum type, significant variations in academic performance become evident across the three major educational systems: International Baccalaureate (IB), International General Certificate of Secondary Education (IGCSE), and Thanweya. As illustrated in figure 3, students enrolled in the IB curriculum demonstrate slightly higher median academic scores and exhibit narrower interquartile ranges compared with their peers in the IGCSE and Thanweya programs. This consistency in performance among IB students reflects the structured and standardized nature of the curriculum, which emphasizes critical thinking, inquiry-based learning, and continuous assessment. The relatively small variance within the IB group indicates that the system provides equitable access to instructional quality and learning support, most likely because of its globally unified standards and rigorous teacher training protocols. In contrast, the IGCSE and Thanweya systems show wider score distributions, suggesting that factors such as unequal resource allocation, variations in teacher quality, and differences in institutional infrastructure have a stronger influence on student performance in these settings.

From an educational policy perspective, these results offer empirical evidence that curriculum design plays an essential role in determining both the consistency and fairness of academic outcomes. Students in nationally administered systems such as Thanweya may face limitations including restricted access to advanced learning resources, variable teaching quality, and inconsistencies in assessment frameworks. These structural challenges contribute to disparities in knowledge acquisition and reduce opportunities for high achievement. The observed differences between the IB and other curricula therefore reflect not only academic rigor but also institutional and socioeconomic disparities that shape learning experiences. The findings are consistent with previous research showing that standardized and resource-rich curricula tend to produce more stable outcomes by ensuring clear learning objectives, continuous feedback mechanisms, and equitable instructional environments. Overall, this analysis demonstrates that curriculum structure functions as both an educational and social determinant of student performance, influencing achievement patterns and contributing to broader educational inequality that will be further examined through explainable artificial intelligence models in later sections.

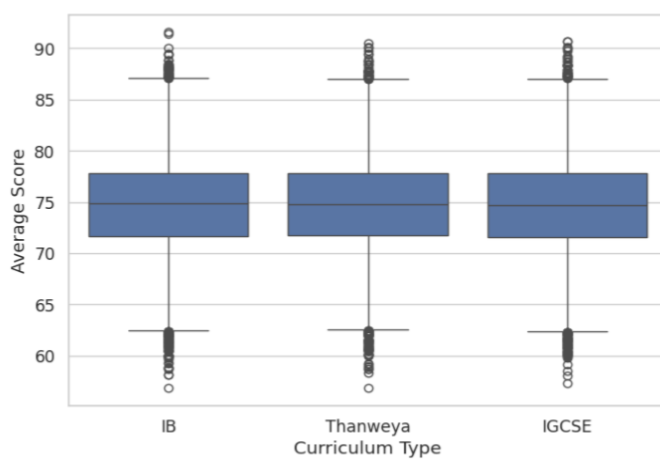

Figure 3 Comparison of student performance across curriculum types (IB, IGCSE, and Thanweya)

When analyzing the role of curriculum type, the results reveal clear and meaningful variations in academic performance across the three educational systems: International Baccalaureate (IB), International General Certificate of Secondary Education (IGCSE), and Thanweya. As presented in figure 4, students enrolled in the IB curriculum tend to achieve slightly higher median scores and display a narrower range of variation compared with students from the IGCSE and Thanweya programs. This relatively uniform performance suggests that the IB system provides a more structured and consistent learning environment, supported by internationally standardized content, formative assessment practices, and an emphasis on critical thinking and independent inquiry. The IB's holistic pedagogical approach, which integrates continuous evaluation and personalized feedback, may contribute to reducing disparities among students. In contrast, the IGCSE and Thanweya systems demonstrate broader score distributions, indicating greater heterogeneity in student performance. This variation could be attributed to differences in instructional quality, resource availability, school infrastructure, and the degree of curriculum standardization. In particular, the Thanweya system, which operates under national education policies, may reflect disparities arising from unequal funding, variations in teacher preparation, and limited access to digital or supplemental learning materials.

