JPPIPA 11(10) (2025)

Jurnal Penelitian Pendidikan IPA

http://jppipa.unram.ac.id/index.php/jppipa/index

Parental Income and Education as Predictors of Physics Exam Success: A Neural Network and Random Forest Regression Analysis

Mutia Rosiana Nita Putri[1], Kertanah[2*], Mugni Bustari[3], Muhammad Aminuddin[4], Baiq Husnul Khotimah[5]

[1] Mutia Rosiana Nita Putri, Tadris Kimia, Institut Studi Islam Sunan Doe, East Lombok, Indonesia.
[2] Statistika, Universitas Hamzanwadi, East Lombok, Indonesia.
[3] Sekolah Monte Sienna, Batam, Indonesia.
[4] Tadris IPA, Institut Studi Islam Sunan Doe, East Lombok, Indonesia.
[5] SMA Negeri 4 Praya, Central Lombok, Indonesia.

Received: July 25, 2025
Revised: September 09, 2025
Accepted: October 25, 2025
Published: October 31, 2025

Corresponding Author:
Mutia Kertanah
kertha90@gmail.com

DOI: 10.29303/jppipa.v11i10.12307

Abstract: This study examines the relationship between the socioeconomic status (SES) of tenth-grade students at SMA Negeri 4 Praya and their final physics exam scores for the 2022/2023 academic year. SES indicators include parents' income and education level, collected via qualitative questionnaires and quantitative assessment of physics exam scores. Random Forest Regression and Neural Network techniques were used for analysis. The results showed no significant relationship between SES and physics scores. For parents' education level, Neural Network Regression yielded a Mean Squared Error (MSE) of 323.78 and an R^2 score of -0.0129, while Random Forest Regression produced an MSE of 327.08 and an R^2 score of -0.0232. Similarly, for parents' income, Random Forest Regression resulted in an MSE of 327.08 and an R^2 score of -0.0232, and Neural Network Regression yielded an MSE of 323.78 and an R^2 score of -0.0129. These negative R^2 scores indicate that SES does not significantly impact physics exam scores, highlighting the complexity of factors influencing academic performance. This research suggests that other variables may play a more critical role in determining students' success in physics. This research underscores the need for a more comprehensive approach to understanding and supporting student achievement in education.

Keywords: Academic performance; Neural network; Physics exam score; Random forest regression; Socio-economic status.

Introduction

Social-Economic Status (SES) is considered an important determinant of psychological and life outcomes in many aspects (Duncan & Menestrel, 2019). Therefore, it is necessary to define, conceptualize, SES in the first place (Antonoplis, 2023). Some studies show the definition of SES such as Dubois et al. (2015) that it is people's relative standing in society based on wealth and/or education. Next, research from Hittner et al., (2019) that SES can be defined as a representation of an individual's relative position in an economic-social-cultural hierarchy tied to power, prestige, and control over resources. In the same way, Belmi et al. (2020) find that SES is a multidimensional construct that encompasses people's objectives resources (i.e., income, education, parental education) as well as their subjective assessments of their standing in society (e.g., subjective rank).

How to Cite:
Putri, M. R. N., Kertanah, Bustari, M., Aminuddin, M., & Khotimah, B. H. (2025). Parental Income and Education as Predictors of Physics Exam Success: A Neural Network and Random Forest Regression Analysis. *Jurnal Penelitian Pendidikan IPA*, *11*(10), 581–588. https://doi.org/10.29303/jppipa.v11i10.12307

Exploring literature about socio-economic status (parental income and education) and students' achievement in physics exam is necessary to support this study. Many literatures propose SES as predictors of students' academic achievement and much evidence about this popular belief and evidence found in developing countries. Erdem & Kaya (2023) reveal that there is a positive correlation between SES and student achievement. Study in secondary school about physics performance also shares similar trends in college for students majoring in physics. Similar study by Krishnan et al. (2023) found out that SES is one of the most studied and consistent predictors of students' academic achievement. Thus, unfortunately, children from low-income families face disadvantages in developmental outcomes, particularly cognitive areas (Washbrook et al., 2014).

