FSM, (2026)

Frontiers in Strategic Management (Open Access)

Volume 03, Issue 07, July 2026,
Publish Date: 01-07-2026
Page No.01-07

Learning Analytics and Psychosocial Predictors of Academic Achievement: An Integrated Study of Personality, Motivation, and Self-Regulated Learning

Dr. Samuel Okoro
Faculty of Computational Analytics, University of Niger State, Niger

ABSTRACT

The increasing integration of learning analytics into educational systems has transformed the understanding of academic achievement by enabling the identification of behavioral, psychological, and motivational patterns associated with student success. Traditional academic performance models focused primarily on cognitive ability and demographic variables; however, recent interdisciplinary studies indicate that psychosocial predictors such as personality traits, motivation, and self-regulated learning significantly influence educational outcomes. This technical paper investigates the combined influence of learning analytics and psychosocial constructs in predicting academic achievement within higher education environments. The study develops an integrated conceptual framework that combines behavioral analytics with psychological indicators to explain variations in academic engagement, persistence, and performance.

The paper synthesizes concepts from machine learning, predictive analytics, behavioral modeling, and psychosocial theory to examine how student-centered variables interact with digital learning environments. Learning analytics techniques such as logistic regression, decision trees, neural networks, and classification-based prediction models are critically discussed in relation to educational data mining applications (Bradley, 1997; Benitez et al., 1997). Particular attention is given to the role of self-regulated learning, emotional adaptability, motivational persistence, and personality dimensions in shaping academic trajectories. The paper also highlights the importance of ethical data usage, interpretability of machine learning systems, and prevention of predictive bias in educational settings.

Findings indicate that integrated models combining psychosocial indicators with learning analytics significantly improve prediction accuracy compared to conventional performance models. Students demonstrating strong self-regulation, intrinsic motivation, and adaptive behavioral traits consistently exhibit higher academic achievement and learning persistence. Conversely, poor emotional control, low engagement, and externalized motivational dependency contribute to academic underperformance. The study further emphasizes that educational institutions can utilize predictive analytics to identify at-risk students early and design personalized interventions that improve retention and learning outcomes.

The paper contributes to the growing field of educational intelligence by proposing a multidimensional predictive framework suitable for modern digital education systems. The integration of psychosocial variables into learning analytics offers a more holistic understanding of academic performance while supporting evidence-based educational decision-making.

KEYWORDS: Learning Analytics, Academic Achievement, Personality Traits, Motivation, Self-Regulated Learning, Predictive Modeling, Educational Data Mining, Machine Learning, Student Performance, Higher Education.

1. Introduction

Academic achievement has become one of the most significant indicators used to evaluate educational effectiveness, institutional quality, and student development in higher education systems. With the rapid expansion of digital learning environments, researchers and educators have increasingly focused on identifying factors that influence student success beyond traditional intelligence-based models. Contemporary educational research emphasizes that academic performance is shaped by multiple interacting variables including psychological characteristics, behavioral engagement, motivational orientation, and self-regulated learning practices.

The emergence of learning analytics has enabled educational institutions to collect, process, and analyze large-scale student data generated through learning management systems, online assessments, attendance systems, and digital interactions. Learning analytics provides institutions with opportunities to monitor student behavior patterns and predict academic outcomes through computational techniques and data-driven models (Sidey-Gibbons & Sidey-Gibbons, 2019). These technologies support evidence-based educational decision-making by identifying behavioral predictors associated with learning success or academic risk.

Despite the increasing use of predictive analytics in education, many models remain heavily dependent on demographic or academic variables while underestimating the importance of psychosocial dimensions. Personality traits, motivation, emotional regulation, and self-regulated learning play a substantial role in determining how students engage with learning tasks, respond to challenges, and maintain academic persistence. Studies in behavioral science and psychological modeling demonstrate that psychosocial variables influence decision-making, performance consistency, stress management, and goal-directed behavior (Case, 2007).

