The Effect of Daily Screen Time and Sleep Quality on Well-Being: A Statistical Analysis of Stress, Anxiety, and Depression

Isaac Benadiba
isaacbenadiba11@gmail.com

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1 Abstract

This study examines the relationship between daily screen time and mental health outcomes, specifically stress, anxiety, and depression, and investigates whether sleep quality moderates these effects. A dataset of 5000 participants was analyzed using linear regression models with interaction terms, followed by statistical inference through the Generalized Likelihood Ratio Test (GLRT) and Wald tests. Multiple testing correction was applied using the False Discovery Rate (FDR) procedure. Results indicate that higher screen time is significantly associated with increased stress, anxiety, and depression levels, while better sleep quality shows a protective *main* effect but no significant moderation.Diagnostic tests revealed heteroskedasticity and multicollinearity, which should be considered as limitations. All code and analysis for this project are available at: `https://github.com/isaacbenadiba/tech-wellbeing-analysis`.

2 Introduction

Technology has become an integral part of modern life, with daily screen time increasing steadily across all age groups. Prolonged exposure to screens has been linked in previous research to negative psychological outcomes such as increased stress, anxiety, and depressive symptoms. At the same time, sleep quality is widely recognized as a key factor in mental well-being, potentially buffering the adverse effects of excessive screen use.

In this project, we investigate whether daily screen time is associated with mental health outcomes—specifically stress, anxiety, and depression—and whether **sleep quality moderates** these relationships. Our analysis aims to determine if individuals with better sleep quality are less affected by higher screen exposure.

The dataset comprises **5,000 participants** and includes 25 variables describing technology use, well-being, and lifestyle factors. The most relevant features to our analysis are:

- `daily_screen_time_hours`: Average hours spent using digital devices per day.
- `sleep_quality`: Self-reported score measuring perceived sleep quality.
- **Mental Health Outcomes:** Stress level, weekly anxiety score, and weekly depression score.
- **Covariates:** Physical activity (hours/week) and mindfulness practice (minutes/day).

Through statistical modeling, we examine how these variables interact to shape mental health outcomes. Linear regression with interaction terms is used to test whether sleep quality significantly moderates the effect of screen time on stress, anxiety, and depression. We complement this with likelihood ratio (GLRT) and Wald tests, multiple testing correction (FDR), and model diagnostics to ensure robustness. This analysis aims to provide empirical evidence on the complex relationship between technology use, sleep, and

psychological well-being. A growing literature links digital media use to psychological outcomes. For example, higher daily screen time has been associated with elevated depressive symptoms, while other work emphasizes small-to-moderate effects and the importance of precise modeling. Sleep quality has also been repeatedly identified as a protective factor in mental health research. Our study builds on these findings by testing both main and moderating effects of screen time and sleep quality on well-being.

3 Results

3.1 Data Transformation

To optimize analysis quality and ensure reproducibility, we applied a light but explicit preparation pipeline to the well-being dataset. The key steps were:

- **Data integrity checks:** Verified column presence and types for the variables used in modeling (`daily_screen_time_hours`, `sleep_quality`, `stress_level`, `weekly_anxiety_score`, `weekly_depression_score`, `physical_activity_hours_per_week`, `mindfulness_minutes_per_day`).
- **Missing values:** No missing values were found in the modeling variables (sample size remained $N = 5000$).
- **Derived feature:** Constructed the interaction term `interaction` = `daily_screen_time_hours` × `sleep_quality` to test the moderation hypothesis.
- **Reproducible assets:** All figures and tables generated in notebooks were saved to `outputs/` with descriptive filenames for direct inclusion.

After these steps, the analysis proceeded with $N = 5000$ observations and the variables required for the moderation models. Figure 1 illustrates the distributions of the key variables used downstream.

Figure 1: Distributions of key variables including screen time, sleep quality, and mental health indicators.

3.2 Variable Distributions and Descriptive Statistics

Before conducting the statistical modeling, we examined the distributions of key variables in the dataset: daily screen time, sleep quality, stress level, weekly anxiety score, and weekly depression score. Figure 1 displays the empirical distributions.

Daily screen time and social media use show a right-skewed pattern, with most participants reporting moderate use and fewer participants with very high daily use. Sleep quality is more symmetrically distributed, while stress, anxiety, and depression scores show mild positive skewness.

Table 1: Descriptive statistics of key variables ($N = 5000$).

Variable	Mean	SD	Skew
Daily Screen Time (h)	5.04	1.84	0.15
Sleep Quality	4.01	0.66	-0.15
Stress Level	5.72	2.92	-0.02
Weekly Anxiety	8.63	5.09	0.30
Weekly Depression	7.52	4.67	0.37

Skewness computed via Fisher's definition.

