Does Long Screen Time Really Jeopardize Mental Well-being?

Luyi Lin * 1 **Yangxu Su** * 1 **Sheng Gao** * 1 **Wenjie Wang** * 1 **Jianxing Lou** * 1

Abstract

Public intuition widely posits that prolonged screen time harms mental well-being. However, the performance of simple correlation in complex health scenarios remains limited, and focusing on a single factor often obscures core psychological drivers. To address these challenges, we present an optimized multivariate framework utilizing LASSO Regression to rigorously untangle the hierarchical factors influencing the Mental Wellness. Our analysis conducted on the Screen Time vs Mental Wellness Survey - 2025 dataset. Experimental results demonstrate that the observed negative effect of screen time is largely confounded by the dominant and independent contributions of Stress Level, Sleep Quality, and Productivity. This evidence strongly challenges conventional wisdom, suggesting that targeted public health interventions should prioritize stress management and sleep optimization over screen time reduction. Our work is open-sourced at https://github.com/Louis1612/Does-Long-Screen-Time-Really-Jeopardize-Mental-Well-being.

1. Introduction

With the growing prevalence of digital devices in our lives, understanding the link between screen time, sleep quality, stress, and productivity is a crucial research area for data science, psychology, and public health.

In out society, it's been a long time for public to hold a strong belief that long screen time indeed does great harm to our health conditions both physically and mentally. However, we argue that such an opinion rises from intuition rather than rigorous data evidence, which is not reliable. What's worse, the overconfidence in a single factor might lead to the ignorance of other deeply influential factors that truly have an impact.

To overcome this problem and unveil the secret behind the scene, we carry out this study utilizing advanced regression modeling, specifically LASSO Regression with the Screen Time vs Mental Wellness Survey - 2025 dataset.

Through three-stage modelling, we demonstrate that the observed detrimental effect of screen time is largely confounded by the dominant and independent contributions of Stress Level, Sleep Quality, and Productivity. In the final, stable model, these three factors emerge as the primary drivers of mental wellness. The LASSO technique further confirmed that the independent negative effect of total screen time is marginal after controlling for these core psychological and physiological metrics, thereby challenging the conventional wisdom that screen time is the direct, primary antagonist of mental health.

In a nutshell, our contributions can be summarized as follows:

- We argued that long screen time may not always jeopardize our mental well-being and offered rigorous data evidence for our opinion.
- We revealed the true influencing factors of mental health and clarified the complex influencing web of several factors, paving the way for further research.
- We open-sourced our data, code and result to ensure reproducibility.

2. Data Analysis

2.1. Dataset

We use **Screen Time vs Mental Wellness Survey - 2025**[1] dataset in this study. The dataset was compiled from a survey of **400** participants to examine the relationship between screen time and mental wellness. It includes **14** variables: a dependent variable, the mental wellness index, and **13** influencing factors that cover metrics like daily screen usage, weekly time occupation, and various other related factors. Specifically, the 13 influencing factors consist of **8** continuous and 5 discrete variables, with the overall goal of capturing strong evidence and valuable insights into the

*Equal contribution [1]Beijing Jiaotong University. Correspondence to: Luyi Lin <luyilin@bjtu.edu.cn>.

[1]This dataset is opensourced at https://www.kaggle.com/datasets/adharshinikumar/screentime-vs-mentalwellness-survey-2025

impact of prolonged screen time on an individual's mental well-being.

2.2. Factors Analysis

In order to form a basic understanding of the data distribution, we calculate key statistics for important continuous variables like screen time, sleep hours, stress level and mental wellness index in Table1.

Table 1. Key Statistics for Core Continuous Variables

VARIABLE	MEAN	MEDIAN	SD.
SCREEN TIME	9.02	9.09	2.49
MENTAL WELLNESS INDEX	20.33	14.80	20.38
SLEEP HOURS	7.01	7.03	0.85
STRESS LEVEL	8.15	8.80	2.09

Note: SD. represents the standard deviation. Screen Time and Sleep Hours are measured in hours. Mental Wellness Index is on a 0-100 scale, and Stress Level is on a 0-10 scale.

