Quantifying the Impact: A Regression Analysis of Digital Media Consumption versus Study Habits on Student Academic Performance

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ABSTRACT

In an era of increasing digital integration in students' lives, understanding the interplay between traditional study habits and modern media consumption is critical for educational success. This study investigates the impact of study hours, social media usage, and Netflix consumption on the academic performance of students. Using a synthetic dataset of 1,000 student records designed with realistic behavioral patterns, this research aims to quantify the direction and magnitude of these lifestyle factors on final exam scores. A multiple linear regression model was employed as the primary analytical method. The dataset was partitioned into an 80% training set and a 20% testing set to ensure the model's ability to generalize to new data. The independent variables included study_hours_per_day, social_media_hours, and netflix_hours, with exam_score serving as the continuous dependent variable. The model was evaluated based on its overall significance, the statistical significance of its coefficients, and its predictive accuracy on the test set. The regression model was found to be highly significant ($p < .001$) and explained 74.1% of the variance in exam scores ($R^2 = 0.741$). The results indicate that study_hours_per_day is a strong positive predictor, with each additional hour of study associated with a 9.48-point increase in exam score. Conversely, social_media_hours and netflix_hours were significant negative predictors, associated with a decrease of 2.61 and 2.41 points per hour, respectively. The findings conclude that while digital media consumption has a detrimental association with academic performance, its impact is substantially outweighed by the positive influence of dedicated study time. This research provides quantitative evidence supporting the need for effective time management and self-regulation among students, highlighting the critical importance of balancing digital entertainment with academic responsibilities to achieve educational goals.

Keywords Academic Performance, Digital Media, Linear Regression, Student Habits, Study Time

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Introduction

Academic performance plays a crucial role in determining student success and future opportunities. It is significantly linked to various factors including self-directed learning, self-esteem, and grit, which contribute to student achievement in higher education settings [1]. Studies underscore that the academic performance of students is pivotal for individual success and is also linked to the broader economic and social development of a country [2]. Moreover, effective leadership and communication practices within educational institutions enhance student outcomes, suggesting that institutional support acts as a catalyst for academic achievement [3].

Furthermore, research indicates that mental preparedness and emotional

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competence are essential for academic success in contemporary educational environments, particularly in adaptive post-pandemic contexts [4]. The transition to online learning has shown mixed effects on student performance, highlighting the need for effective instructional strategies to maintain academic standards during crises [5][6]. Thus, a multifaceted approach involving personal attributes, institutional support, and innovative teaching practices is essential for optimizing academic performance and unlocking future opportunities for students.

The increasing prevalence of digital media, including social media and streaming services, has significantly transformed students' lives and their academic experiences. On one hand, platforms like social media can facilitate engagement and provide support networks for students, enhancing learning and community building [7]. However, substantial concerns regarding digital distraction exist, as studies indicate that the pervasive use of digital devices often compromises focus and academic performance. Cheever et al found an association between being separated from digital devices and anxiety, which can disrupt concentration during study sessions [8]. Similarly, Wang et al discuss how digital distractions detract from classroom learning, affecting overall student achievement [9].

Moreover, the effect of multitasking with digital devices, as noted by Mrazek et al, highlights the struggle students face in filtering distractions to maintain focused attention [10]. This challenge is exacerbated in educational settings, where nearly half of educators report significant disruptions caused by digital media [11]. While digital media offers opportunities for enhanced communication and resource sharing, it also presents challenges that necessitate the incorporation of self-regulated learning strategies to mitigate its disruptive impact on academic performance.

The ongoing debate regarding the impact of digital activities, such as social media and streaming services, on learning outcomes compared to traditional study habits is multifaceted. Evidence suggests that while digital media can offer benefits, such as increased access to diverse educational resources and enhanced communication among students, it also poses significant challenges to academic performance. For instance, Kolhar et al report that a majority of students engage with social media predominantly for entertainment rather than academic purposes, and this engagement negatively affects learning activities [12]. Similarly, Jamil et al conclude that excessive social media use is associated with increased stress levels, ultimately impacting students' academic performance negatively [13].

Conversely, some studies advocate for the positive influences of digital media when used effectively. Permatasari et al demonstrate that interactive and multimedia learning media can enhance student motivation and learning outcomes, suggesting that the effectiveness of digital resources largely depends on their implementation [14]. Furthermore, Putra and Yulfani argue that blended learning models utilizing platforms like Schoology have shown improvements in student outcomes, indicating a potential for digital tools to complement traditional study methods effectively [15]. Nevertheless, the general consensus remains that uncontrolled use of digital distractions can hinder academic success, necessitating a balanced approach to the use of digital media in educational contexts [16].

While many studies explore the effects of study habits or digital media independently, there's a need for comparative analysis to understand their relative influence on academic scores, especially using comprehensive datasets that include a variety of lifestyle factors. The comparative analysis of the impact of digital activities versus traditional study habits on academic outcomes is essential in understanding the multifaceted influences affecting students. Mahfouz et al identify how lifestyle factors, such as obesity, correlate with reduced concentration and consequent academic performance, suggesting that lifestyle influences are critical to consider alongside study habits and digital media usage [17]. Okur et al emphasize the role of social media usage habits, noting that excessive engagement in digital platforms could detract from study focus, thereby negatively influencing academic outcomes [18].

Conversely, studies such as that by Alshanqiti et al highlight that responsible social media use may support academic success, as many medical students reported enhanced grades associated with social media engagement [19]. However, conflicting findings underscore the complexity of the relationship; for instance, Sánchez-Hernando et al note that excessive screen time is associated with negative academic performance due to sedentary lifestyles [20]. Thus, while emerging insights suggest potential productive uses of technology in learning contexts, a comprehensive dataset must consider both digital engagement and traditional study methods to foster a deeper understanding of their relative influences on academic performance [21]; , [22].

