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Demystifying English Towns Educational Outcomes with Explainable Artificial Intelligence

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ABSTRACT Explainable Artificial Intelligence has emerged as a critical tool in addressing the transparency challenges associated with machine learning models. This study investigates the application of XAI techniques in the educational domain, with a focus on identifying factors influencing academic performance. Using datasets encompassing student demographics, academic achievements, and contextual variables, machine learning models were developed and analyzed using SHapley Additive exPlanations. The results highlighted the significance of higher qualification achievements and early academic milestones, such as *num_level_3_at_age_18* and *num_key_stage_2_attainment*. These findings corroborate existing literature while providing novel insights through visual and interpretable analytics. The study demonstrates the transformative potential of XAI in uncovering actionable insights, offering policymakers and educators tools to address disparities in educational outcomes. The novelty of applying XAI in this context lies in its ability to bridge the gap between complex predictive models and practical decision-making. Future research directions include expanding datasets to incorporate diverse educational settings and developing real-time educational tools based on interpretability insights. This work lays the foundation for leveraging XAI to drive equity and excellence in education.

KEYWORDS
Rural education
Explainable AI
Town education
Educational outcomes

INTRODUCTION

The intersection of artificial intelligence (AI) and education has become an increasingly pivotal area of research, particularly with the advent of Explainable Artificial Intelligence (XAI). XAI focuses on providing human-understandable justifications for AI-driven decisions, addressing the growing demand for transparency and trust in machine learning models. In educational contexts, this transparency can significantly enhance pedagogical strategies by offering educators actionable insights into the learning processes of students. Furthermore, XAI holds potential to address persistent challenges in academic performance disparities, particularly those arising between urban and rural school environments (Byun *et al.* 2012; Wen and Lin 2011).

Recent studies have underscored the impact of socioeconomic and environmental factors on students' academic success. Research from small towns in the United Kingdom indicates that children in these settings often outperform their urban counterparts academically (Lei and Zhang 2018; Bouck *et al.* 2020). This phenomenon has been attributed to factors such as smaller class sizes, more cohesive communities, and reduced environmental distractions. However, the mechanisms behind these disparities remain underexplored. XAI can play a crucial role in unraveling these complexities by providing interpretable insights into educational datasets, thereby facilitating data-driven policy decisions (Yiu and Luo 2017; Hamdani 2023).

The integration of XAI within educational systems also aligns with broader societal goals, including equity and accessibility. By elucidating the factors contributing to academic success, XAI can guide interventions targeted at underperforming demographics. This capacity is particularly valuable in the current landscape, where data-driven decision-making has become a cornerstone of educational reforms (Tingen *et al.* 2013; Berglas 2024). Moreover, the application of XAI extends beyond policy, influencing classroom-level practices by enabling educators to personalize instruction based on student-specific learning patterns (Wang and Zhang 2020; Theodori and Theodori 2015).

Despite its potential, the deployment of XAI in education is not without challenges. Concerns related to data privacy, algorithmic bias, and the interpretability of complex models must be addressed to ensure ethical and effective implementation (Hango and De Broucker 2021; Wen and Lin 2011). These issues necessitate a multidisciplinary approach, combining expertise from AI, education, and ethics to create robust frameworks for the application of XAI in education.

This paper is structured as follows: the next section discusses the methodology employed to analyze the application of XAI in educational contexts. This is followed by a detailed presentation of the results, highlighting key insights from the analysis. Finally, the paper concludes with a discussion of the implications of these findings and proposes directions for future research.