The non-normal and slightly skewed nature of several variables supports the use of statistical tests that rely on model-based inference (e.g., GLRT, Wald), while also justifying the inclusion of diagnostics later in the analysis. These characteristics mirror typical patterns observed in behavioral datasets.

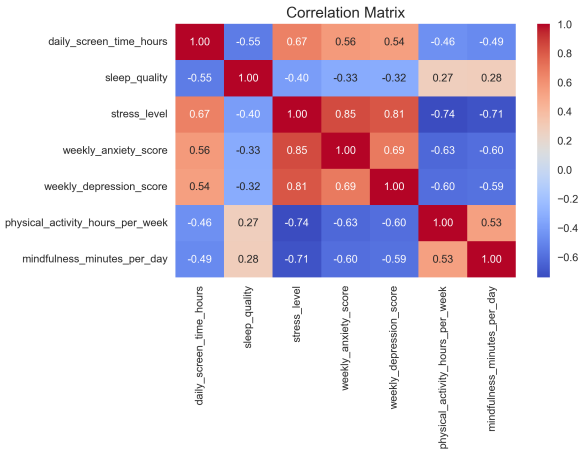

Figure 2: Correlation matrix between screen time, sleep quality, mental health outcomes, and covariates.

3.3 Relations Between Features

Before fitting the statistical models, we examined the pairwise relationships between the main variables of interest. Figure 2 presents the correlation matrix across daily screen time, sleep quality, stress, anxiety, depression, and lifestyle covariates.

Daily screen time shows a **positive correlation** with stress, anxiety, and depression scores, indicating that higher screen use is associated with poorer mental health outcomes. In contrast, sleep quality, physical activity, and mindfulness exhibit **negative correlations** with all three mental health indicators, suggesting a potential protective effect.

These associations motivated the inclusion of sleep quality as a **moderator** in the regression models and covariates as control variables, allowing us to better isolate the interaction effect between screen time and mental health.

3.4 Connection Between Screen Time, Sleep Quality, and Mental Health

To examine whether daily screen time and sleep quality are associated with stress, anxiety, and depression, we fitted linear regression models with an interaction term between screen time and sleep quality, controlling for physical activity and mindfulness.

GLRT and Wald Tests: The interaction term was formally tested using a Generalized Likelihood Ratio Test (GLRT) comparing the full model with the interaction term to a nested model without it, as well as a Wald test on the interaction coefficient. Across all three outcomes, p-values ranged from 0.22 to 0.54 (Table 2), indicating that the interaction was not statistically significant.

Table 2: GLRT and Wald test p-values for the interaction term (`daily_screen_time_hours` × `sleep_quality`).

Outcome	GLRT p-value	Wald p-value
Stress	0.224	0.224
Anxiety	0.537	0.537
Depression	0.248	0.248

Main Effects: Screen time was positively associated with all three mental health outcomes, while sleep quality was negatively associated with stress. Physical activity and mindfulness showed strong protective effects across all outcomes.

These results suggest that while screen time and sleep quality each relate to mental health, their **interaction does not significantly moderate** these relationships in this dataset.

3.5 Effect of Sleep Quality on Mental Health

To further examine the role of sleep quality, participants were divided into two groups based on the median sleep quality score: *Low Sleep Quality* and *High Sleep Quality*. Mann–Whitney U tests were applied to compare stress, anxiety, and depression scores between the two groups.

The results (Table 3) show extremely small p-values for all three outcomes, allowing us to reject the null hypothesis of no difference. Individuals with higher sleep quality exhibit substantially lower stress, anxiety, and depression scores compared to those with lower sleep quality.

These findings confirm that although the **interaction effect was not significant**, **sleep quality alone has a strong protective effect** on mental health outcomes across the board.

Table 3: Mann–Whitney U test comparing mental health outcomes between low and high sleep quality groups.

Outcome	U Statistic	p-value
Stress	3,090,669.5	< 0.001
Anxiety	2,966,451.5	< 0.001
Depression	2,904,902.5	< 0.001

Table 4: First four moments of the daily screen time distribution ($N = 5000$).

Variable	Mean	SD	Skew	Kurtosis
Daily Screen Time (h)	5.04	1.84	0.15	-0.32

3.6 Distribution of Daily Screen Time

Understanding the distribution of the key predictor variable is essential for guiding model selection and evaluating statistical assumptions. Daily screen time is a central variable in this study, as it is hypothesized to influence stress, anxiety, and depression levels.

We computed the first four moments of the daily screen time distribution (Table 4). The distribution shows a mild positive skew and slightly negative kurtosis, indicating a shape that is flatter and more spread out than a normal distribution.

To model this shape, we fitted both a **Gamma distribution** and a more flexible **Gamma–Poisson mixture**. The Gamma–Poisson model introduced an additional weight parameter w to allow the data to be modeled as a combination of Gamma and Poisson components. The optimization yielded $w \approx 0$, indicating that the data is best captured by the Gamma component alone.