Interestingly, a different outcome, study from Rodríguez-Hernández et al. (2020) extensively investigated the relationship between SES and academic performance. The content analysis from this study examines how SES and academic performance are measured. This study conducts a meta-analysis that estimates the effect size of the relationship between SES and academic performance in higher education. Findings suggest that SES is measured through education, occupation, income, household resources, and neigh bour hood resources, while academic performance in higher education is measured through achievement, competencies, and persistence. Furthermore, the meta-analysis reveals a positive yet weak relationship between SES and academic performance in higher education. Prior academic achievement, university experience, and working status are more strongly related to academic performance than SES. Even though, the study conducted for higher education, there is a valuable insight about the weak correlation between Socio-economic status and academic performance.

There is a huge tendency to associate parents' education and income, which are the components of SES, with students' performance and achievement at scientific literacy. Scientific literacy is essential skills and OECD as International Organization regularly conduct Program for International Student Assessment (PISA) to evaluate and measure Secondary school students in math, science, and reading. The Scientific Literacy test in PISA can be used to assess students' understanding of fundamental physics principles and their rationality in applying them, including decision-making (Deta et al., 2024).

There is an intertwined relationship between students' attitude towards physics and their family background. This is because the SES background of the family belongs to the environmental factors and in particular to the contextual affordances, it precedes and formulates both educational and socio-cognitive mechanisms. In particular, students from low socio-economic level were less interested in studying in STEM fields than their counterparts from higher socio-economic levels. The interest to continue study in STEM, also caused by students' way of thinking and claim that "Science is not for me". These claims about lower students' achievement in secondary school, particularly in physics mostly frond in public secondary school around developing countries include Indonesia. Students low interest towards physics, which influence the exam result, also one of the effects from their family background. Many study that mostly poor family do not concern for their children education. For example, study from Vadivel et al. (2023) concluded that most of the students with low socioeconomic status had poor achievements in their academics, which led them into the labour market at an early age. It has been found that parents with low socioeconomic backgrounds were less interested in educating their children. Kids from low SES backgrounds are more focused on employment instead of pursuing their studies after completing their secondary education. Such students end up in unskilled or blue-collar jobs. There is a need for parental education and awareness programs as well conducted by schools/universities and other concerned authorities. It can be concluded that parents' perspective towards science also influence the students' perception about science.

Based on the definition given by Nafea (2018), Machine learning is a branch of artificial intelligence (AI), enables computers and teaching machines to learn from past data and make informed decisions. Machine learning (ML) is recognized as one of the most promising areas of application in information technology, with its potential uses being nearly limitless, which has captured the interest of researchers and scientists, particularly in the field of education (Kucak et al., 2018) although its impact on research and practical applications in the educational sciences is still limited, it is continually growing (Hilbert et al., 2021).

There are several advantages of machine learning in educational context as follows (Nafea, 2018): tailored and personalized learning experiences to meet the needs of all students; content analytics to facilitate personalized learning; streamlined grading processes to minimize the time required for assessing student work; automation of repetitive tasks to help teachers save time on monotonous activities; and teachers can track students' progress to identify patterns and optimize their teaching methods.

Although still relatively new in the education sector, machine learning is increasingly being utilized as a tool to enhance educational outcomes. Therefore, this study aims to contribute to educational research by employing machine learning techniques to uncover valuable insights.

Despite extensive research on student satisfaction, there is a notable gap in the application of advanced machine learning techniques to analyse and predict the factors influencing this vital metric. Most previous studies have primarily utilized traditional statistical methods, which may not sufficiently capture the complex, nonlinear relationships among the various determinants of student satisfaction (Riyanto et al., 2024). To address this gap, the present research intends to leverage machine learning techniques, specifically Neural Network and Random Forest Regression, to explore the relationships between these variables while comparing the outcomes from both models.

This study has two primary objectives: to evaluate the impact of two key aspects of socioeconomic status (SES)—parental education and income—on physics exam scores through machine learning techniques; to compare the predictive accuracy and effectiveness of these models in uncovering the intricate relationships among the variables.

By implementing these machine learning approaches, this research aims to address the limitations of prior studies and provide a more robust and comprehensive understanding of the relationship between SES and physics exam scores. The comparative analysis of Random Forest and Neural Networks will not only illuminate the strengths and weaknesses of each model but also inform future research and practical applications within educational contexts.

