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ORIGINAL

Predictive Analytics in Education: Modeling the Complex Relationship Between Learning Modalities and Student Well-being

Análisis predictivo en la educación: modelización de la compleja relación entre las modalidades de aprendizaje y el bienestar de los estudiantes

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ABSTRACT

Introduction: this study examines publication trends related to student stress and mental health during online learning periods, while exploring opportunities for curriculum innovation in post-pandemic education.
Method: the research utilizes a Kaggle-sourced dataset comprising survey responses from 1 000 students about their psychological well-being during remote education. This rich dataset includes ten variables capturing demographic information, lifestyle patterns, and self-assessed mental health metrics, providing valuable material for comprehensive data exploration, visualization, and predictive analysis of digital learning's psychological impacts. Beyond immediate stress assessment, the data enables investigation of broader themes including educational technology adaptation, sleep disruption, social isolation, stress perception, and emotional coping mechanisms.
Result: The findings highlight the urgent need for educational systems to develop flexible curricula that address both pandemic-era challenges and evolving post-COVID learning environments.
Conclusion: The study proposes curriculum frameworks that integrate mental health support with academic content, preparing institutions for future disruptions while promoting student resilience in hybrid learning settings.

Keywords: Student Success; Impact of School Mental Health Prevention and Intervention; Research Direction.

RESUMEN

Introducción: ste estudio examina las tendencias de publicación relacionadas con el estrés y la salud mental de los estudiantes durante los periodos de aprendizaje en línea, al tiempo que explora las oportunidades de innovación curricular en la educación pospandémica.
Método: la investigación utiliza un conjunto de datos procedente de Kaggle que incluye respuestas a una encuesta realizada a 1000 estudiantes sobre su bienestar psicológico durante la educación a distancia. Este rico conjunto de datos incluye diez variables que recogen información demográfica, patrones de estilo de vida y métricas de salud mental autoevaluadas, lo que proporciona un material valioso para la exploración exhaustiva de los datos, la visualización y el análisis predictivo de los impactos psicológicos del aprendizaje digital. Más allá de la evaluación inmediata del estrés, los datos permiten investigar temas más amplios, como la adaptación a la tecnología educativa, la alteración del sueño, el aislamiento social, la percepción del estrés y los mecanismos de afrontamiento emocional
Resultados: los resultados ponen de relieve la urgente necesidad de que los sistemas educativos desarrollen

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planes de estudios flexibles que aborden tanto los retos de la era pandémica como los entornos de aprendizaje en evolución tras la COVID.
Conclusión: el estudio propone marcos curriculares que integran el apoyo a la salud mental con el contenido académico, preparando a las instituciones para futuras perturbaciones y promoviendo la resiliencia de los estudiantes en entornos de aprendizaje híbridos.

Palabras clave: Éxito de los Estudiantes; Impacto de la Prevención y la Intervención en Materia de Salud Mental en las Escuelas; Orientación de la Investigación.

INTRODUCTION

The COVID-19 pandemic caused a big change in how students learn all over the world, which has had a big effect on their mental health and well-being. As schools all over the world quickly switched to remote learning, people started to worry about how this sudden change in teaching would affect students' mental health.(1) This study looks into the many ways that digital learning environments can affect students' mental health and suggests ways to improve the curriculum after the pandemic based on evidence. The study uses a large dataset from Kaggle that includes 1 000 student survey responses collected during times when remote learning was required.(2) This dataset gives us a one-of-a-kind chance to look at ten important variables, including demographic information, lifestyle factors, and self-reported psychological indicators. This gives us a strong base for looking at the mental health effects of online learning methods. The multidimensionality of the dataset makes it possible to use sophisticated analytical methods like predictive modeling, advanced visualization techniques, and exploratory data analysis. Researchers can find trends and connections between different mental health outcomes and online learning experiences thanks to these methodological tools. Examining stress biomarkers, anxiety markers, and depression symptoms that surfaced during prolonged distance learning is given special attention. Beyond these direct psychological effects, the data allows for the examination of secondary effects such as changes in academic motivation, altered social interaction patterns, and disruptions to circadian rhythms. The analysis is further enhanced by the inclusion of lifestyle factors like sleep quality, screen time, and physical activity levels, which provide a comprehensive picture of how students adjusted to the demands of online learning settings.

