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Final Report – Screen Use Association Project

Introduction:

As social media platforms and apps become more ubiquitous, more people worldwide are spending more time on social media (Rahardja, 2022). While there are many claims that this increased screen use is negatively impacting student lives, there is mixed information on the degree of impact that increased screen use is having on student lives, and the lifestyle drivers, including social media use, that may be causing students to spend more time on their phones. The dataset I am using was compiled in 2025 from students aged 16-25 across multiple countries, and contains 12 variables spanning various student use patterns of various social media platforms on phones as well as lifestyle, personal, and academic indicators. The goal of this project is to use a dataset of global student screen time and lifestyle metrics to determine if different social media platforms, life stages, and lifestyle choices can be associated with different average daily phone use times.

Methodology: techniques used and justification

My first approach was to check linearity assumptions for a linear model fit to this dataset. The dataset consists of 12 continuous, discrete, and categorical predictor variables. The dataset did not have any outliers or empty cells, but it did have multicollinearity between variables and unstable residuals for some variables that needed to be addressed. At first, I tried a few transformations for the predictor Sleep_Hours_Per_Night, but the residual pattern was star shaped, and so I determined that it would be most valuable for the project to remove it and continue with analysis. Similarly, Addicted_Score had the highest VIF value, which made sense from a domain perspective, as the screen addiction would inherently have high multicollinearity with screen use. I decided that removing the variable would allow for the most valuable insights. I still was having trouble getting the dataset to meet independence assumptions, and after many hours of trying different interaction terms and random slopes and intercepts of variables, I was unable to identify the source of the non-independence, potentially indicating that the non-independence was emerging from absent and critical covariates. The non-independence in addition to the banding that I saw in the residuals led me to decide to stick with the best performing mixed-effects model and use bootstrapping to estimate confidence intervals and conduct hypothesis tests.

To trial two variable selection algorithms, I used Lasso and Elastic Net regularization algorithms. These two approaches performed well. When compared with the cross-validated RMSE and MAE values from the mixed effects model (which required a new

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package, LASSO and Elastic Net models did perform better for prediction. RMSE and MAE provide a representation of the average size of error in the model, with MAE treating errors equally, and RMSE penalizing outliers and larger errors more heavily. However, even though the models arising from variable selection performed better according to RMSE and MAE values, the mixed effects model still performed reasonably well, and I decided that the mixed effects model would be more appropriate when paired for bootstrapping for inference and hypothesis testing, which is the objective of this project.

For hypothesis testing, confidence interval generation, and inference, I used a combination of linear mixed-effects modeling and bootstrapping-based inference. This approach was appropriate because the data included non-independent observations which I could partially address with mixed-effects modelling by including random effects for group-based correlations, such as including the random effect of country. However, after trying various random effects and interaction terms, non-independence and banding in the residuals still presented a concern, so I decided to use non-parametric bootstrapping with the bootMer function from the lme4 package which allows for resampling the data structure while preserving the mixed-effects framework. Bootstrapping allowed me to produce robust confidence intervals for model parameters that do not rely on parametric assumptions.

Results:

The mixed effects model with bootstrapping revealed several statistically significant 95% confidence intervals for predictors. In the context of this model, each coefficient represents the change in average daily screen time (in hours) associated with a one-unit increase in the corresponding predictor, holding all other variables constant. Age was found to have a small but statistically significant positive association with screen time, with a confidence interval between 0.04 to 0.17 hours. Undergraduate academic level was associated with significantly higher screen time compared to the reference group (Graduate) with a confidence interval between 0.15 to 0.55 hours. Most used platform variable had several contrasting results by platform. Those that most frequently use LinkedIn spending significantly *less* time on social media than Facebook users, (-0.91, -0.24), followed with TikTok (-.37, -0.004), with Twitter (0.01, 0.5) and Whatsapp users spending significantly *more* time on social media than Facebook users (0.5, 0.95). Mental health score was significantly, and negatively associated with screen time, with every one-point increase in reported mental health, average screen time decreased by 0.59 to 0.35 hours per day. Individuals who already think that social media is impacting their lives in the form of academic performance were associated with lower screen use (-0.54, 0.04). Finally, individuals who reported experiencing conflicts on social media spent more time on social media (0.47, 0.78).

