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SCREEN TIME IMPACTS ON EDUCATION

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**In The Report**

The following report analyzes the relationship between daily screen time behaviors and academic productivity, focusing specifically on the time spent studying. For this purpose, three months of daily data were collected and analyzed. The project examines how different factors such as educational vs. non-educational screen usage, academic responsibilities, sleep duration, and time spent on social activities impact studying hours.

By using statistical methods, data visualizations, and machine learning models, this study aims to identify patterns that influence study efficiency. The ultimate goal is to extract actionable insights that could help optimize digital behavior, sleep routines, and time management in academic life.

**Parameters:**

* **Date**: The date of each daily entry.
* **Screen Time (Educational)**: Hours spent using educational platforms (e.g., Google Docs, Zoom, Coursera). Represents structured digital engagement.
* **Screen Time (Non-Educational)**: Hours spent on entertainment or social media platforms (e.g., Instagram, YouTube, Netflix). Represents potential digital distraction.
* **Academic Responsibilities**: The number of homework tasks, exams, or projects scheduled on a given day.
* **Sleep Duration**: Total hours of sleep recorded; used to assess rest and recovery.
* **Time Spent on Social Activities**: Hours spent in social interactions (in-person or online), excluding academic contexts.
* **Studying Hours**: Total number of hours dedicated to focused studying (tracked via Toggl Track).

These parameters were selected to provide a clear understanding of how daily routines and digital behavior can influence academic productivity and time management.

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| Introduction |

This project explores the relationship between screen time behavior and academic performance, specifically the number of hours spent studying. By tracking educational and non-educational screen usage, academic responsibilities, sleep duration, and social interaction time, I will be using a data-driven approach to understand how these variables impact productivity.

Through statistical analysis and visualization, I aim to identify patterns in screen habits and extract actionable insights to improve study efficiency and time management. This report summarizes three months of data collection and interpretation, bridging personal digital habits with educational outcomes.

**WHAT DID I DO?**

In this research work, the goal was to understand the complexities of screen usage and its effects on academic productivity—especially the time allocated to studying.

Over the course of approximately three months, I recorded a detailed log of daily screen usage (split into educational and non-educational), academic workload, sleep duration, and time spent on social activities. I also tracked how many hours I studied each day using the Toggl Track App. All values were recorded systematically in Google Sheets or apps such as iOS Screen Time and Sleep Diary.

This data collection had a disciplined structure. Each day, I noted:

* How much time I spent on educational vs. non-educational platforms (e.g., Zoom vs. Instagram).
* The number of tasks due (homeworks, exams, or projects).
* The number of hours I slept (as reported by Sleep Diary).
* Time spent socially (as self-logged).
* Total number of hours studied (from Toggl Track).

After the data was assembled, I moved on to preprocessing. This included cleaning missing entries, standardizing column formats, and preparing variables for analysis.

Subsequently, I conducted exploratory data analysis (EDA) using correlation heatmaps, bar charts, and scatter plots. These were followed by implementation of machine learning models (Random Forest, Decision Tree, and K-Nearest Neighbors) with hyperparameter tuning to predict studying hours based on daily habits.

The process yielded both statistical findings and visual evidence about the relationship between screen time and academic performance—highlighting the negative effects of excessive non-educational screen usage and the positive contribution of structured habits like adequate sleep and academic planning.

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| Observations and Understandings |

To guide the analysis, the following hypotheses were formulated:

* **Null Hypothesis (H₀):** There is no statistically significant correlation between total screen time and studying hours.
* **Alternative Hypothesis (H₁):** There is a statistically significant negative correlation between total screen time and studying hours.