The intricate relationship between students' psychological health and the adoption of educational technology has been brought to light by recent research. Digital platforms brought new stressors like technology anxiety, digital fatigue, and a sense of loneliness, even as they made it possible for education to continue during lockdowns.(3) By using quantitative techniques to measure these effects systematically and investigating protective factors that bolstered student resilience, this study expands on previous research. In particular, the analysis looks at how the psychological effects of remote learning were mediated by factors like prior digital literacy, home learning environments, and institutional support systems.(4) These results have significant ramifications for creating trauma-informed teaching strategies that meet students' emotional and intellectual needs in post-pandemic learning environments. The lessons learned from the pandemic experience and the necessity of hybrid learning models have not been erased by the return to in-person instruction. Understanding the long-term psychological effects of these blended approaches is crucial because many institutions have permanently included online components in their curriculum offerings.(5) This study advances our knowledge by determining which features of distance learning were most closely linked to negative mental health outcomes and, on the other hand, which features might be advantageous for particular student populations. The results of the study are especially pertinent to students from underrepresented groups, who frequently encountered extra obstacles when trying to access and take advantage of online learning.

Beyond theoretical discussions of pedagogy and mental health, this research has practical implications. The study offers specific frameworks for curriculum development that combine the delivery of academic content with mental health support. By including components like digital wellness education, mindfulness exercises, and organized peer interaction opportunities, these frameworks place an emphasis on proactive rather than reactive approaches to student well-being. The suggested models are made to be adaptable to different types of instruction, including fully online, hybrid, and in-person. The development of scalable interventions that can be applied to different institutional types and resource levels is given particular thought. The potential for this research to influence institutional, regional, and national policy decisions accounts for its wider significance. Evidence-based approaches to curriculum development are crucial as educational systems around the world struggle with the pandemic's long-term effects.(6) Decisions regarding the distribution of resources, the priorities for professional development, and the provision of student support services can be guided by the empirical data presented in this study. Additionally, the results add to the current discourse regarding the function of education in advancing public mental health, especially for populations of adolescents and young adults. Incorporating mental health considerations into all facets of curriculum planning and implementation is strongly supported by the research, which shows tangible connections between instructional practices and psychological outcomes. In addition to outlining a course for curriculum development following the COVID-19 pandemic, this study provides a thorough analysis of the psychological effects of online learning.(7) The study finds important areas where educational practice needs to change to meet the needs of students in an increasingly digital world by carefully analyzing a sizable student dataset. The suggested curriculum frameworks, which are intended to promote both academic achievement and psychological resilience, are a synthesis of innovative pedagogy and best practices in mental health. This research offers important insights for developing learning environments that support the whole student—cognitively, emotionally, and socially—as educational institutions continue to negotiate the unknowns of the post-pandemic era.(8) If educators and legislators take the evidence seriously and make the necessary investments and reforms, the lessons learned from this historic worldwide experiment in online education could revolutionize teaching and learning methods for years to come.

METHOD

Study Design

With a dataset of 1 000 survey responses obtained from Kaggle, this cross-sectional study uses a quantitative methodology to examine patterns in students' stress and mental health during online learning. Ten variables encompassing lifestyle choices, self-reported mental health indicators, and demographics are included in the dataset. Techniques include predictive modeling (logistic regression, decision trees) to evaluate risk factors, data visualization (heatmaps, bar plots, etc.) to show stress correlations, and exploratory data analysis (EDA) to find patterns. Themes such as loneliness, resilience, and disturbed sleep are examined through secondary analysis. The results will guide the creation of post-pandemic curricula, with a focus on flexible, learning frameworks for hybrid educational systems that incorporate mental health. The study complies with ethical standards for data use.