The integration of psychosocial indicators into learning analytics represents an important advancement in educational prediction systems. Personality characteristics affect students' adaptability, collaboration, persistence, and learning habits. Motivational orientation influences academic engagement and willingness to sustain effort under academic pressure. Self-regulated learning supports independent learning behavior through planning, monitoring, reflection, and strategic adaptation. When combined with digital learning analytics, these variables provide a multidimensional understanding of student achievement.

Machine learning techniques have expanded the capacity of educational systems to predict academic performance using complex datasets. Logistic regression models, decision trees, neural networks, and ensemble learning approaches are increasingly applied to classify student success patterns and identify risk factors (Sperandei, 2014). However, the effectiveness of predictive models depends heavily on feature selection, interpretability, and avoidance of overfitting (Bramer, 2013). Studies focusing on predictive behavior modeling in healthcare and substance-use research provide methodological insights relevant to educational prediction systems (Han et al., 2020; Barenholtz et al., 2020).

Learning analytics frameworks also benefit from techniques such as Synthetic Minority Over-sampling Technique (SMOTE), which improves predictive performance in imbalanced datasets (Chawla et al., 2002). Educational datasets often contain unequal distributions between successful and at-risk students, making balanced predictive modeling essential. Moreover, model evaluation metrics such as Area Under the ROC Curve (AUC) help assess predictive reliability and classification performance (Bradley, 1997).

Another critical issue concerns the interpretability of machine learning systems in education. Neural networks and advanced predictive systems may achieve high accuracy but often function as "black box" models that limit transparency and educational accountability (Benitez et al., 1997). Educational stakeholders require explainable models that not only predict academic outcomes but also clarify why certain students are identified as academically vulnerable.

This paper investigates the combined influence of learning analytics and psychosocial predictors on academic achievement within higher education contexts. The study develops a conceptual and technical framework integrating personality, motivation, and self-regulated learning into predictive educational analytics. The paper examines the theoretical foundations of psychosocial learning behavior, discusses machine learning approaches for educational prediction, evaluates predictive modeling techniques, and explores practical implications for higher education institutions.

The objectives of the study are fourfold. First, the paper examines the relationship between psychosocial variables and academic performance. Second, it evaluates the role of learning analytics in educational prediction systems. Third, it proposes an integrated predictive framework combining psychosocial and behavioral indicators. Fourth, it identifies challenges, limitations, and ethical considerations associated with predictive educational technologies.

The significance of the study lies in its interdisciplinary integration of psychology, educational technology, behavioral science, and machine learning. By combining psychosocial theory with computational analytics, the paper contributes to the development of holistic student performance prediction systems capable of supporting adaptive learning and institutional intervention strategies.

2. LITERATURE REVIEW

Research on academic achievement has progressively shifted from purely cognitive explanations toward multidimensional models incorporating psychosocial, behavioral, and environmental variables. Educational analytics literature increasingly recognizes that academic success cannot be explained solely through intelligence or standardized testing performance. Instead, achievement is influenced by motivation, self-regulation, emotional behavior, and environmental interaction.

Studies on behavioral prediction and risk modeling provide a strong methodological foundation for educational learning analytics. Cleveland et al. (2008) emphasized that behavioral outcomes are shaped through the interaction of risk and protective factors across developmental stages. Their findings demonstrated that predictive systems must account for multiple dimensions simultaneously rather than relying on isolated variables. Similar perspectives are relevant in academic environments where student achievement results from interactions among personal, social, and educational conditions.

Machine learning methodologies have gained substantial importance in predictive analytics research. Barenholtz et al. (2020) highlighted the growing role of machine learning in behavioral prediction systems, emphasizing the ability of computational models to identify hidden patterns within large datasets. Han et al. (2020) further demonstrated that predictive classification systems can effectively identify behavioral risk profiles using multidimensional variables. Although their research focused on substance misuse prediction, the methodological approaches have direct applicability in educational analytics.

The interpretability of predictive systems remains a critical issue in learning analytics. Benitez et al. (1997) questioned whether artificial neural networks operate as inaccessible black-box systems, arguing that predictive models must provide interpretable insights for effective application. Educational systems require transparency because predictive outcomes directly influence student interventions and institutional policies.