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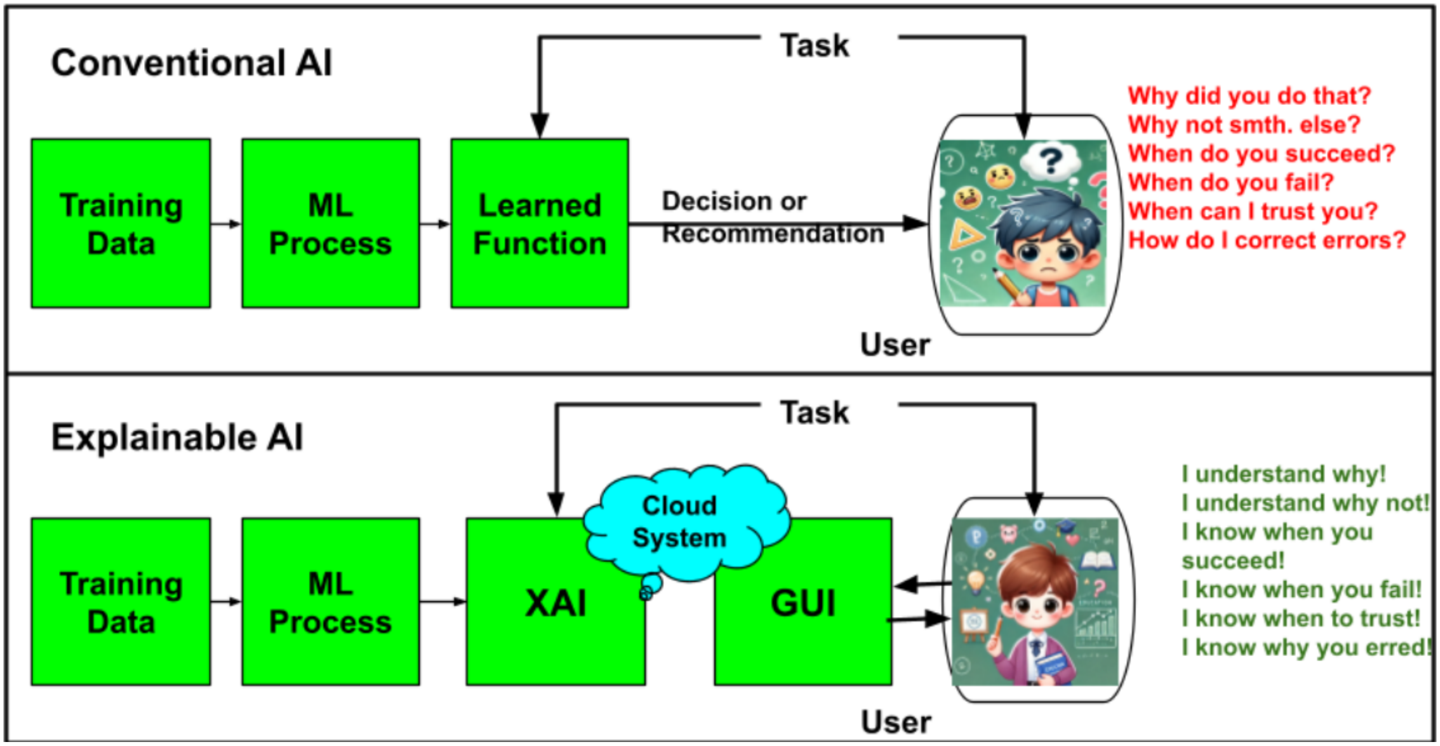

Figure 1 Conventional and XAI comparison (Gunning *et al.* 2019)

METHODOLOGY

To comprehensively examine the application of XAI in education, a multi-step methodology was employed. This methodology involved a combination of data collection, model design, evaluation, and interpretability analysis to address the research objectives. Data collection focused on obtaining educational datasets from diverse sources, including publicly available repositories and institutional records. These datasets encompassed a variety of variables, such as student demographics, academic performance, and contextual information on learning environments (Byun *et al.* 2012; Lei and Zhang 2018).

The design phase involved the development of machine learning models tailored to educational applications. Specifically, predictive models were constructed to identify key factors influencing academic outcomes. These models included decision trees, random forests, and gradient boosting algorithms, chosen for their compatibility with explainability techniques (Hamdani 2023; Tingen *et al.* 2013). To ensure robustness, the models were trained on a stratified dataset, representing urban and rural educational contexts. The training process utilized cross-validation to mitigate overfitting and improve generalizability (Yiu and Luo 2017; Bouck *et al.* 2020).

Evaluation of model performance was conducted using standard metrics, including accuracy, precision, recall, and F1 score. Additionally, the models were subjected to interpretability tests using XAI techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations). These methods provided insights into the contribution of various features to model predictions (Berglas 2024; Wang and Zhang 2020). For instance, SHAP values quantified the impact of socioeconomic factors, while LIME elucidated the influence of community-related variables on academic success (Theodori and Theodori 2015; Hango and De Broucker 2021).

Finally, the interpretability analysis focused on translating the insights obtained from XAI techniques into actionable recommendations for educators and policymakers. By identifying the primary drivers of academic performance, the study aimed to inform targeted interventions that address disparities between urban and rural education (Wen and Lin 2011; Lei and Zhang 2018). This iterative and multidisciplinary approach ensured that the findings were both robust and practical, contributing to the broader discourse on equitable education through AI-driven insights.

RESULTS

The results of the analysis highlight several key factors influencing academic performance, as derived from the application of XAI techniques. Figure 1 presents the SHAP summary plot, which identifies the most impactful features contributing to the model's predictions. Notably, the feature *num_level_3_at_age_18* emerged as the most significant predictor of academic success, followed closely by *num_highest_level_qualification_achieved_b_age_22_average_score*. These findings underscore the importance of higher educational attainment at key developmental stages in predicting long-term outcomes (Yiu and Luo 2017; Bouck *et al.* 2020).