Moreover, we visualize the distribution of these core variables in Figure1(a)to1(d).

Based on the descriptive statistics and the visualizations of the core continuous variables, a preliminary analysis of the distributions reveals several significant insights into the sample's well-being and habits.The most critical finding pertains to the Mental Wellness Index and Stress Level, both of which exhibit highly non-normal and concerning distributions. The Mental Wellness Index is characterized by a pronounced positive skew, with the vast majority of scores clustered in the lower range. This suggests a generalized trend of low self-reported mental wellness across the surveyed participants. Conversely, the Stress Level displays a strong negative skew, being highly concentrated in the upper tiers. The simultaneous prevalence of low mental wellness and elevated stress levels constitutes an adverse trend that warrants deeper investigation into potential contributing factors.

In contrast, the time-based variables demonstrate greater stability and central tendency. Screen Time shows a distribution that is approximately Gaussian, with the mean (9.02 hours) and median (9.09 hours) being closely aligned. The data suggests a consistent pattern of daily screen usage around nine hours for most participants. Similarly, Sleep Hours is also centered around an approximate daily average of seven hours (Mean $= 7.01$, Std. Dev. $= 0.85$). The minimal variability in sleep hours, evidenced by the smallest standard deviation, indicates that this variable is highly consistent across the sample, with most individuals adhering closely to the seven-hour mark.

2.3. Correlation Analysis

The Correlation Analysis results clearly delineate the factors most closely associated with the Mental Wellness Index. Both the Pearson(r) and Spearman(ρ) coefficients yielded highly consistent values, confirming that the relationships are robust and generally linear or monotonic.The analysis reveals three variables exhibiting an extremely strong correlation (absolute value ≥ 0.75) with mental wellness: Stress Level ($r = -0.914$), Productivity ($r = 0.902$), and Sleep Quality ($r = 0.750$). The near-perfect negative correlation with Stress Level indicates that as self-reported stress increases, the mental wellness index dramatically decreases. Conversely, the strong positive correlation with Productivity suggests that high self-perceived productivity is a primary correlate of better mental well-being in this sample.

Furthermore, Screen Time is identified as a factor with a strong negative correlation ($r = -0.636$, $\rho = -0.649$). This supports the central hypothesis of the study, indicating that longer daily screen exposure is significantly linked to a poorer mental wellness index. The components of screen time show a gradient, with Leisure Screen Hours ($r = -0.464$) having a stronger negative association than Work Screen Hours ($r = -0.286$). Finally, factors such as Sleep Hours ($r = 0.581$) show a moderate positive correlation, suggesting its importance, while Exercise Minutes per Week, Social Hours per Week, and Age exhibit very weak or negligible correlation with the Mental Wellness Index in this dataset.

These findings collectively suggest that addressing stress, supporting productivity, and improving sleep quality and duration are the most immediate pathways to improving mental wellness for this surveyed group, with screen time reduction being a significant secondary factor.