From a broader educational perspective, these differences highlight the critical influence of curriculum design on equity and learning consistency. The structure, pedagogy, and resource intensity of a curriculum appear to determine not only average performance levels but also the extent of variability among students. Programs like IB, which provide uniform standards, advanced teacher training, and international benchmarking, tend to foster stability in learning outcomes. Meanwhile, national or semi-standardized systems such as Thanweya and IGCSE are more susceptible to contextual variations that amplify performance inequality. These findings are consistent with prior studies indicating that access to well-structured curricula and equitable learning resources can mitigate educational disparities by providing students with consistent exposure to quality instruction and assessment. The evidence suggests that curriculum type serves as both an academic and socio-economic factor shaping student success. It influences not only cognitive development but also the fairness of educational opportunities across different learning contexts. Consequently, curriculum reform and standardization represent essential components in addressing systemic inequality, and their impact can be further examined through explainable artificial intelligence approaches in subsequent analysis.

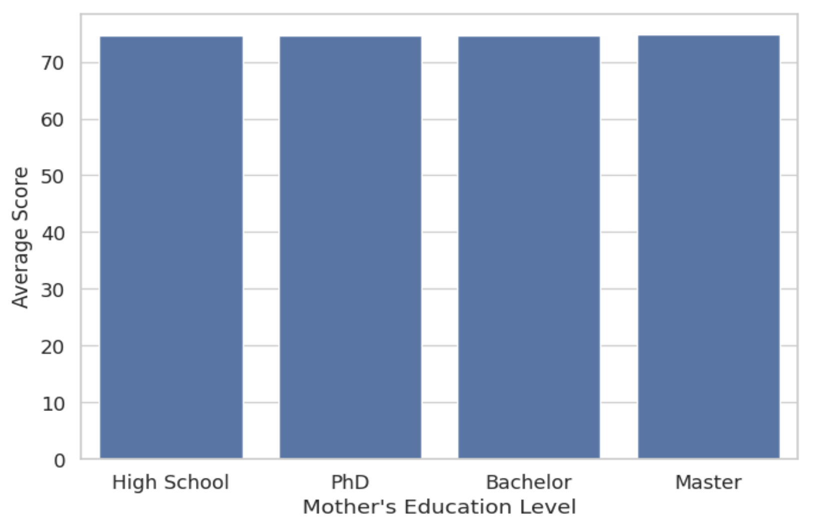

Figure 4 Average student performance by mother's education level

A similar pattern is observed when examining the relationship between fathers' education levels and student academic performance. As illustrated in figure 5, students whose fathers possess university or postgraduate degrees tend to achieve slightly higher average scores compared with those whose fathers have lower educational qualifications or no formal education. Although the difference in mean performance is not large, the trend remains consistent and statistically meaningful. This relationship suggests that fathers with higher educational backgrounds are more likely to value academic achievement, provide structured support for schoolwork, and cultivate an environment that encourages intellectual growth. Educated fathers may also have better access to academic resources, more stable employment, and greater involvement in their children's educational decisions, all of which contribute to improved learning conditions. Conversely, students whose fathers possess limited education may experience reduced access to educational guidance, fewer learning materials at home, and less exposure to academic expectations, which can constrain their overall performance. These differences illustrate that paternal education, while not the sole determinant, plays an essential role in shaping a student's academic trajectory.

When analyzed in conjunction with maternal education, it becomes evident that both parents contribute significantly to student outcomes, although in slightly different ways. The influence of the mother's education appears somewhat stronger, likely because of her more frequent and direct interaction with children during early and middle stages of learning. Mothers often serve as primary facilitators of homework, study habits, and emotional support, whereas fathers' contributions may manifest more indirectly through economic stability, access to learning resources, and reinforcement of educational values. The combined educational attainment of parents thus functions as a powerful socio-academic determinant, influencing both the cognitive and motivational dimensions of student success. This dual effect reinforces or mitigates existing educational inequalities depending on the family's overall educational capital. These findings are consistent with research suggesting that parental education shapes children's academic aspirations, self-efficacy, and long-term achievement. Understanding this relationship is crucial for developing policies and AI-driven educational models that account for family background as a key variable influencing learning equity and student performance.