The theoretical framework for this study draws on the relationship between socioeconomic status (SES) and academic achievement, specifically focusing on parental education and income as key indicators of SES. Numerous researches suggest that SES can significantly impact students' educational outcomes, often affecting access to resources, learning environments, and academic support. In this study, SES is hypothesized to influence students' physics exam scores, with parental income and education level serving as predictive variables. To test this relationship, Neural Network and Random Forest Regression algorithms are applied to analyse the data, leveraging these machine learning methods to explore both linear and nonlinear associations between SES and academic performance. The results contribute to a better understanding of the impact of SES on educational achievement in physics, offering insights that may be valuable for educational policy and support interventions aimed at enhancing academic success across diverse socioeconomic backgrounds.

Method

The research employed 5 main stages as is shown in Figure 1, from data collection to model interpretation/evaluation.

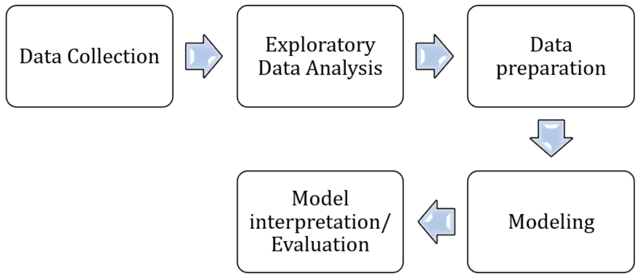


Figure 1. Research method flowchart

Data Collection

This study was conducted at SMA Negeri 4 Praya with a focus on tenth-grade students during the 2022/2023 academic year. Participants is consisted of approximately 107 students. The sample consisted of students who completed their final physics exams, and data related to their socioeconomic status (SES) was gathered. SES indicators were defined as parents' income and education level, as these variables are commonly associated with academic achievement in previous studies.

To collect SES data, a qualitative questionnaire was administered to the students, asking them to report their parents' highest level of education and monthly income. The final physics exam scores were used as the dependent variable, serving as a quantitative measure of student academic performance. The exam scores were sourced from the school records to ensure accuracy and standardization.

Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a method that utilizes descriptive statistics and visual tools to deepen understanding of data, primarily aimed at gaining insights, identifying outliers and anomalies, and evaluating underlying assumptions, making it a crucial first step before applying further statistical techniques (Camizuli & Carranza, 2018). The EDA was performed to achieve a thorough understanding of the raw dataset and to detect missing values, duplicates, and outliers (Riyanto et al., 2024).

The dataset comprises 2,147 entries across 20 columns, each representing different socio-economic statuses pertinent to the study. The included features are parental education, parental income, and the target variable, which is the physics exam score. These columns contain numerical data in the form of strings and integers, with only a few missing values, indicating minor incompleteness in the dataset. Visualisations were employed to investigate the relationships between variables, and these steps were essential for preparing the data for subsequent analysis.

Data preparation

During the data preparation phase, various techniques were employed to enhance the quality of the dataset. Missing values were addressed through imputation methods utilizing mean, median, and mode, ensuring that the data remained robust and complete. Duplicate entries were systematically removed to maintain the integrity of the dataset. Outliers were carefully identified and managed to reduce their potential impact on the analysis.

Additionally, feature selection was conducted to identify the most relevant variables for the study, allowing for a more focused and efficient analysis. Data transformations, including normalization and standardization, were applied to ensure that all features were on a comparable scale, promoting effective analysis. Hierarchical encoding was utilized to convert categorical variables into a numerical format, making them suitable for analytical procedures. Finally, the dataset was divided into training and testing sets, facilitating a comprehensive evaluation of the models.