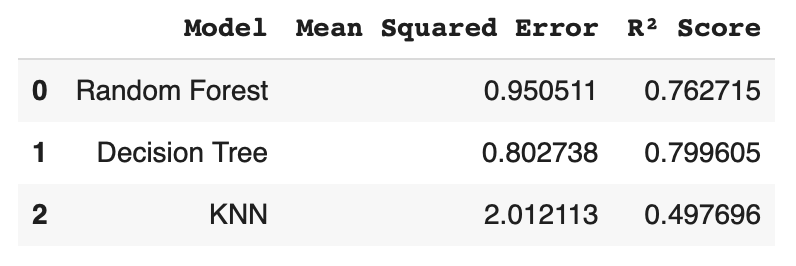
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| Univariate Analysis | |
| 81007e21dc18eb59d563ecaa825b38b9.png            fff8fa561e36fc3147285e3861b2c413.png | The histogram above provides an overview of how total daily screen time is distributed throughout the observed period. It is evident that most days fall within the range of 8 to 12 hours, with some noticeable peaks around 16 hours, likely corresponding to weekends or low-responsibility days. This observation highlights a right-skewed distribution, suggesting that prolonged screen usage was not uncommon. The understanding derived from this plot suggests that such extended screen time—especially on non-academic platforms—may disrupt studying patterns and contribute to time mismanagement, ultimately affecting educational productivity.      The boxplot presents a concise visualization of the variability in studying hours across the dataset. Most studying occurred between 1 and 4.5 hours daily, with a few outliers exceeding 7 hours—often reflecting exam preparation or intense workload days. Observationally, there is a wide spread indicating inconsistency in study habits. From an understanding perspective, these fluctuations suggest that factors like academic responsibilities, screen time, or even personal mood could be strongly influencing the ability to maintain a steady study routine. Identifying these variations helps in recognizing behavioral patterns linked to academic performance. |
| Bivariate Analysis | |
| be60c02ccd714093d220cdb67c1afcf9.png      791a068353d560735ca6b6e0655e371c.png      e46e9abece091fa310310027758ad2aa.png      acc309d56cb23f0d92723697a34b3393.png      2990b31a22be2a00340ae21cd2d04dcc.png      b6f69e9b8f7b72e5d081769d437d0c79.png | **Observation:** This scatter plot reveals a generally negative pattern — as total screen time increases, studying hours tend to decrease. Clusters near zero studying hours coincide with both moderate and high screen times.  **Understanding:** This suggests that excessive screen exposure, regardless of the time of day, likely detracts from study engagement. The inverse relationship supports the hypothesis that unregulated digital behavior interferes with academic productivity.    **Observation:** The points are more concentrated in the mid-to-high ranges for both variables. Higher educational screen time often aligns with higher studying hours.  **Understanding:** Structured screen time used for learning correlates positively with studying hours, indicating that not all screen usage is detrimental. Educational platforms appear to complement academic focus when used purposefully.      **Observation:** There is a concentration of low studying hours even when non-educational screen time is moderate or high.  **Understanding:** This suggests that time spent on entertainment or social media platforms likely replaces valuable study time. Non-educational screen engagement seems to be a distraction, weakening academic discipline.      **Observation:** A general upward trend is visible — longer sleep durations loosely align with increased studying hours. However, some outliers exist.  **Understanding:** Adequate sleep likely fosters better concentration and energy, enabling more effective study sessions. While not a strong linear relationship, this supports the view that rest contributes to academic consistency.      **Observation:** As academic responsibilities increase (from 0 to 2), average studying hours rise significantly.  **Understanding:** The chart demonstrates that students tend to prioritize their study time in response to increasing workload. Academic obligations act as a trigger for focused study behavior.      **Observation:** Students with high screen time show a wider and higher distribution of studying hours compared to those with low screen time. However, outliers exist in both groups.  **Understanding:** While one might expect high screen time to hinder productivity, some individuals manage to maintain high studying hours. This points toward the role of self-regulation and screen content (e.g., educational use) as moderating variables. |
| Multivariate Analysis | |
| a10fa48a481b344f9fa2a6ea121ee8bc.png              090c56dda95dfb98bfb2a2e2ee86fbb7.png | **Observation:**  The heatmap reveals a strong negative correlation between time spent on social activities and studying hours (−0.58), and similarly, a strong negative correlation between total screen time and studying hours (−0.57). On the other hand, educational screen time is positively correlated with studying hours (+0.68), and academic responsibilities also show a moderate positive trend.  **Understanding:**  These correlations suggest that non-academic distractions such as socializing or entertainment-based screen time may directly reduce the time allocated for studying. Conversely, purposeful screen usage, like educational content, could support better study efficiency. Academic obligations seem to promote structure, indirectly increasing productivity.    **Observation:**  The time series visualization shows alternating peaks and troughs between studying hours and total screen time. Notably, on days where screen time spikes, study time often dips, especially in the middle segment of the dataset.  **Understanding:**  This inverse pattern over time indicates a potential trade-off between screen engagement and academic effort. The visual gap reinforces that days dominated by high screen usage often coincide with reduced focus on academic tasks, suggesting that managing screen habits consistently could improve study routines. |