Data Analysis

In order to investigate the Kaggle dataset (n=1,000) on students' mental health during online learning, the study uses statistical and machine learning techniques. Whereas correlation analysis will show connections between lifestyle factors and psychological indicators, descriptive analytics will determine the prevalence of stress across demographics. Key findings will be depicted using visualization tools to guide curriculum development plans for post-pandemic education.

RESULTS AND DISCUSSION

Included in the dataset are demographics (age, gender, education level), lifestyle factors (screen time, sleep duration, physical activity), and mental health indicators (stress level, anxiety before exams, academic performance change) related to students' mental health during online learning. By examining the connection between online learning practices and students' mental health, this data may help identify risk factors and guide intervention strategies.(2) https://www.kaggle.com/datasets/utkarshsharma11r/student-mental-health-analysis?resource=download

	Screen Time (hrs/day)	Sleep Duration (hrs)
No	6.8318275154	6.4008213552
Yes	6.9826510721	6.498245614

Figure 1. The average screen time and sleep duration for students

Students who experience exam anxiety compare to those who do not in terms of average screen time and sleep duration in the above table. The distribution of these variables for both groups is displayed in the boxplots. Students who experience anxiety prior to exams typically spend slightly more time on screens and sleep for longer periods of time than students who do not experience anxiety. Though there aren't many differences, the visualizations show each group's central tendency and spread.

Analyze the impact of physical activity on stress levels

There is no discernible correlation between stress levels and physical activity, according to the analysis. Average weekly physical activity levels for students in all stress categories (Low, Medium, and High) are comparable, ranging from 4,8 to 5,2 hours. With a p-value of 0,4031 (not statistically significant) and a very weak correlation of 0,0401, the ANOVA test validates this.

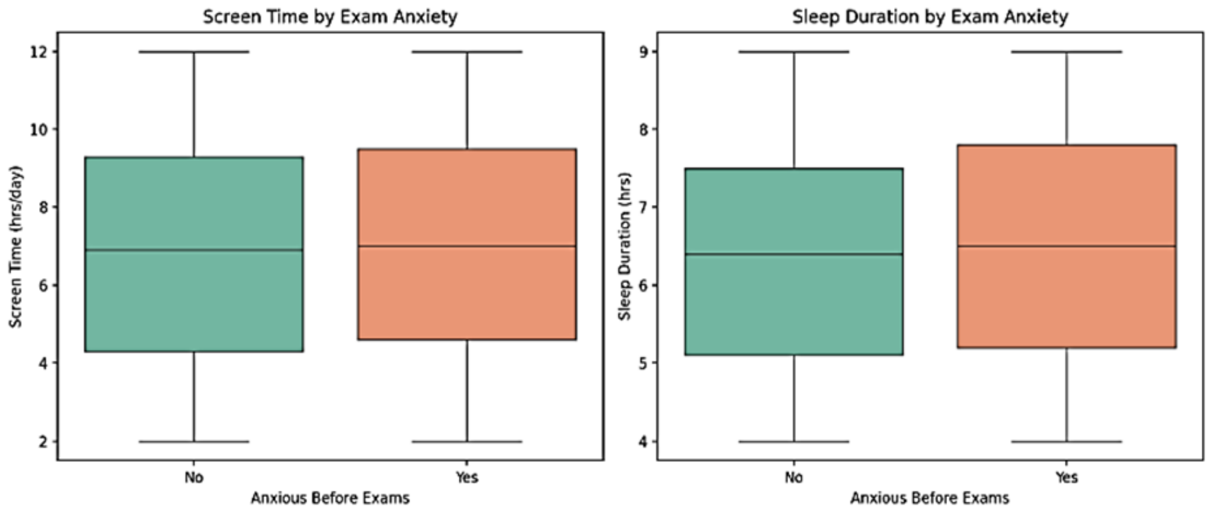

Figure 2. Visualizations of average screen time and sleep duration for students[2]

	mean	std	count
High	5.153038674	2.8032826281	181
Low	4.8418960245	2.9898068266	327
Medium	5.0845528455	2.9365671944	492