Modeling

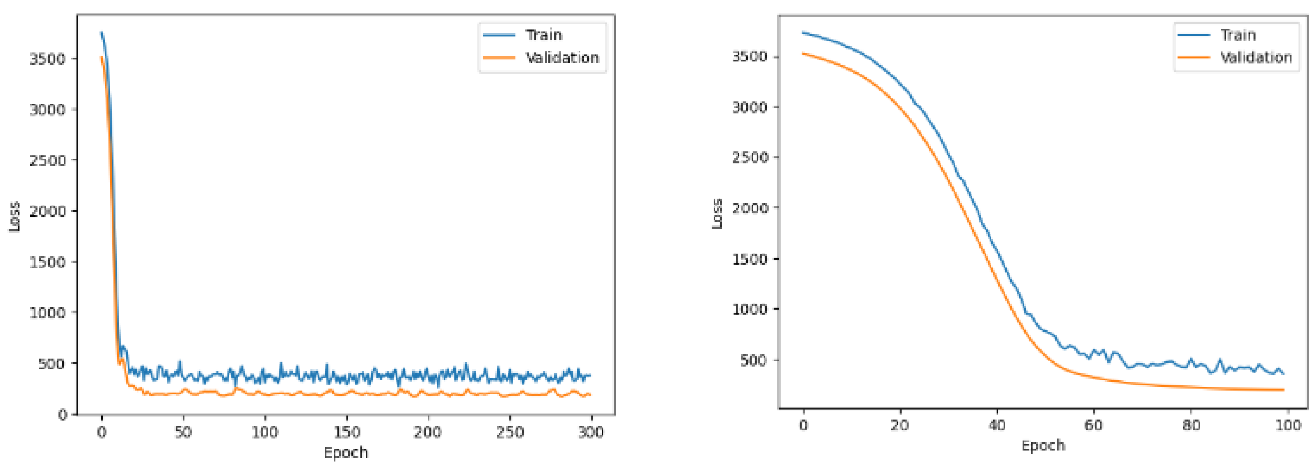
The relationship between socioeconomic status and physics exam scores was analysed using two machine learning techniques: Neural Network Regression and Random Forest Regression. These methods were chosen due to their ability to model complex, non-linear relationships between predictor and outcome variables. Both models were trained and tested using the same dataset.

Neural Network Regression

This deep learning method was used to model the relationship between SES and exam scores. Neural networks provide several benefits, such as creating feature-based classifiers, non-linear predictive models, easy to be implemented, learning faster with only less human's intervention, and potential to utilize both linear regression and classification algorithms comprehensively (Scardapane & Wang, 2017).

The neural network architecture involved several layers of neurons, each connected by weighted edges, to capture non-linear relationships (Scabini & Bruno, 2023). The analyses were conducted using Python, with libraries such as Keras for Neural Network implementation. Data was split into training and testing sets to validate the model's performance with ratio 80-20. The model architecture incorporated ReLU activation functions and was compiled with the Adam optimizer. Training was performed across 100-300 epochs with a batch size set to 32-64.

Plot training and validation loss of train and validation for both variables against physics exam score are illustrated in Figure 2a and 2b.



(a) (b)

Figure 2. Plot training and validation against physics exam score: (a) Parental education; and (b) Parental income

Random Forest Regression

Random forest is a robust machine learning algorithm that has shown significant success in various applications (Gong et al., 2018). This ensemble learning method was employed to assess the potential predictive power of SES variables on physics exam scores. Random Forest creates multiple decision trees based on subsets of the data and aggregates their results to improve accuracy and robustness (Doz et al., 2023; Mastour et al., 2023). The analyses were conducted using Python, with libraries such as Scikit-learn (Ahn, 2022; Rajamani & Iyer, 2023; Tran et al., 2022). Data was split into training and testing sets to validate the model's performance using the split ratio of 80-20. This ensemble technique trained several decision trees and combined their predictions through averaging, aiming to boost accuracy and reduce overfitting.

Model interpretation/evaluation

To assess the relationship between the models in predicting parental education and income with physics exam score, two metrics were employed. The first one is Mean Squared Error (MSE) Mean Squared Error (MSE) is a metric that measures the average squared difference between predicted and actual values in a model. Mathematical formula for MSE as represented by Formula 1.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (1)$$

A lower MSE indicates that the model's predictions are closer to the actual values, reflecting better performance and a higher accuracy in capturing data patterns. In contrast, a higher MSE suggests that the model's predictions deviate more significantly from the actual values, indicating poorer performance. Generally, a lower MSE is desirable, as it signifies closer alignment between the model's predictions and the real data.

Secondly, R^2 Score or coefficient of determination, measures how well a regression model explains the variability of the dependent variable. It quantifies the proportion of variance in the target variable that is predictable from the independent variables, which has Formula 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_1)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (2)$$

A high R^2 score indicates that the model accounts for a large proportion of the variance in the target variable, signifying a good fit to the data, while a low R^2 score suggests that the model explains only a small portion of the variance, indicating a poorer fit. R^2 is widely used to assess the quality of regression models, with a value closer to 1 representing a better fit and a value closer to 0 indicating that the model fails to capture much of the data's variability.