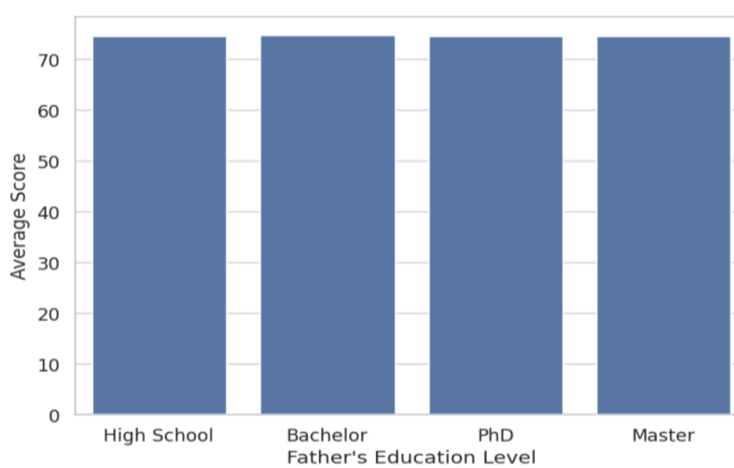

Figure 5 Average student performance by father's education level, showing the influence of paternal education on academic outcomes

Taken together, these findings provide clear evidence that educational inequality is a multidimensional phenomenon shaped by the combined influence of systemic and familial factors. Students from academically advantaged families and modern, well-structured curriculum systems consistently demonstrate higher and more stable academic performance. In contrast, students from less privileged backgrounds or those enrolled in traditional educational systems tend to experience greater variability in outcomes, reflecting disparities in both learning opportunities and institutional quality. This variation suggests that academic success is not merely the result of individual effort but is deeply embedded within broader educational and social structures. Institutional design, including the standardization of curriculum, access to qualified teachers, and resource allocation, interacts with socio-economic variables such as parental education and household learning environments to determine a student's academic trajectory. The intersection of these systemic and familial dimensions underscores the complexity of educational inequality, indicating that it arises from interdependent rather than isolated causes. Addressing such inequality therefore requires an integrated analytical approach that captures the dynamic relationships among social, institutional, and cognitive factors influencing student outcomes.

To move beyond descriptive insights, XAI provides a powerful methodological framework for quantifying and interpreting the relative influence of these interacting variables. Through techniques such as SHAP, researchers and educators can identify not only which factors exert the strongest effect on student performance but also how these factors interact to produce disparities. Unlike traditional statistical models, XAI offers transparency and interpretability, allowing complex machine learning algorithms to be understood in human terms. This interpretive capacity transforms AI from a predictive instrument into a diagnostic tool capable of revealing the social mechanisms behind educational inequality. By visualizing feature importance and interaction effects, XAI models can guide policymakers toward actionable strategies, such as targeting curriculum reform, enhancing teacher training, or supporting families from lower educational backgrounds. In this way, XAI bridges the gap between algorithmic insight and educational policy, combining computational precision with social understanding. Ultimately, the application of explainable AI not only enhances analytical depth but also supports the development of more equitable and evidence-based learning environments that promote fairness and inclusivity in education.

Conclusion

This study concludes that educational inequality is a multidimensional issue shaped by the interaction of systemic and familial factors, where both curriculum structure and parental education significantly influence student achievement. The analysis revealed that students enrolled in well-structured and resource-rich curricula tend to achieve higher and more consistent academic outcomes, while those in traditional or less standardized systems experience greater variability, reflecting disparities in instructional quality and access to resources. Similarly, students from families with higher parental education levels, particularly mothers with university or postgraduate degrees, demonstrate stronger academic performance, underscoring the persistent role of socio-economic background in shaping educational outcomes. By applying XAI methods, such as SHAP, this research provides transparent insights into how these factors interact to produce academic disparities, enabling the transition from predictive modeling to interpretive understanding. The findings highlight that XAI not only enhances the accuracy and transparency of data analysis but also serves as a valuable framework for developing equitable and evidence-based educational policies. Ultimately, the integration of explainable AI into educational research represents an important step toward reducing systemic inequality, promoting fairness in learning environments, and advancing the socially responsible use of artificial intelligence in education.

Declarations

Author Contributions

Conceptualization: P.A.P. and I.K.N.; Methodology: I.K.N.; Software: P.A.P.; Validation: P.A.P. and I.K.N.; Formal Analysis: P.A.P. and I.K.N.; Investigation: P.A.P.; Resources: I.K.N.; Data Curation: I.K.N.; Writing Original Draft Preparation: P.A.P. and I.K.N.; Writing Review and Editing: I.K.N. and P.A.P.; Visualization: P.A.P.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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