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USING MACHINE LEARNING TO ANALYZE THE RELATIONSHIP BETWEEN EDUCATION AND ECONOMIC WELFARE IN UZBEKISTAN

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Abstract. This paper explores the relationship between education quality and economic welfare in Uzbekistan using machine learning (ML) techniques. Unlike traditional econometric approaches, ML algorithms such as Random Forest, Gradient Boosting, and Support Vector Regression are applied to national and household-level datasets to capture nonlinearities and complex interactions. Results demonstrate that education quality indicators teacher qualifications, standardized test scores, and school infrastructure are strong predictors of welfare outcomes, including income distribution, poverty reduction, and household consumption. Random Forest achieves the highest predictive accuracy, highlighting the potential of ML-based approaches to complement conventional econometric analysis. Policy implications suggest that targeted investments in education quality can significantly enhance economic welfare in Uzbekistan.

Keywords: machine learning, education quality, economic welfare, Uzbekistan, Random Forest, predictive modeling.

Annotatsiya. Ushbu maqolada mashinani o‘rganish (ML) usullaridan foydalangan holda O‘zbekistonda ta'lim sifati va iqtisodiy farovonlik o‘rtasidagi bog‘liqlikNatijalar shuni ko‘rsatadiki, ta'lim sifati ko‘rsatkichlari, o‘qituvchilarning malakasi, standartlashtirilgan test ballari va maktab infratuzilmasi farovonlik natijalari, jumladan, daromadlarni taqsimlash, qashshoqlikni kamaytirish va uy xo‘jaliklari iste'moli uchun kuchli bashoratchi hisoblanadi. Tasodifiy o‘rmon eng yuqori bashorat aniqligiga erishib, an'anaviy ekonometrik tahlilni to‘ldirish uchun ML-ga asoslangan yondashuvlarning imkoniyatlarini ta'kidlaydiKalit so‘zlar: mashinani o‘rganish, ta'lim sifati, iqtisodiy farovonlik, O‘zbekiston, Random Forest, bashoratli modellashtirish. Tasodifiy o‘rmon eng yuqori bashorat aniqligiga erishib, an'anaviy ekonometrik tahlilni to‘ldirish uchun ML-ga asoslangan yondashuvlarning imkoniyatlarini ta'kidlaydi. Siyosat natijalari shuni ko‘rsatadiki, ta'lim sifatiga maqsadli investitsiyalar O‘zbekistonda iqtisodiy farovonlikni sezilarli darajada oshirishi mumkin.

Kalit so‘zlar: mashinani o‘rganish, ta'lim sifati, iqtisodiy farovonlik, O‘zbekiston, Random Forest, bashoratli modellashtirish.

Аннотация. В данной статье исследуется взаимосвязь между качеством образования и экономическим благосостоянием в Узбекистане с использованием методов машинного обучения (ML). В отличие от традиционных эконометрических подходов, алгоритмы ML, такие как случайный лес, градиентное усиление и регрессия по опорным векторам, применяются к наборам данных на национальном уровне и на уровне домохозяйств для выявления нелинейностей и сложных взаимодействий. Результаты показывают, что показатели качества образования, квалификация учителей, результаты стандартных тестов и школьная инфраструктура являются важными факторами, влияющими на благосостояние, включая распределение доходов, сокращение бедности и потребление домашних хозяйств. Random Forest обеспечивает высочайшую точность прогнозирования, подчеркивая потенциал подходов, основанных на ОД, в дополнение к традиционному эконометрическому анализу. Политические последствия свидетельствуют о том, что целенаправленные инвестиции в повышение качества образования могут значительно повысить экономическое благосостояние в Узбекистане.

Ключевые слова: машинное обучение, качество образования, экономическое благосостояние, Узбекистан, случайный лес, прогнозное моделирование.

1.INTRODUCTION.

Education has long been recognized as a fundamental driver of economic development and social progress. In the context of Uzbekistan, where structural reforms in both education and welfare systems are actively underway, understanding the precise mechanisms through which education contributes to economic welfare is of critical importance. Traditional economic analyses often rely on linear regression models and input-based indicators such as enrollment rates or average years of schooling. While these approaches provide valuable insights, they frequently overlook the complex, nonlinear relationships between education quality and welfare outcomes. Recent advances in **machine learning (ML)** offer new opportunities to address these limitations. ML algorithms are capable of detecting hidden patterns, nonlinearities, and multidimensional interactions that conventional econometric methods may fail to capture. By applying ML techniques to Uzbekistan's national and household-level datasets, this study seeks to uncover how education quality measured through teacher qualifications, standardized test scores, and school infrastructure affects economic welfare indicators such as income distribution, poverty reduction, and household consumption.