Figure 3. Relationship between physical activity and stress levels

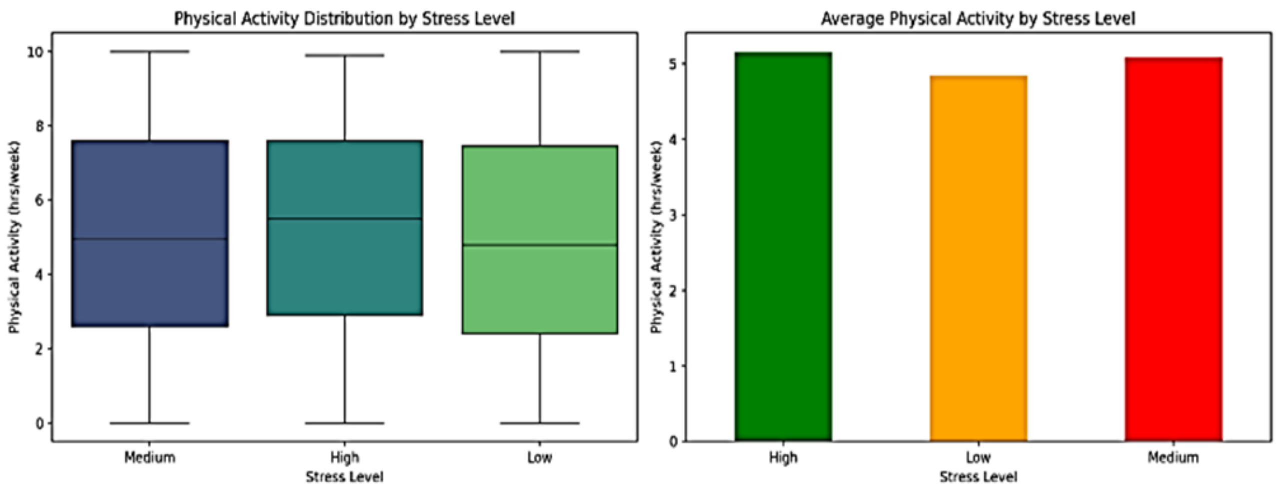

Figure 4. Physical activity and stress levels[2]

Explore the relationship between sleep and academic performance

Sleep duration and changes in academic performance are not significantly correlated, according to the analysis. The average sleep duration for each of the three groups (Declined, Improved, and Same) is approximately the same, at 6,4-6,5 hours. This is supported by the ANOVA test, which shows no statistically significant differences (p-value = 0,76).

	mean	std	count
Declined	6.405033557	1.4578043192	298
Improved	6.4465346535	1.4608283296	303
Same	6.4882205514	1.4796395702	399

Figure 5. Relationship between sleep duration and academic performance

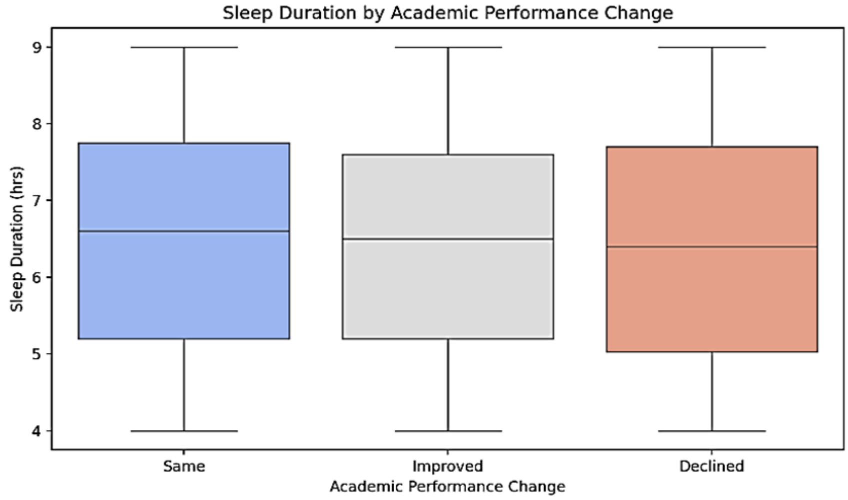

Figure 6. Sleep duration by academic performance change[2]