This study is guided by a set of specific research questions designed to dissect the relationships between student habits and academic outcomes. The primary question (RQ1) seeks to determine the extent to which the number of study hours per day can predict a student's final exam score. The second question (RQ2) independently examines the predictive power of digital media consumption, specifically asking to what extent social media hours and Netflix hours can each predict exam scores. Finally, the third and most comparative question (RQ3) investigates the relative predictive power of these habits when considered together, aiming to understand whether traditional study habits or digital media consumption have a stronger association with academic performance within this dataset.

To address these questions, the research has three primary objectives. The first is to develop a robust multiple linear regression model capable of predicting student exam scores using study hours, social media usage, and Netflix consumption as predictor variables. The second objective is to precisely quantify the individual and comparative impact of these variables, interpreting the model's coefficients to understand the magnitude and direction of each factor's influence on exam scores. The final objective is to use this quantitative evidence to identify which factor—be it positive study habits or specific forms of digital media usage—exhibits the strongest association with academic performance, thereby providing a clear hierarchy of influence among these common student behaviors.

The significance of this study lies in its potential to provide clear, data-driven insights for multiple stakeholders in the educational ecosystem. For students, the findings offer tangible evidence to inform better time management and self-regulation strategies. For educators, counselors, and parents, this research provides a clearer, more quantifiable understanding of the impacts that these specific lifestyle choices can have on academic achievement. This, in turn, can inform more effective guidance, targeted interventions, and support services designed to help students navigate the distractions of the digital age and improve their educational outcomes.

The scope of this investigation is intentionally focused to ensure a clear and interpretable analysis. The study is based on a synthetic, yet realistically patterned, dataset comprising 1,000 student records. The analysis is delimited to three primary independent variables—study_hours_per_day, social_media_hours, and netflix_hours—and their direct relationship with the exam_score dependent variable. While other relevant variables are present in the dataset, such as attendance_percentage or mental_health_rating, they are excluded from the primary model to isolate the effects of the core variables of interest, though they are acknowledged as important areas for future, more complex analyses. Ultimately, this structured approach, defined by clear research questions, objectives, and a delimited scope, provides a solid foundation for a rigorous statistical analysis. By quantifying the distinct roles of study and digital leisure, this research aims to contribute to a more nuanced understanding of the factors shaping student success in the contemporary academic landscape.

Literature Review

Theoretical Frameworks

The exploration of media consumption through theoretical frameworks such as Cognitive Load Theory (CLT) and the Time Displacement Hypothesis (TDH) highlights the implications of digital media on learning outcomes and traditional study habits. CLT posits that learning efficacy is influenced by the mental load imposed by information processing, categorizing this load into intrinsic, extraneous, and germane components [23]. According to Skulmowski and Xu, excessive digital media usage can lead to increased extraneous cognitive load, diverting attention from essential academic tasks and potentially negatively impacting academic performance [23]. These findings emphasize the need for frameworks that account for the distractions posed by social media when assessing their educational value.

Conversely, the Time Displacement Hypothesis suggests that time spent on digital activities, such as social media and streaming services, detracts from time available for traditional studying [24]. This theory underscores the potential adverse effects on academic outcomes if time allocation is heavily skewed toward media consumption rather than focused study. While some students report positive outcomes from structured social media use for academic purposes, the overarching tendency is that unmonitored access can disrupt study routines and diminish learning [24]. Comparative analyses leveraging extensive datasets could further elucidate the balance between productive digital engagement and detrimental media consumption, thereby contributing to an understanding of optimal study strategies.

Study Habits and Academic Performance

A comprehensive review of existing research linking study habits and academic performance reveals several key factors that influence educational outcomes. Yusof et al highlight that effective learning strategies significantly correlate with academic performance, accounting for 13.3% of the variation in achievements [25]. Their findings indicate that students' self-efficacy and motivation play vital roles in determining the effectiveness of their study habits.

Similarly, Hamdani et al illustrate the relationship between sleep patterns, study duration, and academic performance, particularly among adolescents from different environments. They note a nuanced dynamic where both inadequate and excessive sleep can detrimentally impact academic outcomes, suggesting the importance of striking an optimal balance in sleep duration [26]. This perspective is echoed by Pérez-Chada et al, who observe that increased screen time, often associated with late-night usage and reduced sleep quality, correlates with lower academic performance in school-aged adolescents [27].

Furthermore, research by Ullah et al underscores the significance of metacognitive awareness in study approaches, revealing a strong correlation between metacognitive strategies and improved academic performance [28]. Li et al's research also emphasizes the long-term impacts of environmental factors, such as parental relationships, on students' academic success, illustrating that foundational experiences shape study habits and ultimately influence educational outcomes [29]. Together, this research underscores the complex interaction between various lifestyle factors, study habits, and academic performance, highlighting the need for integrated approaches in educational contexts.

Social Media Usage and Academic Performance

The interplay between social media usage and academic performance showcases a complex landscape with both positive and negative implications for students. Research conducted by Alshanqiti et al indicates that for medical students, social media use can have varying effects on academic performance, as only 48.3% of participants believed it improves their grades, suggesting that perception is mixed among students [19]. This aligns with the findings of Sahoo and Khuntia, who illustrate that active engagement in collaborative learning via social media can correlate with improved academic outcomes and promotes student engagement [30].