Result and Discussion

Relationship between parents' education and physics exam scores

The first analysis focused on parental education as a predictor of physics exam scores. The performance of the two models was as in Table 1.

Both models exhibited poor performance in predicting physics exam scores based on parental education. The negative R^2 scores suggest that neither Random Forest nor Neural Network models could explain the variability in students' performance using this predictor. The visualisation of these variables can be seen in Figure 1.

Table 1. Result of metrics between parents' education and physics exam scores

Model	MSE	R^2 Score
Neural Network Regression	323.77975	-0.01289
Random Forest Regression	327.08010	-0.02321

These findings imply that parental education, as measured in this study, does not have a significant impact on students' physics exam outcomes. This contradicts some previous studies that have identified parental education as an important factor in academic success. The inconsistency may be attributed to contextual factors unique to the student population at SMA Negeri 4 Praya, or other latent variables that were not captured in the analysis.

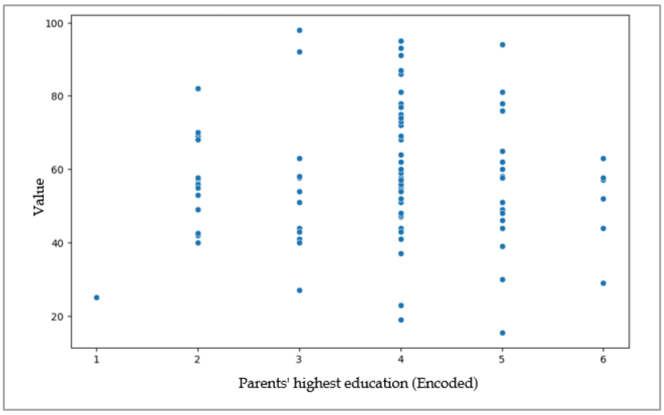


Figure 3. Visualisation of the relationship between parental education and physics exam score

Relationship between parents' income and physics exam scores

The second analysis focused on parental income as a predictor of physics exam scores. The performance of the two models was as in Table 2.

Table 2 Result of metrics between parents' income and physics exam scores

Model	MSE	R^2 Score
Neural Network Regression	323.78	-0.0129
Random Forest Regression	327.08	-0.0232

Similar to the findings for parental education, both machine learning models indicated that parents' income does not significantly explain the variation in physics exam scores. The negative R^2 values again suggest that the models performed worse than a baseline mean model, indicating that income is not a key determinant of students' performance in physics. While socioeconomic status has been linked to academic success in several studies, the findings of this study highlight the complexity of factors that influence student achievement (Raza et al., 2023). These findings imply that parental income, as measured in this study, does not have a significant impact on students' physics exam outcomes.

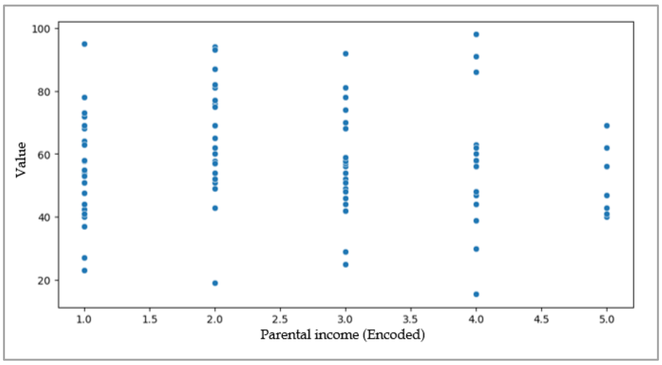


Figure 4. Visualization of the relationship between parental income and physics exam score

Interpretation of result

The lack of a significant relationship between SES and physics exam scores in this study suggests that socioeconomic variables, such as parents' income and education, may not play as critical a role in shaping students' physics performance at SMA Negeri 4 Praya as previously thought. These results underscore the importance of considering other contributing factors, such as the quality of teaching, school resources, and individual student motivation. It is possible that these variables exert a stronger influence on physics achievement than SES alone.