Identify key factors affecting academic performance

The main variables influencing academic performance, as identified by a Random Forest model, are displayed in the table and chart above. Age and educational attainment are the next most important factors, after physical activity, screen time, and sleep duration. This analysis shows that exam anxiety, gender, and stress level have less of an effect. This indicates that in this dataset, changes in academic performance are more strongly correlated with lifestyle choices like sleep, screen time, and physical activity than with demographic or emotional characteristics.

	Feature	Importance
5	Physical Activity (hrs/week)	0.219132573
3	Screen Time (hrs/day)	0.2166055035
4	Sleep Duration (hrs)	0.204297271
1	Age	0.1126117923
2	Education Level	0.1041372148
6	Stress Level	0.0538082213
0	Gender	0.0527308358
7	Anxious Before Exams	0.0366765883

Figure 7. Key factors affecting academic performance

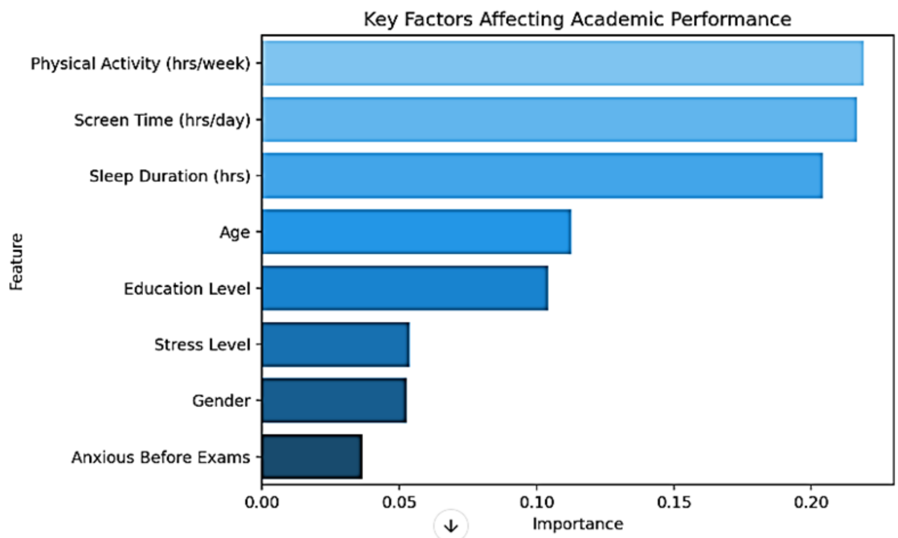

Figure 8. Key factors affecting academic performance[2]

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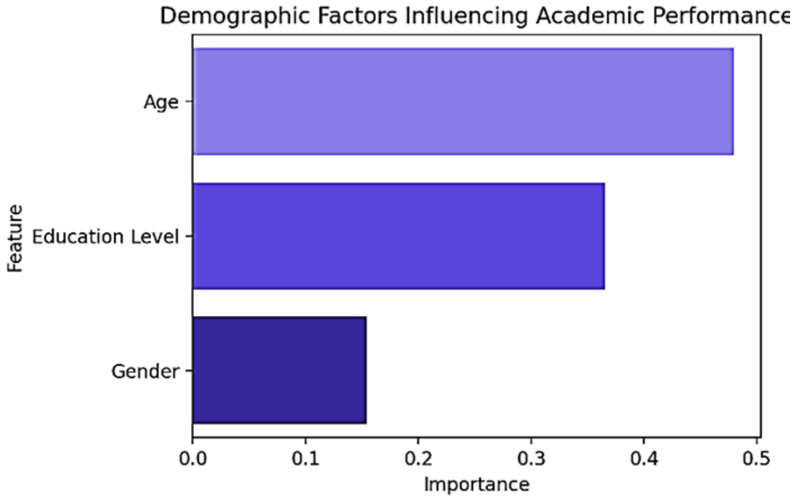