3. Method

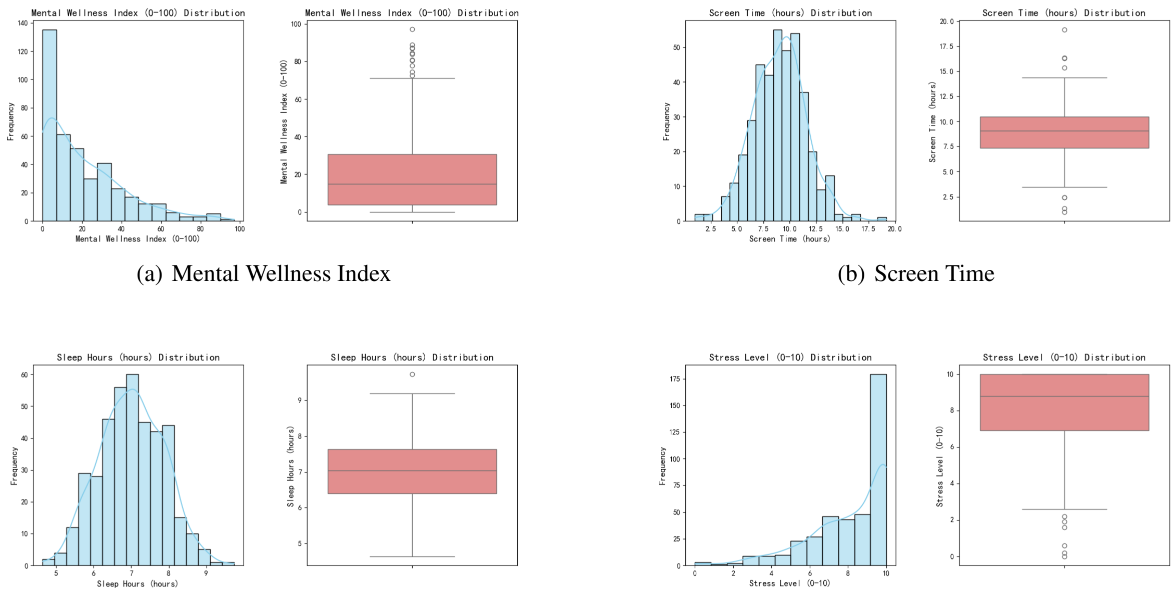
We carry out a three stage modelling strategy, through which we optimize our model step by step and eventually jump out of obvious suboptimal solution.

We firstly build a multiple linear regression model to express the relationship between mental wellness and many influence factors to find out which one or two factors truly have influences. Then, we perform model verification to unveil potential multi-collineerity problem. Finally, we use lasso regression to optimize our pre-built suboptimal model.

3.1. Model Construction

We build multiple linear regression(Jobson, 1991) in this study.

Let Y denotes Mental Wellness Index. All nominal variables were one-hot encoded, and continuous variables were



(a) Mental Wellness Index (b) Screen Time

(c) Sleep Hours (d) Stress Level

Figure 1. The Distribution of Key Variables. (a) Mental Wellness Index, (b) Screen Time, (c) Sleep Hours, and (d) Stress Level.

explicitly cast to numeric types to ensure data compatibility . Let X_i denotes the i-th influencing factors, β_i denotes the i-th regression coefficient, β_0 denotes the intercept of the model, ϵ denotes the error that cannot be captured by the model. Let n denotes the number of independent variables. Then we get:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon \tag{1}$$

We use the least squares method to fit the corrected model:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{2}$$

The estimation result is listed in Table 5.

3.2. Model Diagnosis

The Variance Inflation Factor (VIF) analysis is crucial for diagnosing multicollinearity among the independent variables in the Ordinary Least Squares (OLS) model.

$$\text{VIS}_i = \frac{1}{1 - R_i^2} \tag{3}$$

The assessment of multicollinearity, as detailed by the VIF results in Table 3, identified two critical issues within the predictive model. Most notably, the model suffers from perfect multicollinearity, evidenced by the infinite VIF values assigned to screen time, work screen hours, and leisure screen hours. This perfect linear dependency necessitates the exclusion of at least one variable from this group before stable coefficient estimates can be obtained. Furthermore, two key psychological and performance indicators showed concerning levels of collinearity. The VIF for productivity is $\mathbf{6.29}$, exceeding the commonly accepted diagnostic threshold of 5. Similarly, stress level registered a high VIF of 4.83, approaching the threshold.

Consequently, cautious interpretation is warranted for these variables, and model adjustments (such as removal or aggregation) must be considered prior to final inference.

3.3. Model Optimization

To tackle with the super serious collinearity problem in our model, we apply LASSO regression(Tibshirani, 2018), which has the capability to perform both coefficient stabilization and automatic feature selection by setting the coefficients of redundant predictors precisely to zero:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 + \alpha ||\beta||_1 \tag{4}$$

As the results in Table 4 show, the LASSO model not only demonstrates an excellent fit to the data but also successfully resolved the perfect multicollinearity issue and clarified the independent influence of the highly correlated variables.