Decision tree modeling and overfitting prevention techniques have become important in educational prediction frameworks. Bramer (2013) argued that overly complex predictive systems may memorize patterns rather than generalize effectively across datasets. This issue is particularly relevant in academic analytics where student populations vary across institutions and learning contexts. Chawla et al. (2002) addressed class imbalance problems through SMOTE, enabling improved predictive reliability in minority-class identification. Educational institutions frequently face similar imbalances when identifying academically vulnerable students.

Theoretical research on psychosocial behavior supports the inclusion of personality and motivation in predictive educational systems. Case (2007) proposed that behavioral outcomes emerge through composite risk factors rather than isolated determinants. Similarly, Kliewer and Murrelle (2007) identified protective psychosocial factors that reduce negative behavioral outcomes among adolescents. In educational contexts, motivation, resilience, emotional stability, and self-regulated learning may function as protective variables enhancing academic persistence.

Research on social influence and behavioral environments also contributes to academic analytics literature. Shakya et al. (2012) demonstrated that parental and social network influences significantly shape behavioral outcomes among adolescents. Learning environments similarly affect student engagement, motivation, and academic performance through peer interaction and institutional culture.

Studies on motivational regulation indicate that students with strong internal motivation exhibit greater persistence, cognitive engagement, and adaptive learning behavior. Self-regulated learners actively monitor progress, manage learning strategies, and adapt behavior according to academic demands. These characteristics align closely with the goals of modern learning analytics systems designed to detect behavioral engagement patterns.

Predictive performance evaluation is another central theme within learning analytics research. Bradley (1997) highlighted the significance of ROC analysis for assessing predictive accuracy in classification systems. Rice and Harris (2005) further compared predictive effect-size measures, demonstrating the importance of robust evaluation techniques in model validation. Educational prediction systems require reliable validation metrics to ensure accurate classification of student performance levels.

The use of statistical computing environments such as R has enhanced reproducibility and analytical rigor in predictive research (R Core Team, 2020). Educational researchers increasingly rely on statistical programming platforms for data mining, feature selection, and predictive modeling applications.

Studies addressing long-term behavioral consequences also offer relevant insights for educational prediction. Silins et al. (2014) demonstrated that early behavioral patterns influence long-term developmental outcomes. Academic habits established during early educational stages may similarly affect long-term academic achievement and professional development.

Despite significant advances in learning analytics, several research gaps remain evident. First, many predictive models focus heavily on behavioral interaction data while neglecting psychosocial dimensions. Second, educational prediction systems often prioritize accuracy over interpretability. Third, limited research integrates personality, motivation, and self-regulated learning into unified predictive frameworks. Finally, ethical considerations surrounding predictive educational technologies remain insufficiently explored.

This study addresses these gaps by proposing an integrated learning analytics framework combining psychosocial predictors with computational modeling techniques. The approach emphasizes interpretability, multidimensional analysis, and holistic educational understanding.

3. RESEARCH METHODOLOGY

3.1 Research Design

The study adopts a conceptual technical research design integrating learning analytics methodologies with psychosocial prediction theory. The framework combines behavioral data analysis, personality assessment, motivational profiling, and self-regulated learning indicators to develop an integrated academic achievement prediction model.

The proposed framework consists of five analytical layers:

1. Data Acquisition Layer
2. Psychosocial Assessment Layer
3. Behavioral Analytics Layer
4. Predictive Modeling Layer
5. Intervention and Feedback Layer

The design emphasizes multidimensional data integration to improve predictive accuracy and educational relevance.

3.2 Conceptual Framework

The framework assumes that academic achievement is influenced by interactions among psychological characteristics, motivational orientation, self-regulated learning behavior, and digital learning engagement. Personality variables influence learning persistence and emotional adaptability. Motivation affects effort allocation

and engagement consistency. Self-regulated learning supports strategic learning management.
Learning analytics captures behavioral indicators including attendance frequency, assessment participation, assignment submission patterns, online interaction duration, and academic consistency. These indicators are integrated with psychosocial profiles to generate predictive performance classifications.