Additionally, the negative R^2 scores obtained from both models point to potential limitations in the dataset or the models' suitability for this particular analysis. The findings suggest that SES might not fully capture the range of factors affecting academic performance, particularly in specialized subjects like physics, where cognitive abilities and specific skill sets may be more influential.

Conclusion

In conclusion, this study found no significant relationship between socioeconomic status and physics exam scores among tenth-grade students at SMA Negeri 4 Praya. The results indicate that while SES has been widely studied as a predictor of academic success, its influence on physics exam performance in this context appears minimal. Future research should consider additional variables such as cognitive abilities, instructional quality, and student engagement to develop a more comprehensive understanding of the factors that contribute to academic success.

Acknowledgments

The author would like to express sincere gratitude to the physics teachers and students at SMA Negeri 4 Praya for their invaluable assistance in providing the data required for this research. Their support and cooperation greatly contributed to the completion of this study.

Author Contributions

Conceptualization, M.R.N.P.; methodology, M.R.N.P. and K.; software, M.R.N.P. and K.; validation, M.R.N.P. and K.; formal analysis, M.R.N.P. and B.H.K.; investigation, M.R.N.P. and B.H.K.; resources, M.R.N.P., B.H.K. and M.B.; data curation, M.R.N.P., K. and B.H.K.; writing—original draft preparation, M.R.N.P. and M.B.; writing—review and editing, M.R.N.P.; visualization, M.R.N.P.; supervision, K. and M.A.; project administration, M.R.N.P., B.H.K. and M.A.; funding acquisition, M.R.N.P., K., B.H.K., M.B. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding

Conflicts of Interest

The authors declare no conflict of interest.

References

Ahn, S. (2022). Building and analyzing machine learning-based warfarin dose prediction models using scikit-learn. *Translational and Clinical Pharmacology*, *30*(4), 172. https://doi.org/10.12793/tcp.2022.30.e22

Antonoplis, S. (2023). Studying Socioeconomic Status: Conceptual Problems and an Alternative Path Forward. *Perspectives on Psychological Science*, *18*(2), 275–292. https://doi.org/10.1177/17456916221093615

Belmi, P., Neale, M. A., Reiff, D., & Ulfe, R. (2020). The social advantage of miscalibrated individuals: The relationship between social class and overconfidence and its implications for class-based inequality. *Journal of Personality and Social Psychology*, *118*(2), 254–282. https://doi.org/10.1037/pspi0000187

Camizuli, E., & Carranza, E. J. (2018). Exploratory Data Analysis (<scp>EDA</scp>). In *The Encyclopedia of Archaeological Sciences* (pp. 1–7). Wiley. https://doi.org/10.1002/9781119188230.saseas0271

Deta, U. A., Ayun, S. K., Laila, L., Prahani, B. K., Suprapto, N., & others. (2024). PISA science framework 2018 vs 2025 and its impact in physics education: Literature review. *Momentum: Physics Education Journal*, *8*(1), 95–107. https://doi.org/10.21067/mpej.v8i1.9215

Doz, D., Cotič, M., & Felda, D. (2023). Random forest regression in predicting students' achievements and fuzzy grades. *Mathematics*, *11*(19), 4129. https://doi.org/10.3390/math11194129

Dubois, D., Rucker, D. D., & Galinsky, A. D. (2015). Social class, power, and selfishness: When and why upper and lower class individuals behave unethically. *Journal of Personality and Social Psychology*, *108*(3), 436–449. https://doi.org/10.1037/pspi0000008

Duncan, G., & Menestrel, S. L. (Eds.). (2019). *A Roadmap to Reducing Child Poverty*. National Academies Press. https://doi.org/10.17226/25246

Erdem, C., & Kaya, M. (2023). Socioeconomic status and wellbeing as predictors of students' academic achievement: evidence from a developing country. *Journal of Psychologists and Counsellors in Schools*, *33*(2), 202–220. https://doi.org/10.1017/jgc.2021.10

Gong, H., Sun, Y., Shu, X., & Huang, B. (2018). Use of random forests regression for predicting IRI of asphalt pavements. *Construction and Building Materials*, *189*, 890–897. https://doi.org/10.1016/j.conbuildmat.2018.09.017