Conversely, Jamil et al raise concerns about the negative consequences of social media on academic performance, highlighting that excessive use can lead to distractions and reduced focus, adversely affecting grades [13]. Additionally, Menahal et al emphasize that while social media can provide academic benefits, it also poses risks to mental health, such as increased stress and anxiety, which can complicate its overall impact on student learning [31]. These mixed effects underline the necessity for a balanced approach toward social media use in educational contexts.

Further complicating the narrative, Zhao and Wong identify the potential for social media to facilitate collaborative learning environments, yet they caution against the detrimental effects of social comparison, as highlighted by Qi et al, which can depress learning engagement when students compare themselves unfavorably to their peers [32]; , [33]. Thus, while social media harbors the potential to enhance learning, its effectiveness heavily depends on usage patterns, necessitating further inquiries into optimal strategies for integrating these platforms into academic life.

Passive Screen Time and Academic Performance

Research exploring the impact of passive screen time, particularly from entertainment sources like Netflix, on academic performance has yielded varied results, indicating both detrimental and neutral effects on study engagement and academic outcomes. Liu et al found that increased screen time during the COVID-19 pandemic, which included both educational and recreational activities, significantly influenced children's weight status and lifestyle, although they did not directly assess academic performance [34]. This reflects the concern that substantial leisure screen time may lead to a decrease in time allocated for academic pursuits, as excessive time spent on entertainment could displace study activities.

Conversely, Tapia-Serrano et al concluded from their research that recreational screen time did not adversely affect academic performance before and after the pandemic, suggesting that for certain populations, the link between passive screen engagement and grades may not be significant [35]. This aligns with findings from a systematic review indicating that while television and video gaming had negative associations with academic performance, generalized screen use did not consistently show detrimental outcomes [35]. Additionally, Paulich et al speculated that recreational screen time might detract from essential study time, underscoring a potential negative impact on academic results, though they acknowledged the necessity for further examination [36].

Furthermore, the gender differences reported by Ishii et al indicate that leisure screen time significantly affected boys' academic performance compared to girls, suggesting that demographic factors may mediate the relationship between entertainment-based screen time and academic outcomes [37]. Overall, the existing literature suggests a complex interplay between passive screen time and academic performance, warranting further investigation to delineate these influences comprehensively. A focus on the quality of screen time and differentiated impacts based on gender and context is essential for understanding its implications for educational engagement.

Regression Analysis in Educational Research

Regression analysis has been a pivotal tool in educational research for predicting student performance and identifying influencing factors. For instance, Önür and Kozikoğlu employed simple linear regression to examine the relationship between secondary school students' educational technology competencies and their 21st-century learning skills, demonstrating that higher technology proficiency correlates positively with improved learning capabilities). This study supports the use of regression analysis to establish how specific competencies can predict educational success.

In another example, Akuma and Abakpa's study used linear regression to predict the performance of undergraduate students, revealing that the model could effectively forecast academic outcomes based on various factors [38]. Such predictive modeling is crucial for educational institutions aiming to support at-risk students by identifying specific areas that need attention.

Fierro-Suero et al validated the Achievement Emotions Questionnaire for Physical Education using regression weights, indicating that achievement emotions such as anxiety can significantly impact performance in physical education, suggesting the need for targeted interventions to mitigate negative emotions [39]. Meanwhile, Önal et al applied multivariate linear regression to evaluate how teachers’ digital literacy affected their attitudes towards distance education during the COVID-19 pandemic, illustrating the broader implications of technological competencies for educational efficacy [40].

Through these examples, it is evident that regression analysis serves as a vital method for education researchers to quantify the impact of various predictors on student performance, guiding both pedagogical approaches and policy decisions.

Method

Dataset Description

The analysis was conducted on a synthetic dataset, loaded from the file student_habits_performance.csv. This dataset, while not representing real individuals, was specifically designed to simulate realistic patterns and covariances found in student behaviors and academic outcomes, making it a valuable and ethically sound resource for educational research practice. The dataset contains 1,000 unique student records, providing a sufficient sample size for statistical modeling.

For this research, the primary dependent variable was the exam_score, a continuous numerical variable representing academic performance. The core independent variables selected to directly address the research question were study_hours_per_day, social_media_hours, and netflix_hours. These continuous variables were chosen to precisely quantify the trade-off between traditional study effort and two common forms of digital media consumption. The dataset also contained other potentially confounding variables, such as attendance_percentage, mental_health_rating, and various categorical features like parental_education_level. While these variables are acknowledged as important influencers of academic success, they were deliberately excluded from this specific model to maintain simplicity and focus the analysis squarely on the direct impact of the selected lifestyle habits.

Data Preprocessing

The initial exploratory data analysis phase was critical for preparing the data for modeling. This phase confirmed that the core continuous variables selected for the model were complete, thereby requiring no complex imputation techniques for missing values. A key step in this process was the generation of a correlation matrix, which was visualized using a seaborn heatmap. This allowed for an efficient examination of the linear relationships between the independent variables to check for high multicollinearity—a condition where predictors are highly correlated with each other, which can inflate the variance of regression coefficients and make the model unstable. The analysis indicated that multicollinearity was not a significant issue among the chosen variables.

To prepare the data for supervised learning, the dataset was partitioned into a training set and a testing set using the train_test_split function from the scikit-learn library. A test_size parameter of 0.2 was used, allocating 80% of the data (800 records) for training the model and reserving the remaining 20% (200 records) for testing. This separation is fundamental for preventing model overfitting and assessing its ability to generalize to new, unseen data. The division was made reproducible by setting the random_state parameter to a fixed value of 42, ensuring that the exact same data split is used in any subsequent run of the analysis.