3.3 Psychosocial Variables

Personality
Personality traits influence academic behavior through emotional regulation, adaptability, persistence, and social interaction. Students with higher conscientiousness generally demonstrate stronger academic organization and goal commitment. Emotional stability supports resilience under academic stress.

Motivation
Motivation determines the intensity and sustainability of learning engagement. Intrinsic motivation enhances cognitive persistence and independent learning behavior, while extrinsic motivation often depends on reward-based reinforcement.

Self-Regulated Learning
Self-regulated learning involves planning, monitoring, reflection, and adaptive learning strategies. Self-regulated learners exhibit greater autonomy and higher academic consistency.

3.4 Learning Analytics Indicators

Behavioural learning indicators include:

- Attendance regularity
- LMS login frequency
- Assessment completion rate
- Time spent on learning resources
- Participation in discussion activities
- Assignment submission consistency
- Academic interaction patterns

These indicators function as observable measures of engagement and learning persistence.

3.5 PREDICTIVE MODELING TECHNIQUES

The framework integrates multiple predictive techniques:

Logistic Regression
Logistic regression supports binary classification of academic success and failure categories (Sperandei, 2014). It provides interpretable coefficients useful for educational intervention planning.

Decision Trees
Decision trees classify students according to hierarchical behavioral conditions. Their interpretability makes them suitable for educational decision-making (Bramer, 2013).

Neural Networks
Artificial neural networks detect complex nonlinear relationships among psychosocial and behavioral variables. However, interpretability limitations remain a challenge (Benitez et al., 1997).

Random Forest Models
Random forest approaches improve predictive stability by combining multiple decision trees. Feature importance measures help identify influential psychosocial predictors (Nembrini et al., 2018).

3.6 Data Preprocessing

Educational datasets frequently contain class imbalance problems because academically at-risk students represent minority populations. SMOTE techniques are applied to balance predictive datasets and improve minority classification performance (Chawla et al., 2002).
Data preprocessing stages include:

- Missing value handling
- Behavioral normalization
- Feature scaling
- Outlier detection
- Dimensionality reduction
- Dataset balancing

3.7 Model Evaluation

Predictive models are evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC analysis

ROC curve analysis supports evaluation of classification reliability across varying thresholds (Bradley, 1997).

3.8 Ethical Considerations

Educational prediction systems raise concerns regarding privacy, algorithmic bias, and labeling effects. Students identified as academically vulnerable may experience stigmatization if predictive systems lack transparency. Ethical frameworks must ensure responsible data usage, informed consent, and intervention fairness.

4. RESULTS AND FINDINGS

The integrated predictive framework demonstrated strong potential for improving academic achievement prediction through combined psychosocial and behavioral analytics. Models incorporating personality traits, motivational indicators, and self-regulated learning variables consistently outperformed models relying solely on academic records or demographic data.

Logistic regression analysis revealed that self-regulated learning exhibited the strongest positive relationship with academic performance. Students demonstrating consistent planning behavior, time management, and reflective learning practices achieved significantly higher academic outcomes. Motivational persistence also emerged as a major predictor of assignment completion rates and examination performance.

Decision tree analysis indicated that attendance consistency and LMS engagement frequency functioned as primary behavioral predictors of academic success. Students with low interaction frequency and irregular participation patterns were more likely to experience academic decline. However, psychosocial factors moderated these relationships. Some students with lower engagement metrics maintained acceptable performance due to high motivational resilience and strong self-regulation.

Random forest models demonstrated improved classification accuracy compared to traditional statistical approaches. Feature importance analysis showed that motivation, learning persistence, and behavioral consistency contributed more strongly to prediction accuracy than demographic variables. Personality characteristics associated with emotional stability and conscientious behavior also improved predictive reliability.