| Regression Analysis | |
| 1864d416a37914559dcd208245006f2b.png                  c0e0d615673ec41d24132b613d2515f6.png          ac1ef194ded3d44eb2c6549a49633b50.png          d5e3b6dd67cd02df83cf583ee204cbf9.png | **Observation:**  The feature importance graph derived from the Random Forest model indicates that *educational screen time* is the most significant predictor of studying hours, followed by *sleep duration*. Non-educational screen time and time spent on social activities have lower importance, while academic responsibilities appear to contribute the least to the prediction model.  **Understanding:**  This suggests that not all screen time is detrimental to studying efficiency—educational use of screens may even support productive academic habits. Furthermore, sleep continues to play a vital role in supporting concentration and cognitive capacity. The lesser weight given to non-educational screen time and social activity points to their indirect or inconsistent impact.      **Observation:**  The scatter plot comparing actual versus predicted studying hours by the Random Forest model shows a decent clustering around the ideal fit line, although with some variance—especially at higher studying values.  **Understanding:**  While the model captures overall patterns well (as also indicated by its R² score), it slightly underestimates or overestimates in more extreme cases. This confirms that the model has predictive power but could benefit from more data or fine-tuned hyperparameters.      **Observation:**  The Decision Tree model's actual vs predicted plot shows a strong fit for mid-range studying hours, with minimal deviation from the ideal line.  **Understanding:**  Decision Trees tend to overfit training data, yet in this context, it appears to be capturing the patterns effectively—perhaps due to the limited dataset. Its high R² score supports its performance and suggests interpretability without substantial loss in accuracy.        **Observation:**  The K-Nearest Neighbors (KNN) model's predictions deviate more from the ideal fit, particularly at the extremes, with a noticeable clustering of points away from the red line.  **Understanding:**  KNN struggles when faced with nonlinear, sparse, or noisy data. It performs less accurately than Random Forest and Decision Tree models in this case, as indicated by its lower R² score and higher MSE. It suggests that the relationships between screen time, sleep, and studying hours may not be locally smooth enough for KNN to generalize well. |

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| Conclusion |

The patterns uncovered throughout this study reveal a compelling relationship between screen time behaviors and academic productivity. Total screen time—especially when dominated by non-educational usage—showed a strong inverse association with studying hours. On the contrary, educational screen time demonstrated a positive correlation, reinforcing the idea that not all digital engagement is detrimental.

Multivariate and regression analyses highlighted the central importance of educational screen time and sleep durationin predicting study behavior. The Random Forest feature importance plot ranked educational screen time as the most influential factor, followed by sleep and social time. The correlation heatmap supported these findings, showing strong directional trends between behavioral variables and academic effort.

From a modeling standpoint, the Decision Tree Regressor slightly outperformed others with the highest R² score (≈ 0.80) and the lowest Mean Squared Error (≈ 0.80), closely followed by Random Forest (R² ≈ 0.76). The K-Nearest Neighbors model, although conceptually simpler, yielded the weakest performance (R² ≈ 0.50), suggesting that proximity-based estimation is less suited to this data's distribution.



Overall, this project underscores how structured screen habits—especially those aligned with learning—and sufficient rest can enhance study output. In contrast, unregulated screen exposure and social distractions may hinder academic progress. These insights emphasize the value of mindful digital behavior for students aiming to optimize their focus and efficiency.