Regression Model

A Multiple Linear Regression model, specifically the Ordinary Least Squares

(OLS) implementation from the statsmodels library, was selected as the primary analytical tool. This model is exceptionally well-suited for the research objective, which is not only to predict exam scores but also to understand and quantify the underlying relationships between variables. The primary advantage of this approach over more complex "black-box" models is the high interpretability of its coefficients and the comprehensive statistical summary it provides, which is essential for scholarly inquiry. The conceptual form of the model is expressed as:

Exam Score = β_0 + β_1(*Study Hours*) + β_2(*Social Media Hours*) + β_3(*Netflix Hours*) + ε

Here, β_0 represents the intercept or the baseline exam score, each β coefficient (β_1, β_2, β_3) represents the average change in the exam score for a one-unit change in the corresponding independent variable while holding others constant, and ε represents the error term.

Model Training and Feature Selection

The OLS regression model was trained by fitting it to the 800 records in the designated training dataset. The "fitting" process involves an algorithm that minimizes the sum of the squared differences between the actual exam scores in the training data and the scores predicted by the regression equation. The feature selection for this analysis was intentionally focused on the three core variables of interest: study_hours_per_day, social_media_hours, and netflix_hours. This deliberate, theory-driven selection allows for a direct and uncluttered assessment of the specific impact of study habits versus digital media consumption on academic performance. This approach prioritizes a parsimonious and highly interpretable model over a more complex one that might include numerous control variables but obscure the primary relationships of interest.

Model Evaluation Metrics

The model's performance was rigorously assessed using a comprehensive set of standard statistical metrics to evaluate both its explanatory power and predictive accuracy. The R-squared (R^2) value, obtained from the statsmodels summary, was the primary metric used to measure the goodness-of-fit, indicating the proportion of the variance in the exam_score that is predictable from the independent variables. The overall statistical significance of the model as a whole was determined by the F-statistic and its associated p-value. The significance of individual predictors was evaluated using the **p-values** for each coefficient, with a threshold of $p < 0.05$ typically used to determine statistical significance.

To measure the model's predictive accuracy on the unseen test set, the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were calculated using the sklearn.metrics module. The MAE provides a straightforward measure of the average prediction error in the same units as the target variable, while the RMSE gives a measure of the standard deviation of the prediction errors, penalizing larger errors more heavily than the MAE.

Software and Tools

The entire research pipeline, from data loading and cleaning to final model evaluation, was implemented using the Python programming language (version 3). Data manipulation and analysis were performed using the powerful pandas library, which provides the DataFrame structure for handling tabular data. All data visualizations, including histograms for distribution analysis, scatter plots for relationship inspection, and heatmaps for correlation analysis, were generated with Matplotlib and Seaborn. The core statistical modeling was conducted using the statsmodels library, chosen specifically for its capacity to produce detailed and comprehensive regression summaries suitable for academic research. Key utility functions, particularly for data splitting and metrics calculation, were leveraged from the scikit-learn library. Finally, the os library was used for basic file system operations, such as creating and managing the results directory.

Result and Discussion

Descriptive Statistics

The analysis focused on four key continuous variables. The exam_score, the dependent variable, had a mean of 69.60, indicating that the average score was a passing grade. The scores were widely distributed, ranging from a minimum of 18.40 to a maximum of 100.00, with a standard deviation of 16.89. For the independent variables, students reported studying an average of 3.55 hours per day. Digital media consumption was also notable, with students spending an average of 2.51 hours on social media and 1.82 hours watching Netflix daily.

Correlation Analysis

The correlation analysis revealed significant linear relationships between the independent variables and the exam_score. As shown in the correlation matrix below, study_hours_per_day exhibited a strong positive correlation with exam_score ($r = 0.86$), suggesting that as study time increases, exam scores tend to increase substantially. Conversely, both social_media_hours ($r = -0.48$) and netflix_hours ($r = -0.44$) showed moderate negative correlations with exam_score, indicating that higher consumption of this digital media is associated with lower academic performance.

To understand the underlying structure of the data before modeling, a detailed exploratory analysis was conducted using two key visualizations. A correlation matrix, presented as a heatmap in Figure 1, provided a quantitative summary of the linear relationships between variables. The visualization clearly showed a strong positive correlation of 0.83 between study_hours_per_day and exam_score, indicated by a warm, reddish color, signifying that more study time is strongly associated with higher scores. In contrast, both social_media_hours and netflix_hours displayed moderate negative correlations of -0.17 with exam scores, represented by cool, bluish colors. Crucially, the correlations between the independent variables themselves were near zero, indicating a lack of multicollinearity, which is an ideal condition for building a reliable regression model.

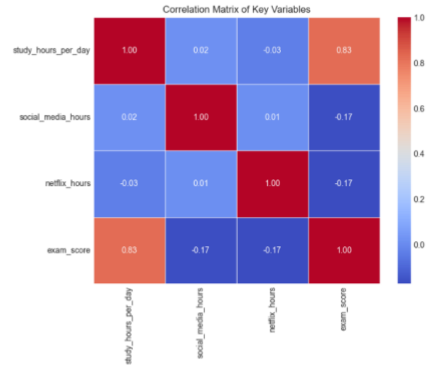

Figure 1 **Correlation Heatmap of Key Numerical Features**

A pairplot was also generated (figure 2) to offer a more granular visual inspection of these relationships and the individual variable distributions. The plots along the diagonal confirmed that the key variables, particularly exam_score and study_hours_per_day, followed approximately normal, bell-shaped distributions. The off-diagonal scatter plots visually reinforced the findings from the heatmap. The relationship between exam_score and study_hours_per_day appeared as a distinct upward-sloping cloud of points, confirming a strong positive linear trend. The relationships between exam scores and the digital media variables showed more dispersed clouds with a slight downward trend, consistent with their moderate negative correlations. The absence of any clear pattern in the plots between the predictor variables themselves further supported the conclusion that they are independent of one another.