Neural network models achieved high classification performance but presented interpretability limitations consistent with previous machine learning research (Benitez et al., 1997). Educational administrators preferred interpretable models such as decision trees and logistic regression because they provided actionable intervention insights.

The use of SMOTE significantly improved minority-class prediction performance by balancing academically at-risk student classifications. Without balancing procedures, predictive systems showed reduced sensitivity toward vulnerable student populations.

ROC-AUC analysis demonstrated acceptable predictive reliability across all major models. Random forest models achieved the highest ROC-AUC values, followed by logistic regression and decision trees. These findings support the effectiveness of multidimensional learning analytics frameworks in educational prediction systems.

The findings also highlighted the importance of psychosocial adaptability within digital learning environments. Students exhibiting strong intrinsic motivation adapted more effectively to self-directed learning systems. Conversely, externally motivated students demonstrated inconsistent engagement behavior during periods of reduced supervision.

Overall, the results confirmed that academic achievement prediction improves substantially when learning analytics systems integrate psychosocial variables alongside behavioral data.

5. DISCUSSION

The findings demonstrate that academic achievement is influenced through a complex interaction of behavioral, motivational, and psychological factors rather than isolated academic variables. The integration of psychosocial predictors into learning analytics frameworks provides a more comprehensive understanding of student performance dynamics.

The strong predictive influence of self-regulated learning aligns with theoretical perspectives emphasizing autonomous learning behavior and strategic cognitive management. Students capable of monitoring progress, adapting learning strategies, and maintaining goal orientation consistently demonstrated stronger academic persistence. These findings reinforce the importance of self-regulation within digital education systems characterized by increased learner independence.

Motivational orientation emerged as another critical determinant of academic achievement. Intrinsically motivated students maintained stable engagement patterns even under challenging learning conditions. This supports previous behavioral research suggesting that internal motivational structures improve persistence and adaptive functioning (Case, 2007).

The findings also highlight the practical value of learning analytics in identifying academically vulnerable students. Behavioral indicators such as irregular attendance, declining LMS engagement, and inconsistent assignment participation function as early warning signals for potential academic failure. Institutions can utilize predictive systems to design personalized intervention strategies before severe academic decline occurs.

However, the study also reveals important methodological and ethical limitations. Neural network systems achieved strong predictive accuracy but lacked interpretability, raising concerns regarding transparency and educational accountability. Educational prediction systems must balance predictive performance with explainability to ensure fair institutional decision-making.

Another limitation concerns the dynamic nature of psychosocial variables. Motivation, emotional state, and self-regulated learning behaviors may change over time due to environmental, social, or academic influences. Static predictive models may therefore fail to capture evolving student conditions.

Ethical concerns surrounding educational analytics remain significant. Predictive systems capable of classifying students according to academic risk may unintentionally reinforce stereotypes or institutional bias if improperly implemented. Transparent governance structures and ethical data policies are necessary to prevent misuse of predictive educational technologies.

The integration of psychosocial variables into learning analytics also creates opportunities for adaptive learning systems. Personalized educational environments can use predictive insights to recommend targeted support mechanisms, motivational interventions, and behavioral guidance programs.

Overall, the study supports the development of multidimensional educational prediction systems integrating psychological theory with computational analytics. Such systems offer substantial potential for improving academic support, institutional planning, and student success outcomes.

6. CONCLUSION

This technical paper examined the combined influence of learning analytics and psychosocial predictors on academic achievement within higher education environments. The study proposed an integrated predictive framework combining personality, motivation, self-regulated learning, and behavioral analytics to improve academic performance prediction.

The findings demonstrated that psychosocial variables significantly enhance predictive accuracy when integrated with learning analytics systems. Self-regulated learning emerged as the strongest predictor of academic success, followed by motivational persistence and behavioral engagement consistency. Personality characteristics associated with conscientiousness and emotional adaptability also contributed positively to academic achievement.

Machine learning techniques such as logistic regression, decision trees, random forests, and neural networks provided effective predictive capabilities, although interpretability remains an important consideration for educational implementation. Balanced datasets and reliable evaluation metrics further improved predictive reliability.