We compared the Ordinary Least Squares (OLS) model with the automatically optimized LASSO regression model. The comparison confirms the necessity of regularization when dealing with collinearity. Despite the presence of

Table 3. VIF Result

VARIABLE	VIF
CONSTANT	416.28
AGE	1.08
SCREEN TIME	∞
WORK SCREEN HOURS	∞
LEISURE SCREEN HOURS	∞
SLEEP HOURS	1.77
SLEEP QUALITY	2.40
STRESS LEVEL	4.83
PRODUCTIVITY	6.29
EXERCISE MINUTES PER WEEK	1.08
SOCIAL HOURS PER WEEK	1.06
GENDER MALE	1.05
GENDER NON-BINARY/OTHER	1.10
OCCUPATION RETIRED	1.15
OCCUPATION SELF-EMPLOYED	1.12
OCCUPATION STUDENT	1.28
OCCUPATION UNEMPLOYED	1.17
WORK MODE IN-PERSON	1.32
WORK MODE REMOTE	3.10

Table 4. LASSO Regression Coefficients ($\alpha = 0.1$)

FEATURE	LASSO COEFFICIENT
SLEEP_QUALITY	5.8057
PRODUCTIVITY	4.9423
EXERCISE_MINUTES_PER_WEEK	1.5550
LEISURE_SCREEN_HOURS	0.0000
WORK_SCREEN_HOURS	-0.1111
SCREEN_TIME	-0.1281
SOCIAL_HOURS_PER_WEEK	-0.4064
STRESS_LEVEL	-10.4942

Note: The table here only contains core coefficient and we leave the complete table in Appendix B.

perfect multicollinearity, the coefficients for Stress Level, Productivity , and Sleep Quality remained remarkably stable across both models. This demonstrates that these factors are the most robust, independent contributors to the Mental Wellness Index.

Conversely, the highly unstable coefficients of the collinear screen time variables in the OLS model (e.g., leisure_screen_hours were successfully rectified by the LASSO model. LASSO achieves optimization by shrinking the coefficients of screen_time_hours and work_screen_hours, and decisively setting the coefficient for the redundant leisure_screen_hours to zero, thereby validating the model's structural integrity and confirming that its explanatory power is primarily rooted in the core psychological and physiological metrics.

4. Model Interpretability

The standardized coefficients from the optimized LASSO model reveal a clear hierarchy of predictors for the Mental Wellness Index. The analysis confirms that mental well-being is overwhelmingly driven by psychological and physiological health factors. Stress Level ($-\mathbf{10.49}$), with the largest negative coefficient, is identified as the single most detrimental factor, demonstrating that a one standard deviation increase in stress leads to a 10.49 standard deviation decrease in the index. Conversely, Sleep Quality ($\mathbf{5.81}$) and Productivity ($\mathbf{4.94}$) are the strongest positive determinants. These findings underscore that interventions aimed at managing stress and optimizing the quality of sleep and perceived productivity will yield the greatest impact on improving mental wellness within this population.

The LASSO model provided critical insight into the relationship between screen usage and wellness through its inherent feature selection mechanism. The coefficient for leisure_screen_hours was precisely set to zero ($-\mathbf{0.0000}$), indicating that its unique contribution to the model is redundant once other predictors are considered. While the coefficients for screen_time_hours ($-\mathbf{0.13}$) and work_screen_hours ($-\mathbf{0.11}$) are non-zero, their magnitudes are minimal compared to the core determinants. This solidifies the conclusion that the strong bivariate negative correlation between screen time and mental wellness is mediated by the dominant effects of stress and productivity, leaving only a marginal independent negative association for the overall and work-related usage components.