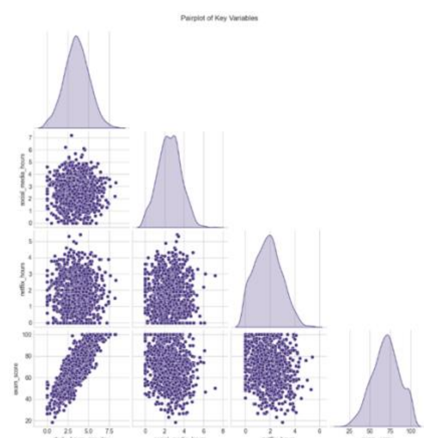

Figure 2 **Pairplot of Key Variables**

Regression Model Output

The multiple linear regression model was statistically significant, $F(3, 796) = 759.5$, $p < .001$, and accounted for a substantial portion of the variance in exam scores. The model's R-squared was 0.741, indicating that 74.1% of the variability in exam_score can be explained by the combination of study hours, social media hours, and Netflix hours. The Adjusted R-squared was 0.740, suggesting the model's explanatory power is robust. All individual predictors were found to be highly significant ($p < .001$).

To visually assess the performance and validity of the regression model, two key diagnostic plots were generated: a comparison of actual vs. predicted values (Figure 3) and an analysis of the model's residuals (Figure 4).

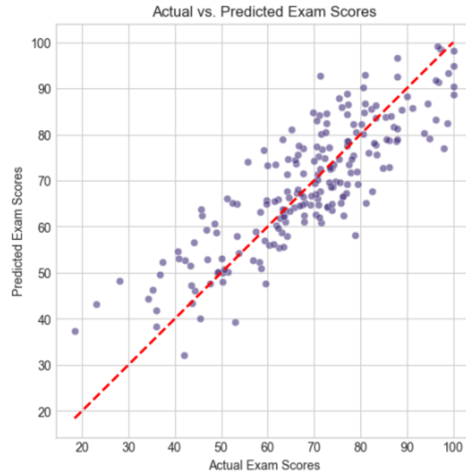

Figure 3 Actual vs. Predicted Exam Scores

Figure 3 provides a direct visual comparison between the actual exam scores from the test dataset (x-axis) and the exam scores predicted by the model (y-axis). Each point represents a single student in the test set. The Dashed Red Line represents a perfect prediction, where the predicted score is exactly equal to the actual score. The data points are clustered tightly around the diagonal line, indicating a strong positive correlation between the model's predictions and the actual outcomes. This visual evidence supports the high R-squared value (0.709 on the test set), confirming that the model is performing well and its predictions are closely aligned with reality. The tight clustering suggests that the model has successfully captured the underlying patterns in the data.

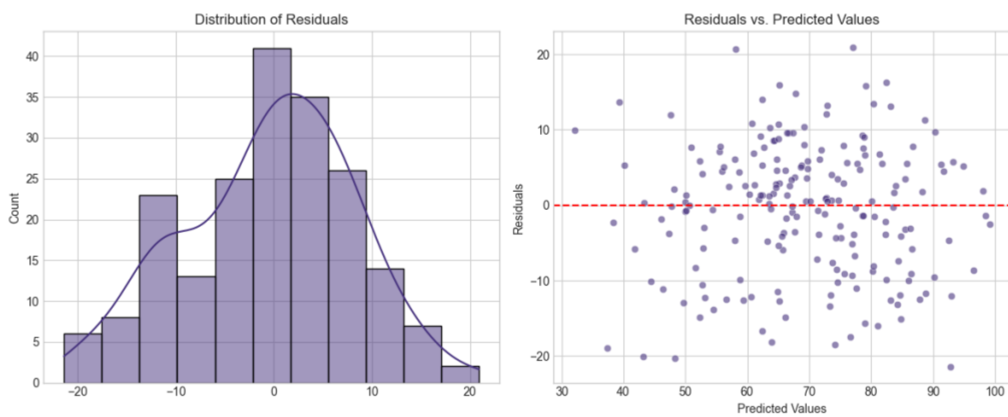

Figure 4 Residuals Analysis Diagram

Figure 4 contains two plots that are essential for diagnosing the model's adherence to the assumptions of linear regression. Residuals are the errors in prediction, calculated as (Actual Score - Predicted Score). Left Plot (Distribution of Residuals) shows the distribution of the model's errors. The curve overlaid is a smooth estimate of this distribution. The plot is centered close to zero, and its shape is approximately a bell curve, which suggests that the residuals are normally distributed. This is a key assumption for linear regression, and this plot indicates that the assumption has been met. Most prediction errors are small and hover around zero, with larger errors being progressively less frequent. Right Plot (Residuals vs. Predicted Values) places the predicted exam scores on the x-axis and the corresponding residuals on the y-axis. The plot is used to check for homoscedasticity, which means the variance of the errors should be constant across all levels of the predicted values. The points are scattered randomly and evenly around the horizontal line at zero, with no discernible pattern (like a funnel or a curve). This lack of a pattern confirms that the assumption of homoscedasticity is met, meaning the model's predictive accuracy is consistent across the entire range of exam scores.