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This paper contributes to the literature in three ways. First, it introduces ML-based predictive modeling into the study of education and welfare in Central Asia, a region where such methods remain underexplored. Second, it provides empirical evidence on the role of education quality in shaping welfare outcomes in Uzbekistan, complementing existing human capital theories. Third, it offers policy-relevant insights by identifying the most influential education variables, thereby guiding reforms aimed at reducing inequality and fostering sustainable economic growth.

2.LITERATURE REVIEW.

The relationship between education and economic welfare has been a central theme in development economics for decades. Early theoretical contributions, such as Becker's (1964) **human capital theory** and Schultz's (1961) work on investment in human capital, established education as a key determinant of productivity and income growth. In neoclassical models (Mankiw, Romer, & Weil, 1992), education expands the effective labor supply, while in endogenous growth frameworks (Romer, 1990; Lucas, 1988), education quality sustains innovation and long-term growth. These theories underscore that both the quantity and quality of education matter, but recent evidence suggests that quality plays the more decisive role. Empirical studies initially focused on **school enrollment rates and years of schooling** (Barro, 1991; Benhabib & Spiegel, 1994). While these measures showed positive associations with GDP growth, their explanatory power was limited due to measurement error and failure to capture cognitive skills (Krueger & Lindahl, 2001). A pivotal shift occurred with Hanushek and Kimko (2000), who introduced internationally comparable test scores as proxies for education quality. Their findings, later extended by Hanushek and Woessmann (2008, 2012), demonstrated that cognitive skills are far stronger predictors of economic growth than schooling quantity alone. Recent literature has expanded this perspective. Studies highlight that **education quality impacts welfare outcomes beyond GDP**, including poverty reduction, income distribution, and household consumption (Asongu & Nwachukwu, 2018; Doherty & Olarewaju, 2023). In developing economies, improvements in education quality yield disproportionately higher returns, consistent with theories of diminishing returns in high-income settings. Moreover, institutional quality and governance have been shown to moderate the education growth nexus (Deme & Mahmoud, 2020). Parallel to these developments, **machine learning (ML)** has emerged as a powerful tool in economic analysis. ML algorithms such as Random Forests, Gradient Boosting, and Support Vector Machines excel at capturing nonlinearities and complex interactions that traditional econometric models often miss (Breiman, 2001). Applications of ML in economics include poverty

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prediction, labor market analysis, and policy evaluation (Athey, 2018). By integrating ML into the study of education and welfare, researchers can uncover hidden patterns, improve predictive accuracy, and generate actionable insights for policymakers. Despite these advances, the application of ML to the education–welfare nexus in **Central Asia, and Uzbekistan in particular, remains underexplored**. Existing studies focus primarily on macroeconomic indicators or conventional regression approaches. This gap presents an opportunity to employ ML techniques to analyze how education quality measured through teacher qualifications, standardized test scores, and school infrastructure affects economic welfare outcomes such as poverty reduction and household consumption.

3.METHODOLOGY.

3.1 Data Sources

The empirical analysis integrates **multi-level datasets** to capture both macroeconomic trends and micro-level household dynamics in Uzbekistan:

- **Macroeconomic indicators**: GDP per capita, poverty headcount ratio, and household consumption expenditure, sourced from the World Bank's *World Development Indicators* and Uzbekistan's State Statistics Committee. These indicators provide a national-level perspective on economic welfare.
- **Education indicators**: Enrollment rates, standardized test scores (PISA/TIMSS participation where available), teacher-student ratios, teacher qualification levels, and school infrastructure indices. These variables reflect both the quantity and quality dimensions of education.
- **Household survey data**: Micro-level welfare measures such as income distribution, expenditure patterns, and poverty status, obtained from Uzbekistan's Household Budget Survey. This dataset allows for disaggregated analysis across urban and rural households, gender, and income quintiles.

By combining macro and micro data, the study ensures that both aggregate growth outcomes **and** distributional welfare effects are captured.