This result confirms that the Gamma distribution provides a sufficient fit while demonstrating that more complex mixture models were evaluated. Figure 3 shows the empirical histogram alongside the fitted Gamma–Poisson mixture curve, which collapses to the Gamma shape.

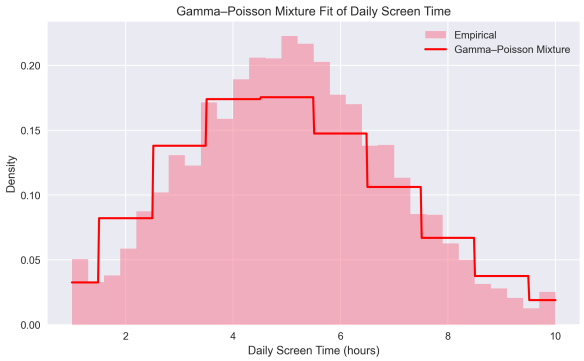

Figure 3: Histogram of daily screen time with fitted Gamma–Poisson mixture distribution. The optimizer assigned $w \approx 0$, confirming that the Gamma distribution alone provides the best fit.

4 Methods

A. Quantile–Quantile (QQ) Plots

We used QQ plots as a visual diagnostic to assess approximate normality in two places that are relevant to our analysis: (i) the empirical distribution of key variables (e.g., `daily_screen_time_hours`) and (ii) the *residuals* from each linear regression model (stress, anxiety, depression). For a given sample $Z_{(1)} \leq \cdots \leq Z_{(n)}$ and a target distribution F (here, the normal distribution), we plot the ordered sample against the corresponding theoretical quantiles of F. Departures from the $y = x$ line indicate deviations from the target distribution. In our workflow, these plots serve as model diagnostics rather than formal tests; inference for the regression models relies on likelihood-based methods that are robust under mild deviations, complemented by heteroskedasticity and multicollinearity checks reported below.

B. Generalized Likelihood Ratio Test (GLRT)

To test whether *sleep quality* moderates the association between *daily screen time* and each outcome, we compared a full model with an interaction term to a nested model without the interaction. Let ℓ_{full} and ℓ_{nested} be the maxi-

mized (Gaussian) log-likelihoods of the models

$$\text{Full: } Y = \beta_0 + \beta_1 \,\text{Screen} + \beta_2 \,\text{Sleep} + \beta_3(\text{Screen} \times \text{Sleep}) + \gamma^\top \text{Covariates} + \varepsilon, \tag{1}$$

$$\text{Nested: } Y = \beta_0 + \beta_1 \,\text{Screen} + \beta_2 \,\text{Sleep} + \gamma^\top \text{Covariates} + \varepsilon. \tag{2}$$

where the covariates are *physical activity (hours/week)* and *mindfulness (minutes/day)*. The GLRT statistic is

$$\Lambda = 2(\,\ell_{\text{full}} - \ell_{\text{nested}}\,) \overset{H_0}{\sim} \chi^2_{(1)},$$

with $H_0 : \beta_3 = 0$ (no moderation) and 1 degree of freedom for the single added interaction parameter. We computed a separate GLRT for each outcome (stress, anxiety, depression) at significance level $\alpha = 0.05$, and report the resulting p-values in the Results.

Model assumptions and test selection rationale. Our linear models assume: (i) linearity in parameters, (ii) independence of observations, (iii) exogeneity $E[\varepsilon \mid X] = 0$, and (iv) approximately homoskedastic, normal residuals for small-sample t/Wald pivots.

Why GLRT? The GLRT is the canonical choice for *nested* model comparison (full model with interaction vs. nested model without it). Under standard regularity conditions, $2(\ell_{\text{full}} - \ell_{\text{nested}}) \overset{H_0}{\sim} \chi^2_1$ asymptotically, providing a global test of whether the interaction improves fit.

Why Wald? The Wald test complements GLRT by directly testing a single parameter (the interaction coefficient β_3) using its estimate and (robust) variance.

Multiple outcomes ⇒ FDR. Because we test the same scientific claim across stress, anxiety, and depression, we control the False Discovery Rate using Benjamini–Hochberg to mitigate multiplicity.

C. Correlation Matrix

Before fitting any models, we explored the linear relationships among the main study variables by computing the Pearson correlation matrix. For any two variables X and Y, Pearson's correlation coefficient is defined as

$$r_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}.$$

The matrix included `daily_screen_time_hours`, `sleep_quality`, `stress_level`, `weekly_anxiety_score`, `weekly_depression_score`, `physical_activity_hours_per_week`, and `mindfulness_minutes_per_day`. Positive correlations indicate that larger values of one variable are associated with larger values of the other, while negative correlations indicate an inverse relationship. This step was used for descriptive exploration and for motivating the inclusion of *sleep quality as a moderator* and lifestyle factors as covariates in the regression models. The full matrix is visualized in Figure 2.