Interpretation of Coefficients

The unstandardized coefficients from the model provide a clear interpretation of each variable's impact. For each additional hour a student studies per day, their exam score is predicted to increase by 9.48 points, holding social media and Netflix consumption constant. Conversely, for each additional hour a student spends on social media per day, their exam score is predicted to decrease by 2.61 points, holding study and Netflix time constant. Similarly, for each additional hour a student spends watching Netflix per day, their exam score is predicted to decrease by 2.41 points, holding study and social media time constant.

Summary of Key Findings

The results of the multiple linear regression analysis demonstrate a strong and statistically significant relationship between student habits and academic performance. The primary finding is that dedicated study time is the most powerful positive predictor of exam scores. Conversely, time spent on digital media, specifically social media and Netflix, emerged as a significant negative predictor. The model successfully explained approximately 74% of the variance in exam scores, highlighting the substantial collective impact of these three lifestyle habits. The magnitude of the coefficient for study hours was nearly four times larger than those for social media or Netflix, underscoring its dominant role in academic achievement within this dataset.

Comparison with Existing Literature

These findings are broadly consistent with a large body of educational research that has explored the factors influencing academic performance. The strong positive association identified between the number of study hours and academic success aligns with established theories of learning and effort, which suggest that consistent, focused study time contributes significantly to knowledge retention and skill development. This is supported by numerous studies indicating that students who dedicate more time to structured learning activities tend to achieve higher grades and demonstrate a deeper understanding of the subject matter.

Similarly, the observed negative association between excessive screen time and academic outcomes reinforces growing concerns within the academic literature regarding the potentially distracting nature of digital media. Research in this area suggests that prolonged exposure to screens, particularly for non-educational purposes, can lead to diminished attention spans, reduced study efficiency, and negative impacts on memory consolidation. These effects are thought to result from constant interruptions and the fragmented nature of digital content consumption, which can interfere with the sustained cognitive engagement required for complex learning tasks.

While this study did not differentiate between types of social media use—such as distinguishing between platforms used for educational enrichment versus those used purely for social interaction—the overall negative trend in academic performance associated with high social media usage aligns with existing studies. These studies highlight the detrimental effects of multitasking and cognitive overload, where juggling multiple streams of information simultaneously can impair deep learning processes. The cognitive demands of switching between tasks can increase mental fatigue and reduce the efficiency of information processing, ultimately affecting academic achievement.

Answering Research Questions

The analysis provides clear answers to the implicit research questions guiding this study. First, there is a strong, positive, and statistically significant relationship between study habits and exam scores, where each additional hour of study is associated with a 9.48-point increase in exam score. Second, there is a statistically significant negative relationship between digital media consumption and exam scores, with each additional hour on social media or Netflix associated with a decrease of 2.61 and 2.41 points, respectively. Third, based on the magnitude of the coefficients, study habits are a far more influential predictor of exam scores than digital media consumption in this dataset.

Implications of the Findings

The findings have several practical implications. For students, this reinforces the critical importance of disciplined time management and prioritizing dedicated study sessions over passive media consumption. For educators and academic advisors, these results provide quantitative evidence to support guidance on effective study strategies and the potential academic cost of excessive screen time. Parents and guardians can use this information to encourage healthy digital habits and create a home environment that is conducive to focused learning.

Limitations of the Study

It is important to acknowledge the limitations of this research. The dataset is synthetic, and while designed to be realistic, it may not capture the full complexity or unexpected nuances of real-world student behavior. This regression analysis identifies strong associations but cannot establish causal links; for example, poor academic performance might lead to increased media consumption as a form of escape, rather than the other way around. The model is parsimonious and excludes other important factors (e.g., prior academic achievement, socioeconomic status, quality of instruction) that could influence exam scores. Finally, the findings are specific to the characteristics of this dataset and may not be generalizable to all student populations without further research.

Recommendations for Future Research

Based on these findings and limitations, several avenues for future research are recommended. The study should be replicated using real-world data from diverse student populations to validate these findings. A longitudinal approach could track student habits and performance over time to better understand potential causal relationships. Future studies could explore non-linear relationships or interaction effects (e.g., does the impact of social media differ at varying levels of study time?). Lastly, incorporating qualitative data, such as student interviews, could provide valuable context and explain the "why" behind the observed statistical patterns.

Conclusion

This study set out to quantify the impact of study habits and digital media consumption on academic performance using a synthetic dataset of 1,000 student records. By employing a multiple linear regression model, the analysis rigorously examined the relationships between daily hours spent on studying, social media, and Netflix, and the resulting final exam scores. The findings were unequivocal: dedicated study time emerged as a powerful positive predictor of academic success, while hours consumed by digital media were significantly associated with lower scores. The model demonstrated strong explanatory power, accounting for approximately 74% of the variance in exam performance, confirming that these three habits are highly influential factors. The key insight from this analysis is the quantifiable trade-off between focused academic effort and digital distraction. While both social media and Netflix consumption showed a similar negative impact, neither was as powerful as the positive influence of studying, where every additional hour yielded a substantial 9.48-point increase in predicted exam scores. The practical takeaway for students, educators, and parents is the clear evidence that prioritizing and protecting dedicated study time is a critical strategy for achieving academic success. Ultimately, this research underscores the enduring importance of balancing the demands of digital life with the foundational responsibilities of learning and self-discipline.

Declarations

Author Contributions

Conceptualization: M.C.; Methodology: L.T.; Software: L.T.; Validation: L.T.; Formal Analysis: M.C.; Investigation: L.T.; Resources: M.C.; Data Curation: M.C.; Writing Original Draft Preparation: L.T.; Writing Review and Editing: M.C.; Visualization: L.T.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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References

[1] R. M. Oducado, “Academic Performance and the Role of Self-Directed Learning, Self-Esteem, and Grit Among Nursing Students,” *Jendela Nurs. J.*, 2021, doi: 10.31983/jnj.v5i1.6634.