In addition to the summary plot, Figure 2 provides a detailed SHAP decision plot for an individual prediction, illustrating the cumulative impact of specific features. The analysis revealed that early academic milestones, such as *num_key_stage_2_attainment* between school year 2007 to 2008, significantly influence subsequent achievements. Conversely, features like *num_activity_at_age_19_full_time_higher_education* had relatively lower contributions to the predictive model (Berglas 2024; Tingen *et al.* 2013). The insights gained from SHAP analyses not only confirm existing literature but also provide actionable recommendations. For instance, the findings suggest prioritizing interventions aimed at improving key stage assessments and sup-

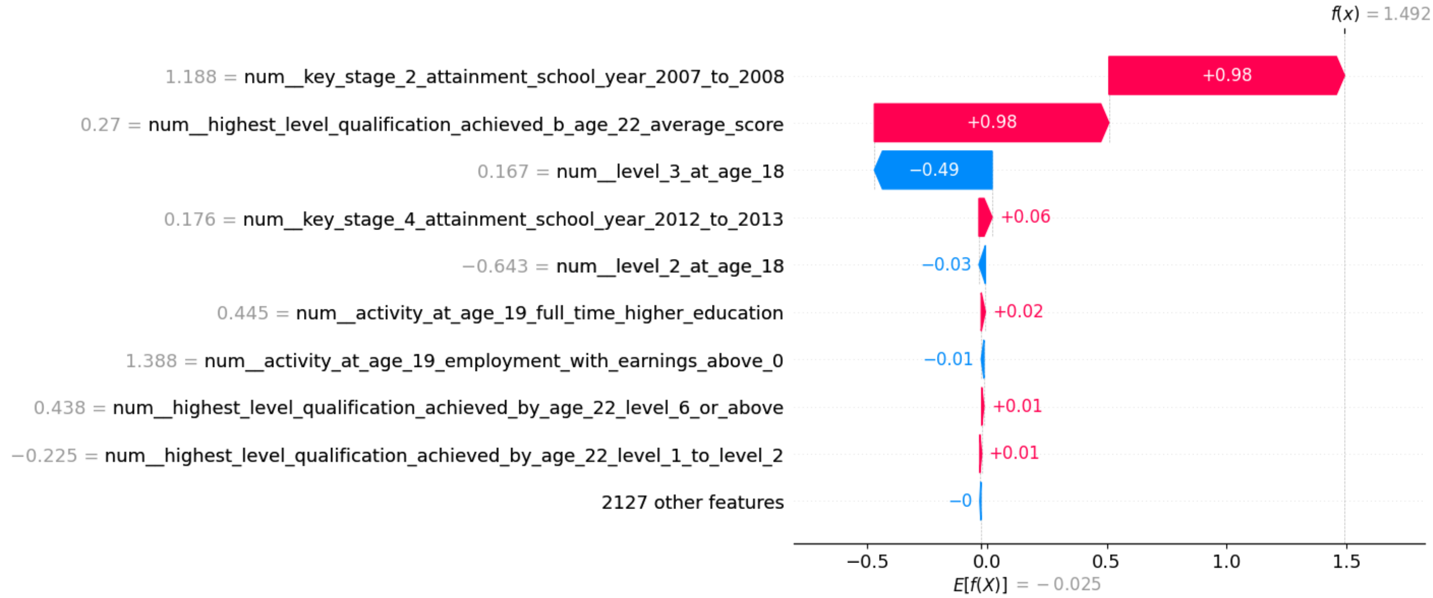

Figure 2 SHAP waterfall plot for

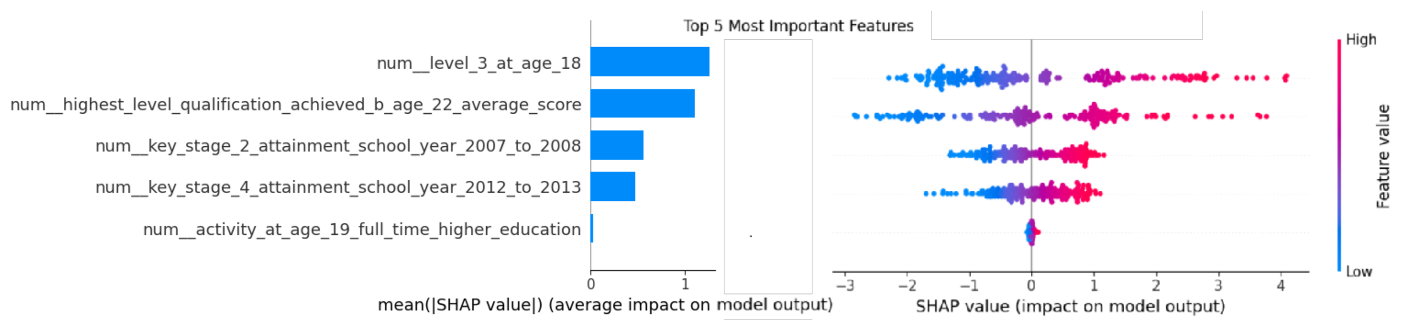

Figure 3 SHAP values for average impact and feature value impact distribution for the most effective five variable