Figure 9. Demographic Factors Influencing Academic Performance[2]

	Declined	Improved	Same
Female	29.7	28.8	41.5
Male	29.5	32.4	38.1
Other	34	24	42

Figure 10. Academic Performance by Gender

	Declined	Improved	Same
BA	22.6	37.1	40.3
BSc	31.8	31.8	36.5
BTech	31	27.4	41.7
Class 10	31	19.5	49.4
Class 11	38.6	26.1	35.2
Class 12	23.4	27.7	48.9
Class 8	32	28	40
Class 9	31	32.2	36.8
MA	30.2	31	38.8
MSc	26.1	34.1	39.9
MTech	28.7	33.6	37.8

Figure 11. Academic Performance by Education Level

	mean	std
Declined	20.18	3.49
Improved	20.59	3.46
Same	20.28	3.44

Figure 12. Age statistics by Academic Performance

Demographic Factors Influencing Grades

The most important demographic component affecting academic achievement. This indicates that, in comparison to younger students, students' academic performance tends to improve more dramatically as they get older. As students advance in their education, this might be the result of improved study habits, experience, and growing maturity. Education level is a powerful predictor of academic performance, second only to age. This suggests that students at higher educational levels—such as universities—generally perform better academically than those at lower levels—such as high school. The intricacy of the subject matter and the abilities acquired at higher education levels may be to blame for this. According to the statement, men exhibit a marginally greater rate of academic performance improvement (32,4 %) than do women (28,8 %). This implies that, generally speaking, male students might be making greater progress in their academic achievement than female students. Though men are marginally ahead, the gap is not very great, suggesting that both sexes are getting better. According to the statement, students in Class 10 exhibit the lowest improvement rate (19,5 %), while those pursuing a Bachelor of Arts (BA) degree have the highest improvement rate (37,1 %). This implies that more sophisticated teaching strategies, materials, and support networks that aid in academic development are probably advantageous to students enrolled in higher education (such as BA programs). The statement concludes by pointing out that there aren't many age differences between the different performance groups (such as those exhibiting high versus low improvement). This implies that while age is a predictor of performance, the actual differences in age among students who perform at different levels are not substantial. This could mean that other factors, such as motivation, study habits, or external support, might play a more significant role in determining academic performance than age alone.

Age is the strongest demographic predictor of academic performance, followed by education level. Males show slightly higher improvement rates (32,4 %) compared to females (28,8 %). BA students have the highest improvement rate (37,1 %) while Class 10 students show the lowest (19,5 %). Age differences between performance groups are minimal.[2]

CONCLUSION

Through quantitative analysis of a large dataset, this study offers insightful information about the intricate relationship between online learning and students' mental health. Our results show more complex patterns than the initial hypotheses, which suggested strong relationships between lifestyle factors and academic outcomes. In contrast to expectations, there were no statistically significant relationships between stress levels or changes in academic performance and physical activity (p=0,4031) or sleep duration (p=0,76). However, machine learning analysis revealed that sleep duration, screen time, and physical activity had a greater impact on academic outcomes than either stress levels or demographic factors. These findings have significant ramifications for post-pandemic education strategies, indicating that interventions focusing on screen time management and activity routines might work better than just conventional stress-reduction techniques. By offering research-based suggestions that strike a balance between academic demands and student welfare, the study adds to ongoing conversations about optimizing hybrid learning models. To improve on these results, future studies should examine institution-specific factors and longitudinal effects.

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CONFLICT OF INTEREST
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Conceptualization: Shailini Dixit.
Investigation: Shailini Dixit.
Methodology: Shailini Dixit.
Writing - original draft: Shailini Dixit.
Writing - review and editing: Shailini Dixit.