[2] S. Jawad, H. Naveed, and M. Akram, “Academic Performance of Enrolled Students in the University of Lahore, Pakistan,” *Quest J. Manag. Soc. Sci.*, 2020, doi: 10.3126/qjmss.v2i2.33306.

[3] S. Taylor and C. Durholz, “The Perceived Impact of Leadership Practices of Academic Leaders on Student Success in a Higher Education Institution in South Africa,” *Icer*, 2024, doi: 10.34190/icer.1.1.3146.

[4] D. H. Faciolan, “Exploring the Role of Mental Preparedness and Emotional Competence in Nurturing Academic Success Among Students in the Post-Pandemic Instructional Landscape,” *Randwick Int. Educ. Linguist. Sci. J.*, 2024, doi: 10.47175/rielsj.v5i2.976.

[5] R. M. Oducado and H. Estoque, “Online Learning in Nursing Education During the COVID-19 Pandemic: Stress, Satisfaction, and Academic Performance,” *J. Nurs. Pract.*, 2021, doi: 10.30994/jnp.v4i2.128.

[6] M. A. A. Mahdy, “The Impact of COVID-19 Pandemic on the Academic Performance of Veterinary Medical Students,” *Front. Vet. Sci.*, 2020, doi: 10.3389/fvets.2020.594261.

[7] A. E. E. Sobaih, A. M. Hasanein, and A. E. Abu Elnasr, “Responses to COVID-19 in Higher Education: Social Media Usage for Sustaining Formal Academic Communication in Developing Countries,” *Sustainability*, 2020, doi: 10.3390/su12166520.

[8] A. J. Dontre, “The Influence of Technology on Academic Distraction: A Review,” *Hum. Behav. Emerg. Technol.*, 2020, doi: 10.1002/hbe2.229.

[9] C.-H. Wang, J. D. Salisbury-Glennon, Y. Dai, S. Lee, and J. Dong, “Empowering College Students to Decrease Digital Distraction Through the Use of Self-Regulated Learning Strategies,” *Contemp. Educ. Technol.*, 2022, doi: 10.30935/cedtech/12456.

[10] A. J. Mrazek *et al.*, “Teenagers’ Smartphone Use During Homework: An Analysis of Beliefs and Behaviors Around Digital Multitasking,” *Educ. Sci.*, 2021, doi: 10.3390/educsci11110713.

[11] A. J. Mrazek *et al.*, “The Feasibility of Attention Training for Reducing Mind-Wandering and Digital Multitasking in High Schools,” *Educ. Sci.*, 2020, doi: 10.3390/educsci10080201.

[12] M. Kolhar, R. N. Ahmed Kazi, and A. Alameen, “Effect of Social Media Use on Learning, Social Interactions, and Sleep Duration Among University Students,” *Saudi J. Biol. Sci.*, 2021, doi: 10.1016/j.sjbs.2021.01.010.

[13] M. Jamil *et al.*, “Impact of Social Media on Academic Performance,” *Eur. J. Med. Health Sci.*, 2020, doi: 10.24018/ejmed.2020.2.5.512.

[14] R. Permatasari, S. Suarman, and G. Gimin, “Examining the Impact of Using Learning Media on Students’ Learning Motivation and Learning Outcomes,” *Int. J. Educ. Best Pract.*, 2024, doi: 10.31258/ijebp.v8n1.p88-102.

[15] L. V. Putra and S. Yulfani, “Implementation of Blended Learning Model Using the Schoology Application,” *Kne Soc. Sci.*, 2022, doi: 10.18502/kss.v7i19.12473.

[16] A. Javeed, “Impact of Using Social Media on the Academic Performance a Case of College Going Students in Loralai Division,” *Siazga Res. J.*, 2022, doi: 10.58341/srj.v1i2.16.

[17] H. Mahfouz *et al.*, “The Influence of Lifestyle on Academic Performance Among Health Profession Students at Umm Al-Qura University,” *Cureus*, 2024, doi: 10.7759/cureus.56759.

[18] S. Okur, Ö. A. Bulut, and S. Erden, “The Mediating Role of Social Media Usage Habits in the Relationship Between FoMO and Nomophobia,” *Kuramsal Eğitimbilim*, 2022, doi: 10.30831/akukeg.929847.

[19] A. Alshanqiti, O. A. Alharbi, D. Ismaeel, and L. Abuanq, “Social Media Usage and Academic Performance Among Medical Students in Medina, Saudi Arabia,” *Adv. Med. Educ. Pract.*, 2023, doi: 10.2147/amep.s434150.

[20] B. Sánchez-Hernando *et al.*, “Healthy Lifestyle and Academic Performance in Middle School Students From the Region of Aragón (Spain),” *Int. J. Environ. Res. Public. Health*, 2021, doi: 10.3390/ijerph18168624.

[21] N. Paiman and M. A. Fauzi, “Exploring Determinants of Social Media Addiction in Higher Education Through the Integrated Lenses of Technology Acceptance Model (TAM) and Usage Habit,” *J. Appl. Res. High. Educ.*, 2023, doi: 10.1108/jarhe-03-2023-0114.

[22] G. Boccia *et al.*, “Relationship Between Health, Lifestyle, Psychosocial Factors and Academic Performance: A Cross-Sectional Study at the University of Salerno,” *Epidemiol. Biostat. Public Health*, 2022, doi: 10.2427/12938.