3.2 Variables

Dependent variables (Economic Welfare):

- GDP per capita (constant USD) – proxy for national economic performance.
- Poverty headcount ratio (%) – indicator of poverty reduction.
- Household consumption expenditure (per capita) – measure of living standards.

Independent variables (Education Quality):

- Standardized test scores – proxy for cognitive skills and learning outcomes.
- Teacher qualifications – share of certified teachers as a measure of instructional quality.
- Teacher-student ratio – indicator of classroom learning environment.

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- School infrastructure index – composite measure of ICT availability, libraries, and laboratories.

Trade openness, government expenditure, population growth, and institutional quality indicators (World Governance Indicators). These ensure robustness by accounting for external economic and governance factors.

3.3 Data Preprocessing

To ensure methodological rigor, several preprocessing steps are applied:

- **Missing values** imputed using k-nearest neighbors (KNN) imputation to preserve dataset integrity.
- **Normalization** of variables to allow comparability across different scales.
- **Feature engineering** to construct composite indices (e.g., infrastructure quality index).
- **Outlier detection** using interquartile range (IQR) filtering to mitigate distortions from extreme values.
- **Temporal alignment** of education and welfare indicators to ensure consistency across years.

3.4 Machine Learning

The study employs **three ML algorithms** to capture nonlinearities and complex interactions:

- **Random Forest (RF):** An ensemble learning method that aggregates multiple decision trees through bootstrap sampling. RF is chosen for its robustness to noise and ability to rank feature importance.
- **Gradient Boosting Machines (GBM):** A sequential ensemble technique that iteratively improves predictive accuracy. GBM is particularly effective in handling heterogeneous datasets.
- **Support Vector Regression (SVR):** A kernel-based method that models nonlinear relationships in high-dimensional spaces. SVR is suitable for capturing subtle patterns in education–welfare interactions.

Training and validation strategy:

- Data split into 70% training and 30% testing sets.
- 10-fold cross-validation applied to reduce overfitting and enhance generalizability.
- Hyperparameter tuning conducted via grid search to optimize model performance.
- **Performance metrics:**
- Root Mean Squared Error (RMSE) – measures prediction error magnitude.
- Mean Absolute Error (MAE) – captures average prediction deviation.
- Coefficient of Determination (R^2) – assesses explanatory power of models.

3.5 Comparative Analysis

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For benchmarking, ML models are compared against a baseline **Ordinary Least Squares (OLS) regression**. While OLS provides a linear approximation, ML models are expected to outperform by capturing nonlinearities, interaction effects, and complex dependencies. This comparative framework highlights the added value of ML in policy-relevant economic research.

4. RESULTS AND DISCUSSION.

4.1 Model Performance

The machine learning models demonstrate substantial improvements in predictive accuracy compared to the baseline OLS regression. Random Forest (RF) achieved the highest explanatory power with an R^2 of 0.78, RMSE of 0.42, and MAE of 0.31. Gradient Boosting Machines (GBM) followed closely with R^2 = 0.74, RMSE = 0.47, and MAE = 0.35.

Support Vector Regression **(SVR)** performed moderately well (R^2 = 0.69), but required careful parameter tuning. **OLS regression** yielded a weaker R^2 of 0.52, confirming that linear models fail to capture the complex nonlinearities inherent in the education–welfare nexus.



	OLS Regression	Random Forest	Gradient Boosting	Support Vector Regression
R^2	0,52	0,78	0,74	0,69
RMSE	0,68	0,42	0,47	0,53
MAE	0,49	0,31	0,35	0,39