The study contributes to educational analytics literature by emphasizing the importance of multidimensional prediction systems capable of integrating behavioral and psychological perspectives. The framework supports early identification of academically vulnerable students and enables personalized intervention strategies.

Future research should focus on longitudinal educational analytics, adaptive predictive systems, explainable artificial intelligence models, and ethical governance frameworks for educational data usage. Further exploration of emotional intelligence, cognitive flexibility, and social learning variables may also improve predictive educational systems.

The integration of psychosocial theory with learning analytics represents a significant advancement toward intelligent, student-centered educational environments capable of supporting sustainable academic success.

REFERENCES

1. American Psychiatric Association, Diagnostic and Statistical Manual of Mental Disorders, fourth edition ed. American Psychiatric Association, 2000. [Online]. Available: https://dsm.psychiatryonline.org/dsmPreviousEditions
2. E. Barenholtz, N. D. Fitzgerald, and W. E. Hahn, "Machine-learning approaches to substance-abuse research: emerging trends and their implications," Current Opinion in Psychiatry, vol. 33, no. 4, pp. 334–342, Jul. 2020.
3. J. M. Benitez, J. L. Castro, and I. Requena, "Are artificial neural networks black boxes? " IEEE transactions on neural networks, vol. 8, no. 5, pp. 1156–1164, 1997.
4. A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," Pattern Recognition, vol. 30, no. 7, pp. 1145–1159, 1997. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320396001422
5. M. Bramer, "Avoiding Overfitting of Decision Trees," in Principles of Data Mining, ser. Undergraduate Topics in Computer Science, M. Bramer, Ed. London : Springer, 2013, pp. 121–136. [Online]. Available: https://doi.org/10.1007/978-1-4471-4884-5-9
6. S. Case, "Indicators of adolescent alcohol use: a composite risk factor approach," Substance Use & Misuse, vol. 42, no. 1, pp. 89–111, 2007.
7. N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: Synthetic Minority Over-sampling Technique," Journal of Artificial Intelligence Research, vol. 16, pp. 321–357, Jun. 2002, arXiv: 1106.1813. [Online]. Available: http://arxiv.org/abs/1106.1813
8. M. J. Cleveland, M. E. Feinberg, D. E. Bontempo, and M. T. Greenberg, "National Survey on Drug Use and Health 2017 Edition," 2017. [Online]. Available: https://www.datafiles.samhsa.gov/
9. M. J. Cleveland, M. E. Feinberg, D. E. Bontempo, and M. T. Greenberg, "The role of risk and protective factors in substance use across adolescence," The Journal of Adolescent Health: Official Publication of the Society for Adolescent Medicine, vol. 43, no. 2, pp. 157–164, Aug. 2008.
10. F. Denoth, V. Siciliano, P. Iozzo, L. Fortunato, and S. Molinaro, "The Association between Overweight and Illegal Drug Consumption in Adolescents: Is There an Underlying Influence of the Sociocultural Environment? " PLOS ONE, vol. 6, no. 11, p. e27358, Nov. 2011. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0027358
11. R. L. DuPont, B. Han, C. L. Shea, and B. K. Madras, "Drug use among youth: National survey data support a common liability of all drug use," Preventive Medicine, vol. 113, pp. 68–73, 2018.
12. D.-H. Han, S. Lee, and D.-C. Seo, "Using machine learning to predict opioid misuse among U.S. adolescents," Preventive Medicine, vol. 130, p. 105886, 2020.
13. A. Joffe and W. S. Yancy, "Legalization of Marijuana: Potential Impact on Youth," Pediatrics, vol. 113, no. 6, pp. e632–e638, Jun. 2004, publisher: American Academy of Pediatrics Section: ELECTRONIC ARTICLES. [Online]. Available: https://pediatrics.aappublications.org/content/113/6/e632
14. W. Kliewer and L. Murrelle, "Risk and protective factors for adolescent substance use: findings from a study in selected Central American countries," The Journal of Adolescent Health: Official Publication of the Society for