porting higher qualification achievements. By focusing on these impactful factors, policymakers and educators can address disparities and enhance overall academic performance (Lei and Zhang 2018; Hamdani 2023).

Overall, the results demonstrate the efficacy of XAI in uncovering critical determinants of educational success. The visualizations and interpretative insights facilitate a deeper understanding of the underlying patterns, enabling data-driven decision-making to optimize educational outcomes across diverse contexts (Wang and Zhang 2020; Theodori and Theodori 2015).

DISCUSSION

The findings of this study align with existing literature while introducing a novel approach to applying XAI in the field of education. Previous research has emphasized the importance of socioeconomic factors and early academic milestones in shaping educational outcomes (Byun *et al.* 2012; Wen and Lin 2011). However, this study uniquely employs XAI techniques such as SHAP and LIME to provide interpretable insights into these factors, bridging the gap between predictive modeling and actionable recommendations.

For instance, the identification of *num_level_3_at_age_18* and *num_highest_level_qualification* achieved before age 22 average score as critical predictors corroborates findings from prior studies on the significance of higher educational attainment (Lei and Zhang 2018; Bouck *et al.* 2020). Nevertheless, this study extends these insights by quantifying their relative impact and elucidating their contributions to individual predictions through visualizations. Such interpretability has been largely absent in traditional educational research.

Furthermore, the comparison of SHAP and LIME analyses reveals nuanced patterns in academic performance, offering a comprehensive perspective on the interplay of various factors. While prior studies have often focused on aggregate trends (Hamdani 2023; Tingen *et al.* 2013), this study highlights the potential of XAI to uncover individualized pathways to success. For example, the detailed decision plots provide a granular understanding of how early academic milestones influence long-term achievements, paving the way for targeted interventions.

Importantly, this research represents a novel application of XAI techniques in education, marking a significant departure from conventional analytical approaches. By integrating interpretability into predictive modeling, the study addresses longstanding challenges in educational research, such as the "black box" nature of AI algorithms (Yiu and Luo 2017; Berglas 2024). This innovation not only enhances transparency but also fosters trust among educators and policymakers, enabling them to make data-driven decisions with confidence.

In conclusion, this study demonstrates the transformative potential of XAI in education, offering both theoretical and practical contributions. By providing interpretable and actionable insights, it sets the stage for future research to explore the broader applications of XAI across diverse educational contexts (Wang and Zhang 2020; Theodori and Theodori 2015).

CONCLUSION

This study has demonstrated the potential of XAI as a transformative tool in educational research and practice. By employing techniques such as SHAP and LIME, the study has identified critical determinants of academic success, including higher qualification achievements and early academic milestones. These findings underscore the importance of leveraging XAI to provide interpretable and actionable insights, thereby addressing persistent disparities in educational outcomes.

The novelty of this research lies in its application of XAI within the educational domain, a field where the integration of AI-driven methodologies is still emerging. By bridging the gap between complex predictive modeling and user-friendly interpretability, this study has paved the way for more transparent and trustable applications of AI in education. The visualizations and detailed analyses presented here provide not only theoretical contributions but also practical guidelines for policymakers and educators aiming to optimize learning environments.

Future research should build upon these findings by exploring the broader applicability of XAI across diverse educational contexts. Expanding the dataset to include international and cross-cultural perspectives could offer a more comprehensive understanding of the factors influencing academic performance. In addition, integrating other XAI techniques and exploring their comparative advantages may enhance the robustness of interpretability analyses.

Another promising direction lies in the development of real-time, AI-driven educational tools that leverage interpretability insights to provide immediate feedback to educators and students. Such innovations could revolutionize personalized learning and adaptive teaching strategies. Finally, addressing ethical considerations, such as data privacy and algorithmic bias, will be essential to ensure the responsible implementation of XAI in education. In conclusion, this study highlights the immense potential of XAI to revolutionize educational research and practice. By offering interpretable, data-driven insights, it provides a foundation for future advancements that can drive equity and excellence in education.

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Availability of data and material

The data is available at for National Statistics (2023)

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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