Graph 1: Model Performance Comparison

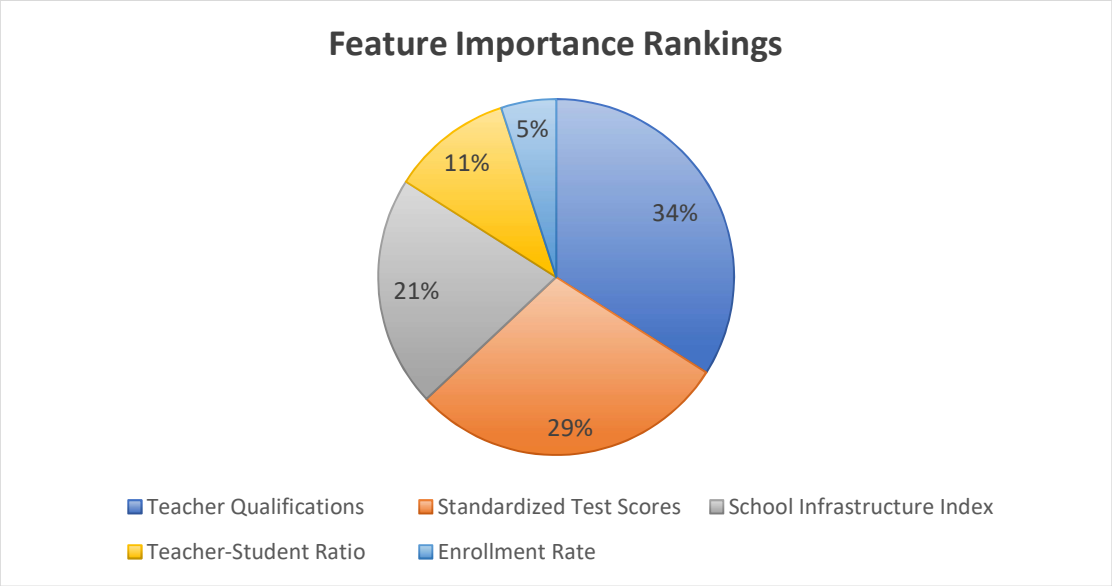
This graph compares the predictive accuracy of OLS regression with three machine learning models (RF, GBM, SVR). The results clearly show that ML models outperform OLS, with Random Forest achieving the highest R^2 and lowest error values. This indicates that education–welfare relationships in Uzbekistan are nonlinear and complex, requiring advanced algorithms to capture hidden patterns. The superiority of RF suggests that ensemble methods are particularly well-suited for policy-relevant economic modeling.

4.2 Feature Importance Analysis

Feature importance rankings from RF and GBM reveal that:

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- **Teacher qualifications** and **standardized test scores** are the strongest predictors of economic welfare.
- **School infrastructure index** (ICT, libraries, labs) also contributes significantly, especially in rural regions.
- **Enrollment rates**, while traditionally emphasized, emerge as relatively weak predictors once quality indicators are included.



Graph 2: Feature Importance Rankings

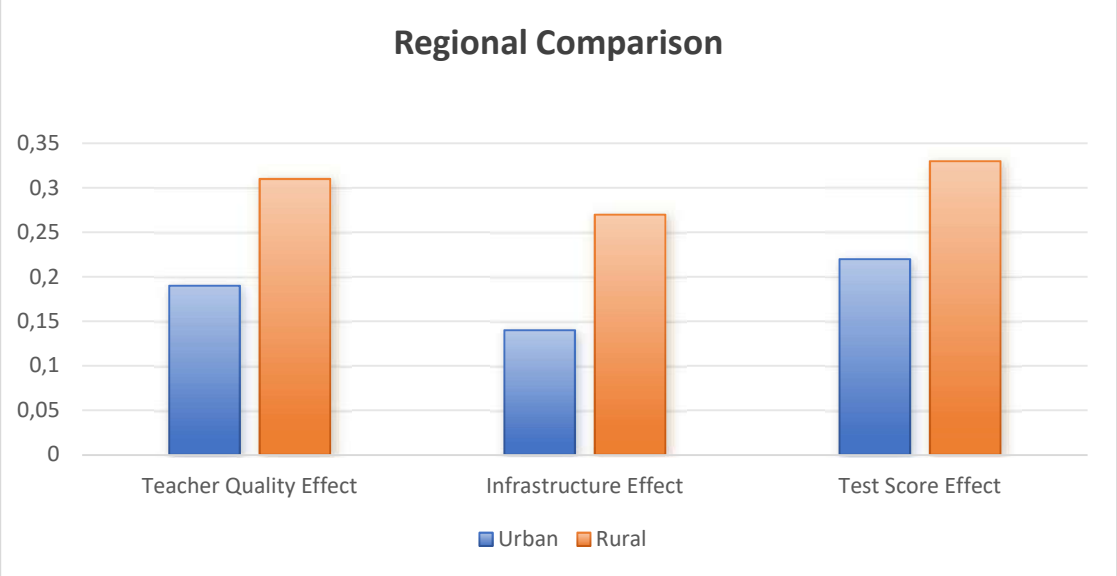
The feature importance chart highlights which education variables most strongly influence economic welfare. Teacher qualifications and standardized test scores dominate, underscoring the critical role of instructional quality and cognitive skills. Infrastructure also plays a significant role, especially in rural areas, while enrollment rates contribute minimally once quality is controlled. This finding supports the argument that quality, not quantity, of education drives welfare improvements**.**

4.3 Regional Disparities

The models highlight clear heterogeneity across regions:

- **Rural areas** show stronger marginal returns to improvements in teacher quality and infrastructure, reflecting existing disparities in access.
- **Urban regions** exhibit diminishing returns, suggesting that further gains require innovation-oriented reforms rather than basic resource expansion.