Beyond the primary factors, the model also highlighted several secondary yet important influences. Exercise Minutes per Week ($\mathbf{1.56}$) provides a notable positive contribution, reinforcing the role of physical activity in mental health. Interestingly, Social Hours per Week showed a small but distinct negative standardized coefficient ($-\mathbf{0.41}$). This counter-intuitive result may suggest that, after controlling for the high explanatory power of stress and productivity, increased time spent socializing could be associated with detrimental factors like social comparison, pressure, or fatigue within this specific sample, rather than a purely beneficial connection. Finally, the model utilized categorical variables like gender_Non-binary/Other ($\mathbf{0.64}$) and penalized other occupation dummies (occupation_Student, occupation_Self-employed) to achieve the final, highly accurate model fit.

References

Jobson, J. D. *Multiple Linear Regression*, pp. 219–398. Springer New York, New York, NY, 1991. ISBN 978-1-4612-0955-3. doi: 10.1007/978-1-4612-0955-3_4. URL https://doi.org/10.

1007/978-1-4612-0955-3_4.

Tibshirani, R. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288, 12 2018. ISSN 0035-9246. doi: 10.1111/j.2517-6161.1996.tb02080.x. URL https://doi.org/10.1111/j.2517-6161.1996.tb02080.x.

A. Model Construction Result

Table 5. OLS Result

	Coefficient	Standard Error	t	P> |t|	[0.025	0.975]
constant	28.9662	5.227	5.542	0.000	18.689	39.243
age	-0.0301	0.036	-0.843	0.400	-0.100	0.040
screen_time	-0.1303	0.121	-1.074	0.284	-0.369	0.108
work_screen_hours	-0.2047	0.155	-1.316	0.189	-0.510	0.101
leisure_screen_hours	0.0744	0.120	0.619	0.537	-0.162	0.311
sleep_hours	0.3065	0.400	0.767	0.444	-0.480	1.093
sleep_quality	9.0027	0.609	14.793	0.000	7.806	10.199
stress_level	-5.0407	0.269	-18.724	0.000	-5.570	-4.511
productivity	0.3298	0.043	7.702	0.000	0.246	0.414
exercise_minutes_per_week	0.0234	0.004	6.138	0.000	0.016	0.031
social_hours_per_week	-0.1041	0.054	-1.934	0.054	-0.210	0.002
gender_Male	-0.0605	0.531	-0.114	0.909	-1.104	0.983
gender_Non-binary/Other	5.4919	1.919	2.862	0.004	1.718	9.265
occupation_Retired	-1.6273	1.498	-1.086	0.278	-4.572	1.318
occupation_Self-employed	-1.9897	0.858	-2.319	0.021	-3.677	-0.303
occupation_Student	-0.5124	0.654	-0.784	0.434	-1.798	0.773
occupation_Unemployed	-0.7382	1.104	-0.669	0.504	-2.909	1.433
work_mode_In-person	-0.2206	0.672	-0.328	0.743	-1.541	1.100
work_mode_Remote	1.3423	0.931	1.442	0.150	-0.488	3.173

B. Model Optimization Result

Table 6. LASSO Regression Coefficients ($\alpha = 0.1$)

FEATURE	LASSO_COEFFICIENT_$\alpha = 0.1$
(INTERCEPT)	20.3268
AGE	-0.0988
SCREEN_TIME	-0.1281
WORK_SCREEN_HOURS	-0.1111
LEISURE_SCREEN_HOURS	-0.0000
SLEEP_HOURS	0.2405
SLEEP_QUALITY	5.8057
STRESS_LEVEL	-10.4942
PRODUCTIVITY	4.9423
EXERCISE_MINUTES_PER_WEEK	1.5550
SOCIAL_HOURS_PER_WEEK	-0.4064
GENDER_MALE	-0.0000
GENDER_NON-BINARY/OTHER	0.6385
OCCUPATION_RETIRED	-0.0845
OCCUPATION_SELF-EMPLOYED	-0.4599
OCCUPATION_STUDENT	-0.0709
OCCUPATION_UNEMPLOYED	-0.0000
WORK_MODE_IN-PERSON	-0.0111
WORK_MODE_REMOTE	0.1616