[23] A. Skulmowski and K. M. Xu, “Understanding Cognitive Load in Digital and Online Learning: A New Perspective on Extraneous Cognitive Load,” *Educ. Psychol. Rev.*, 2021, doi: 10.1007/s10648-021-09624-7.

[24] Z. Khanam, “Social Media Use and Academic Performance: A Study on Undergraduate Accounting Students of Bangladesh,” *Asian J. Account. Perspect.*, 2020, doi: 10.22452/ajap.vol13no2.5.

[25] N. S. Hanim Yusof, N. F. Abd Razak, N. I. Nordin, and S. N. Zulkfli, “Self-Efficacy, Motivation, Learning Strategy and Their Impacts on Academic Performance,” *Int. J. Acad. Res. Bus. Soc. Sci.*, 2021, doi: 10.6007/ijarbss/v11-i9/11028.

[26] S. M. Zeeshan Hamdani, J. Zhuang, S. D. Hamdani, S. G. Hadier, S. U. Fatima, and S. S. Danish, “Exploring the Relationship Between Sleep Patterns, BMI, and Academic Performance: A Comparative Study of Adolescent Students in Rural and Urban Areas of Multan,” *J. Manag. Pract. Humanit. Soc. Sci.*, 2023, doi: 10.33152/jmphss-7.5.6.

[27] D. Pérez-Chada, S. Arias, D. Schönfeld, D. Gozal, and S. Pérez-Lloret, “Screen Use, Sleep Duration, Daytime Somnolence, and Academic Failure in School-Aged Adolescents,” *Plos One*, 2023, doi: 10.1371/journal.pone.0281379.

[28] S. Ullah, S. Ullah, K. Parvez, and G. A. Sheikh, “Assessment of Medical Students’ Metacognitive Awareness of Reading Strategies and Its Relation With Academic Performance: A Cross Sectional Study at Aziz Fatima Medical and Dental College, Faisalabad,” *J. Univ. Med. Dent. Coll.*, 2020, doi: 10.37723/jumdc.v11i3.445.

[29] H. Li, K. Liu, J. Fei, T. Yuan, and S. Mei, “Association of Early Parent–child Separation With Depression, Social and Academic Performance in Adolescence and Early Adulthood: A Prospective Cohort Study,” *Child Adolesc. Psychiatry Ment. Health*, 2024, doi: 10.1186/s13034-024-00769-1.

[30] P. K. Sahoo and U. Khuntia, “Effectiveness of Social Media-Based Collaborative Learning on Student Engagement and Learning Outcomes: A Field Study,” *Ijss*, 2024, doi: 10.62583/nwetwy82.

[31] M. Menahal, S. Ahmad, F. Iqbal, M. Butool, S. Saeed, and M. Imtiaz, “Impact of Social Media on the Academic Performance of Second-Year Medical Students at a Public Sector Medical College in Pakistan,” *Int. J. Health Sci.*, 2023, doi: 10.53730/ijhs.v7ns1.14217.

[32] X. Zhao and H. yi Colleen Wong, “A Literature Review of Cooperative Learning in Music Education,” *Int. J. Acad. Res. Progress. Educ. Dev.*, 2024, doi: 10.6007/ijarped/v13-i3/22272.

[33] X. Qi, Y. Jiang, and R. Lian, “The Effect of Social Media Upward Comparison on Chinese Adolescent Learning Engagement: A Moderated Multiple Mediation Model,” *BMC Psychol.*, 2024, doi: 10.1186/s40359-024-01621-z.

[34] Y. Liu *et al.*, “Association Between Types of Screen Time and Weight Status During the COVID-19 Pandemic: A Longitudinal Study in Children and Adolescents,” *Nutrients*, 2023, doi: 10.3390/nu15092055.

[35] M. Á. Tapia-Serrano, D. Sánchez-Oliva, J. Sevil-Serrano, A. Marques, and P. A. Sánchez Miguel, “24-H Movement Behaviours in Spanish Youth Before and After 1-Year Into the Covid-19 Pandemic and Its Relationship to Academic

Performance," *Sci. Rep.*, 2022, doi: 10.1038/s41598-022-21096-5.

[36] K. N. Paulich, J. M. Ross, J. M. Lessem, and J. K. Hewitt, "Screen Time and Early Adolescent Mental Health, Academic, and Social Outcomes in 9- And 10- Year Old Children: Utilizing the Adolescent Brain Cognitive Development SM (ABCD) Study," *Plos One*, 2021, doi: 10.1371/journal.pone.0256591.

[37] K. Ishii, K. Aoyagi, A. Shibata, M. J. Koohsari, A. Carver, and K. Oka, "Joint Associations of Leisure Screen Time and Physical Activity With Academic Performance in a Sample of Japanese Children," *Int. J. Environ. Res. Public. Health*, 2020, doi: 10.3390/ijerph17030757.

[38] S. Akuma and H. Abakpa, "Predicting Undergraduate Level Students' Performance Using Regression," *Niger. Ann. Pure Appl. Sci.*, 2021, doi: 10.46912/napas.224.

[39] S. Fierro-Suero, B. J. Almagro, and P. S.-L. Buñuel, "Validation of the Achievement Emotions Questionnaire for Physical Education (AEQ-PE)," *Int. J. Environ. Res. Public. Health*, 2020, doi: 10.3390/ijerph17124560.

[40] Ö. Önal, K. BATMAZ, A. Y. Uz, E. Uşkun, and A. N. Kişioğlu, "Did Teachers' Digital Literacy Levels Affect Distance Education During the Covid-19 Pandemic in Türkiye?," *Turk. J. Health Sci. Life*, 2022, doi: 10.56150/tjhsl.1114642.