Discussion:

The results from this project indicate that social media usage time is influenced by a combination of demographic, lifestyle, and behavioral factors. The positive relationship between age and screen time suggests that older individuals in the sample may engage more frequently with social media than younger participants. It is generally assumed that younger people spend more time on social media, and the opposite association in this model may be driven by the age predictor being capped in this dataset at 25 years old. Current 25 year olds have been around social media their whole life, unlike 40 year olds, so perhaps the relationship would be different if the surveyed population included those above 25 years old.

Higher screen time in undergraduate populations underlines that people in undergrad are often focused more on social and cultural connection than those younger or older. They may use social media as a way to connect, relate, and understand their role in social and cultural circles; goals which lose importance as you age. The positive association with undergraduates and screen time aligns with broader trends in the predisposition of undergraduate-age individuals.

Varying platform-specific usage patterns indicate that different social media platforms have different impacts on how much time users spend on their phones. Interestingly, the short-form video platform TikTok was associated with less screen time than facebook, joining LinkedIn in a negative association with screen time. Many people consider short-form video platforms the most addicting platforms (Wu et al., 2021). However, these results suggest that platforms focused on social interactions like Twitter and Whatsapp, are associated with the most consistent daily increase in screen time. Perhaps the pattern of use for short form videos is less consistent and more binge-like, which would be interesting to investigate in a future study.

Those that consider their screen use impacting their academic performance were associated with a decrease in screen use, which suggests that these individuals already consider screen use a bad habit and are either consciously or potentially subconsciously more averse to spending consistent daily time on their phones than those who do not think screen time impacts their academic performance.

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One of the most salient predictors was mental health, which showed a strong negative association with screen time as the user reported better mental health. This relationship indicates a correlation, not causation. However, the correlation aligns with existing beliefs on the negative impact on mental health of platforms that allow individuals to compare themselves to others (Tang et al., 2021).

Individuals who reported engaging more in conflicts on social media spent significanly more time online, which could be due to those actively engaged in a conflict are more compelled to monitor or respond to social tensions on social platforms, leading to increased time on the platforms. Self-reported measures like screen time and mental health may introduce bias or inaccuracies, which may explain the slight skew in mental health ratings towards lower ratings. Also, unobserved confounding variables like occupation, strength of social connections, time management skills, or personality traits would likely present important variables to consider to truly parse out stronger relationship between variables, address non-independence, and help direct causality-based inferences in the future.

While there are interesting correlations presented by this project, the analysis has limitations. Given the mixed model structure of the analysis, causality cannot be established.

Conclusion:

This project contributes to the body of work suggesting that screen time is not solely a function of platform, age, lifestyle, or mental health, but instead that all these variables interact with screen time, and each other, to drive the directionality of those relationships. The results provide potential intervention points associated with certain social media platforms that individuals or parents can use to try and help decrease screen time. Future work should look at the impact of different social media platforms on binging, rather than consistent use, and continue to investigate the interactions between these variables and excluded variables with mixed effects approaches.

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References:

Rahardja, U. (2022). Social media analysis as a marketing strategy in online marketing business. *Startupreneur Business Digital (SABDA Journal)*, *1*(2), 176-182.

Tang, S., Werner-Seidler, A., Torok, M., Mackinnon, A. J., & Christensen, H. (2021). The relationship between screen time and mental health in young people: A systematic review of longitudinal studies. *Clinical psychology review*, *86*, 102021.

Wu, Y., Wang, X., Hong, S., Hong, M., Pei, M., & Su, Y. (2021). The relationship between social short-form videos and youth's well-being: It depends on usage types and content categories. *Psychology of Popular Media*, *10*(4), 467.