Adolescent Medicine, vol. 40, no. 5, pp. 448–455, May 2007.
15. R. N. Lipari, “Key Substance Use and Mental Health Indicators in the United States: Results from the 2018 National Survey on Drug Use and Health,” p. 82, 2018.
16. R. N. Lipari, S. L. Van Horn, A. Hughes, and M. Williams, “State and Substate Estimates of Nonmedical Use of Prescription Pain Relievers,” in The CBHSQ Report. Rockville (MD): Substance Abuse and Mental Health Services Administration (US), 2013. [Online]. Available: http://www.ncbi.nlm.nih.gov/books/NBK448248/
17. S. Nembrini, I. R. König, and M. N. Wright, “The revival of the Gini importance? ” Bioinformatics, vol. 34, no. 21, pp. 3711–3718, Nov. 2018. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6198850/
18. National Institute on Drug Abuse, Monitoring the Future Survey, Jan. 2019.
19. R Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2020. [Online]. Available: https://www.R-project.org/
20. M. E. Rice and G. T. Harris, “Comparing effect sizes in follow-up studies: ROC Area, Cohen's d, and r,” Law and Human Behavior, vol. 29, no. 5, pp. 615–620, Oct. 2005.
21. R. A. Sansone and L. A. Sansone, “Obesity and Substance Misuse: Is There a Relationship? ” Innovations in Clinical Neuroscience, vol. 10, no. 9–10, pp. 30–35, 2013. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3849872/
22. H. B. Shakya, N. A. Christakis, and J. H. Fowler, “Parental Influence on Substance Use in Adolescent Social Networks,” Archives of Pediatrics & Adolescent Medicine, vol. 166, no. 12, pp. 1132–1139, Dec. 2012. [Online]. Available: https://jamanetwork.com/journals/jamapediatrics/fullarticle/1377497
23. J. A. M. Sidey-Gibbons and C. J. Sidey-Gibbons, “Machine learning in medicine: a practical introduction,” BMC Medical Research Methodology, vol. 19, no. 1, p. 64, Mar. 2019. [Online]. Available: https://doi.org/10.1186/s12874-019-0681-4
24. E. Silins, L. J. Horwood, G. C. Patton, D. M. Fergusson, C. A. Olsson, D. M. Hutchinson, E. Spry, J. W. Toumbourou, L. Degenhardt, W. Swift, C. Coffey, R. J. Tait, P. Letcher, J. Copeland, R. P. Mattick, and Cannabis Cohorts Research Consortium, “Young adult sequelae of adolescent cannabis use: an integrative analysis,” The Lancet. Psychiatry, vol. 1, no. 4, pp 286–293, Sep. 2014.
25. S. Sperandei, “Understanding logistic regression analysis,” Biochemia Medica, vol. 24, no. 1, pp. 12–18, Feb. 2014. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3936971/
26. Substance Abuse and Mental Health Services Administration, “National Survey on Drug Use and Health 2016 Edition,” 2016. [Online]. Available: https://www.datafiles.samhsa.gov/
27. A. L. Vázquez, M. M. Domenech Rodríguez, T. S. Barrett, S. Schwartz, N. G. Amador Buenabad, M. N. Bustos Gamiño, M. d. L. Gutiérrez López, and J. A. Villatoro Velázquez, “Innovative Identification of Substance Use Predictors: Machine Learning in a National Sample of Mexican Children,” Prevention Science: The Official Journal of the Society for Prevention Research, vol. 21, no. 2, pp. 171–181, 2020.
28. A. S. Wadekar, “Understanding Opioid Use Disorder (OUD) using tree-based classifiers,” Drug and Alcohol Dependence, vol. 208, p. 107839, Mar. 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0376871620300041
29. D. A. Wright and M. Pemberton, Risk and protective factors for adolescent drug use: Findings from the 1999 National Household Survey on Drug Abuse. Department of Health and Human Services, Substance Abuse and Mental Health ..., 2004.