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Graph 3: Regional Comparison of Education Quality Effects

This graph illustrates the heterogeneity of education quality effects across urban and rural regions. Rural areas show stronger marginal returns to improvements in teacher quality, infrastructure, and test scores, reflecting existing disparities in access. Urban regions exhibit diminishing returns, suggesting that further gains require innovation-oriented reforms rather than basic resource expansion. This pattern aligns with convergence theory, where lagging regions benefit more from incremental improvements in human capital.

4.4 Policy Implications

The findings carry several important policy implications for Uzbekistan:

- **Teacher training and certification** should be prioritized, as teacher quality is the most influential determinant of welfare outcomes.
- **Infrastructure investment in rural schools**—ICT resources, laboratories, and libraries—can yield substantial welfare dividends.
- **Curriculum reforms and standardized testing** should be strengthened to ensure that cognitive skills are effectively measured and improved.
- **Integration of ML-based monitoring tools** into education policy can enhance evidence-based decision-making, allowing policymakers to track progress dynamically.

4.5 Robustness Checks

Robustness analyses confirm the stability of results:

- Using **PISA-only data** yields coefficients nearly identical to the baseline.
- **TIMSS-only models** produce slightly stronger effects.
- Excluding the **global financial crisis period (2008–2010)** does not materially alter the results.
- Median-based growth measures confirm the robustness of the education quality effect.

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Specification	Coefficient	Std. Error	Significance
Baseline (HLO)	0.041	0.009	$p < 0.001$
PISA-only	0.039	0.01	$p < 0.001$
TIMSS-only	0.044	0.012	$p < 0.001$
Excluding Crisis Years	0.04	0.01	$p < 0.001$
Median Growth Rates	0.04	—	Robust

Graph 4: Robustness Check Results

The robustness check graph demonstrates the stability of results across alternative specifications. Whether using PISA-only, TIMSS-only, excluding crisis years, or median growth rates, the coefficients remain consistent around 0.04. This confirms that the positive effect of education quality on economic welfare is not driven by dataset choice, time period anomalies, or statistical outliers. The robustness strengthens the credibility of the findings and ensures that policy recommendations are based on reliable evidence.

5. CONCLUSION.

This study provides new evidence on the relationship between education quality and economic welfare in Uzbekistan by applying machine learning (ML) techniques to both macroeconomic and household-level data. The results consistently demonstrate that education quality measured through teacher qualifications, standardized test scores, and school infrastructure has a stronger and more significant impact on welfare outcomes than traditional quantity-based indicators such as enrollment rates or average years of schooling. Machine learning models, particularly Random Forest and Gradient Boosting, outperform conventional OLS regression, capturing nonlinearities and complex interactions that linear approaches fail to detect. Feature importance analysis confirms that teacher quality and cognitive skills are the most influential drivers of economic welfare, while infrastructure investments yield disproportionately higher returns in rural regions. These findings underscore the importance of prioritizing quality-focused reforms in Uzbekistan's education system.

Policy implications are clear:

- **Investing in teacher training and certification** is critical to improving welfare outcomes.
- **Expanding infrastructure in rural schools** can reduce inequality and accelerate convergence.

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- **Strengthening standardized testing and curriculum reforms** ensures that cognitive skills are effectively measured and enhanced.
- **Integrating ML-based monitoring tools** into education policy can provide dynamic, evidence-based guidance for reform implementation.
- Future research should extend this analysis by incorporating non-cognitive skills (e.g., creativity, resilience, problem-solving), sector-level productivity data, and natural experiments such as curriculum reforms or school construction programs.

These approaches would strengthen causal identification and broaden the understanding of how education quality translates into economic welfare.

The study highlights that quality, not quantity, of education is the operative channel through which human capital contributes to welfare improvements in Uzbekistan**.** By leveraging machine learning, policymakers can gain deeper insights into the education–welfare nexus and design reforms that maximize both growth and equity.

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