Hilbert, S., Coors, S., Kraus, E., Bischl, B., Lindl, A., Frei, M., Wild, J., Krauss, S., Goretzko, D., & Stachl, C. (2021). Machine learning for the educational sciences. *Review of Education*, *9*(3). https://doi.org/10.1002/rev3.3310

Hittner, E. F., Rim, K. L., & Haase, C. M. (2019). Socioeconomic status as a moderator of the link between reappraisal and anxiety: Laboratory-based and longitudinal evidence. *Emotion*, *19*(8), 1478–1489. https://doi.org/10.1037/emo0000539

Krishnan, S., Reston, E., & Sukumaran, S. D. (2023). The Relationship between Malaysian Students' Socio-Economic Status and their Academic Achievement in STEM education. *International Journal of Learning, Teaching and Educational Research*, *22*(6), 533–551. https://doi.org/10.26803/ijlter.22.6.28

Kucak, D., Juricic, V., & Dambic, G. (2018). *Machine Learning in Education - a Survey of Current Research Trends* (pp. 0406–0410). https://doi.org/10.2507/29th.daaam.proceedings.059

Mastour, H., Dehghani, T., Moradi, E., & Eslami, S. (2023). Early prediction of medical students' performance in high-stakes examinations using machine learning approaches. *Heliyon*, *9*(7). Retrieved from https://www.cell.com/heliyon/fulltext/S2405-8440(23)05456-7?uuid=uuid%3A0df8d855-8cd4-4e5b-8a04-788cf7347b15

Nafea, I. T. (2018). Machine Learning in Educational Technology. In *Machine Learning - Advanced Techniques and Emerging Applications*. InTech. https://doi.org/10.5772/intechopen.72906

Rajamani, S. K., & Iyer, R. S. (2023). Machine learning-based mobile applications using Python and Scikit-Learn. In *Designing and developing innovative mobile applications* (pp. 282–306). IGI Global. Retrieved from https://www.igi-global.com/chapter/machine-learning-based-mobile-applications-using-python-and-scikit-learn/322076

Raza, S., Hameed, M., Abbas, N., Rizvi, S. W., & Sarfaraz, A. (2023). The dynamic interplay of socioeconomic factors in educational attainment: a holistic analysis of socioeconomic status and academic success. *Int J Learn Divers Identities*, *30*(2), 204–213. Retrieved from https://shorturl.asia/mW1jz

Riyanto, A. D., Wahid, A. M., & Pratiwi, A. A. (2024). Analysis Of Factors Determining Student Satisfaction Using Decision Tree, Random Forest, Svm, And Neural Networks: A Comparative Study. *Jurnal Teknik Informatika (Jutif)*, *5*(4), 187–196. https://doi.org/10.52436/1.jutif.2024.5.4.2188

Rodríguez-Hernández, C. F., Cascallar, E., & Kyndt, E. (2020). Socio-economic status and academic performance in higher education: A systematic review. *Educational Research Review*, *29*, 100305. https://doi.org/10.1016/j.edurev.2019.100305

Scabini, L. F. S., & Bruno, O. M. (2023). Structure and performance of fully connected neural networks: Emerging complex network properties. *Physica A: Statistical Mechanics and Its Applications*, *615*, 128585. https://doi.org/10.1016/j.physa.2023.128585

Scardapane, S., & Wang, D. (2017). Randomness in neural networks: an overview. *WIREs Data Mining and Knowledge Discovery*, *7*(2). https://doi.org/10.1002/widm.1200

Tran, M.-K., Panchal, S., Chauhan, V., Brahmbhatt, N., Mevawalla, A., Fraser, R., & Fowler, M. (2022). Python-based scikit-learn machine learning models for thermal and electrical performance prediction of high-capacity lithium-ion battery. *International Journal of Energy Research*, *46*(2), 786–794. https://doi.org/10.1002/er.7202

Vadivel, B., Alam, S., Nikpoo, I., & Ajanil, B. (2023). The Impact of Low Socioeconomic Background on a

Child's Educational Achievements. *Education Research International*, *2023*, 1–11. https://doi.org/10.1155/2023/6565088

Washbrook, E., Gregg, P., & Propper, C. (2014). A Decomposition Analysis of the Relationship Between Parental Income and Multiple Child Outcomes. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *177*(4), 757–782. https://doi.org/10.1111/rssa.12074