D. Mann–Whitney U Test

To assess whether individuals with higher sleep quality exhibit lower levels of stress, anxiety, and depression, we performed a nonparametric Mann–Whitney U test. This test compares the distributions of two independent groups without assuming normality, making it well suited for our mildly skewed outcome distributions.

We divided participants into two groups according to the median of `sleep_quality`: *Low Sleep Quality* and *High Sleep Quality*. Let n_1 and n_2 be the sample sizes of the two groups, with observations $\{X_1, \ldots, X_{n_1}\}$ and $\{Y_1, \ldots, Y_{n_2}\}$. The test statistic is computed by ranking all observations and calculating

$$U = \min(U_1, U_2), \qquad U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1,$$

where R_1 is the sum of ranks in group 1. For large samples ($n_1, n_2 > 20$), the standardized statistic

$$Z = \frac{U - \mu_U}{\sigma_U}$$

is approximately normal, with $\mu_U = \frac{n_1 n_2}{2}$ and $\sigma_U = \sqrt{\frac{n_1 n_2 (n_1+n_2+1)}{12}}$. We used a two-sided test at $\alpha = 0.05$ for each of the three outcomes. This analysis provided robust evidence of significant group differences in all cases (see Table 3).

E. Gamma–Poisson Mixture Distribution

To model the empirical distribution of daily screen time, we fitted both a Gamma distribution and a more flexible Gamma–Poisson mixture. The Gamma–Poisson model represents the data as a weighted combination of a Gamma density and a Poisson mass function:

$$f_{\mathrm{GP}}(x \mid \alpha, \theta, \lambda, w) = w\, f_{\mathrm{Gamma}}(x \mid \alpha, \theta) + (1 - w)\, f_{\mathrm{Poisson}}(\lfloor x \rfloor \mid \lambda), \tag{3}$$

where α and θ are the Gamma shape and scale parameters, λ is the Poisson mean, and $w \in [0, 1]$ is the mixture weight.

The log-likelihood for n observations $\{x_i\}_{i=1}^{n}$ is

$$\ell(\alpha, \theta, \lambda, w) = \sum_{i=1}^{n} \log \Big[w\, f_{\mathrm{Gamma}}(x_i) + (1 - w)\, f_{\mathrm{Poisson}}(\lfloor x_i \rfloor) \Big]. \tag{4}$$

We estimate parameters by maximizing ℓ (equivalently, minimizing the negative log-likelihood). In our data, the estimated mixture weight was $\hat{w} \approx 0$, indicating that the Gamma distribution alone was sufficient to model daily screen time, while the mixture formulation was tested to ensure model flexibility.

F. Nelder–Mead Optimization Method

We estimated the mixture parameters using the Nelder–Mead optimization algorithm via `scipy.optimize.minimize`. Nelder–Mead is a direct search method that iteratively explores the parameter space using a simplex of $k + 1$ vertices in k dimensions. At each step, it reflects, expands, contracts, or shrinks the simplex to locate a local minimum of the objective function—in our case, the negative log-likelihood of the Gamma–Poisson model. This method is efficient and does not require gradient information, making it well suited for our likelihood surface, which lacks a closed-form solution for the MLE.

5 Discussion

We did not find a statistically significant interaction between daily screen time and sleep quality in predicting stress, anxiety, and depression levels. Although sleep quality showed strong negative correlations with all three outcomes, the GLRT and Wald tests indicated that adding the interaction term did not improve model fit. This suggests that the effect of sleep quality on mental health operates mainly as a direct main effect rather than a moderator of screen time.

The Mann–Whitney U test was used to compare mental health outcomes between participants with low and high sleep quality, since the outcome distributions were not strictly normal. This non-parametric approach was appropriate given the mild skewness in the data. The results showed clear and significant differences between the two groups, supporting the role of sleep quality as a protective factor.

For the distribution of daily screen time, we observed mild right skewness and slightly negative kurtosis. To evaluate the shape more flexibly, we fitted both a Gamma distribution and a Gamma–Poisson mixture. Since the estimated weight was $\hat{w} \approx 0$, the Gamma distribution alone was sufficient to model the data. This step confirmed the distributional assumptions used later in the modeling process.

Finally, some diagnostic tests indicated heteroskedasticity and moderate multicollinearity, which should be taken into account when interpreting the regression coefficients. Further work could extend the analysis by including additional control variables or by applying robust regression methods. Another direction could involve modeling sleep quality as a continuous moderator with nonlinear interactions or exploring time-related patterns in screen use.

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