How Sleep, Exercise and Screen Time Shape Mental Wellness

Abstract:

Mental wellness is critically influenced by modifiable lifestyle factors, yet their relative impact remains poorly quantified. This study uses data science techniques to analyze how daily habits, specifically sleep, exercise, and screen time, predict mental well-being. A multiple linear regression model was constructed using a dataset of 400 participants, with a mental wellness index (0-100) as the dependent variable. The model explained 77% of the variance in wellness (Adj. $R^2 = 0.768$) and identified sleep quality as the most potent predictor, with a coefficient (18.15) far exceeding other variables. Both work and leisure screen time demonstrated significant negative associations with mental wellness ($\beta = -3.46$ and -3.68, respectively), while exercise minutes per week showed a positive, though smaller, effect. The analysis concludes that while all factors are significant, sleep quality is the major contributor to mental wellness. These findings offer data-driven support for public health strategies that prioritize high-quality sleep, regulated screen time, and consistent physical activity as important approaches to improving mental health outcomes.

1. Introduction:

Mental wellness is a vital part of overall health, and it is one of the topics of concern nowadays in the world as mental health conditions continue to rise globally. Nearly one out of five people experiences a mental health condition annually(Centers for Disease Control and Prevention, 2024). Globally, about one-third of people report symptoms of insomnia (National Institutes of Health, 2005). Lifestyle factors such as sleep quality, physical exercise and screen time strongly influence mental well-being. This result employs data science techniques to analyze how lifestyle habits affect mental health and provide data-driven insights to find strategies to improve mental health support.

2. Objective:

The primary objective of this research is to apply data science techniques and methodologies to evaluate the relationship between mental wellness and variations in lifestyle behaviors such as sleep quality, physical exercise and screen time. Additionally, the goal of this study is to identify the correlation between factors that promote healthy daily habits and support mental health. Key questions addressed include whether sleep alone is enough for mental health, how leisure screen time affects psychological well-being, and whether exercise benefits mental health.

3. Dataset & Methodology:

3.1. Dataset and Data Preprocessing

The dataset is found on Kaggle, released in September 2025. The dataset comprises 400 participants and captures their daily behaviors, including sleep, exercise, and screen time. The descriptive statistics and variable definition table are in the appendix.

All computation and visualization were conducted in R, using the Psych, Car packages and base internal functions. Data cleaning involves converting categorical variables into factors and checking for missing values before regression modeling. For easier interpretation, the variable "exercise_minutes_per_week" was converted from minutes to hours per week.

3.2. Methodology

A multiple linear regression model was constructed to assess how lifestyle factors affect mental wellness. The dependent variable was the **mental wellness index (0–100)**, while the independent variables included:

- Sleep quality (1–5 scale)
- Sleep hours per night
- Exercise hours per week
- Work screen hours per day
- Leisure screen hours per day

Model overall performance was evaluated by the F-statistic and adjusted R^2. Significance of the independent variables was evaluated using ANOVA hypothesis testing. Multicollinearity tests using variance inflation factors from the Car package are used to evaluate. The code and a screenshot of the result are included in the **Appendix**. The five VIF Values are all between 1 to 2. The predictors are statistically independent enough, and there is no evidence of multicollinearity. The regression coefficients are stable and reliable.

The final regression model achieved a multiple R^2 of 0.7713 and an adjusted R^2 of 0.7684, indicating that approximately 77% of the variance in mental wellness can be explained by the selected variables. Besides, the F-statistic of 329 (with degrees of freedom 4 and 395) and an extremely low p-value ($< 2.2e-16$), which can reject the null hypothesis. The model as a whole is highly statistically significant.

4. Results & Findings:

Based on our model, we get a **multiple linear regression equation:**

$$\textit{mental wellness index} = 14.6821 + 18.1498(\textit{sleep quality}) + 1.4654(\textit{sleep hours}) + 1.5(\textit{exercise hours per week}) - 3.4577(\textit{work screen hours per day}) - 3.6828(\textit{leisure screen hours per day})$$

4.1. Sleep Quality as the Top Contributor:

Upon analysis, sleep quality emerges as the most significant predictor influencing a person's mental wellbeing. The model shows that sleep quality has a major impact on mental health with a coefficient ($\beta = 18.15$) much higher than all other factors, which indicates that the improvements in sleep quality dramatically elevate mental health outcomes. Empirical evidence constantly reveals that better sleep quality is inversely correlated with symptoms of depression, stress, anxiety and rumination. Crucially, the relationship between sleep and mental health is not merely a function of duration but is more effectively mediated by quality. For instance, in cases of insomnia, cognitive-behavioral therapy targeting sleep quality produces more significant mental health gains than efforts focused solely on increasing total sleep time. Therefore, optimizing sleep quality should be a primary objective in the development of mental health promotion strategies.

4.2. Significance of Exercise and Screen Time

Both exercise, and screen time for work and leisure time, are noted as highly significant predictors ($p<0.001$). However, their effects on mental health are diametrically opposite. The model indicates that physical activity contributes positively to mental health, with empirical evidence suggesting it functions to lower stress, alleviate depressive symptoms, and enhance overall mood. Even the small increases in regular exercise can act as buffers against the negative effects of stress. Conversely, both working and leisure screen time exposure exhibit negative coefficients (β = -3.46 and -3.68, respectively). As such the model indicates that excessive screen time will disrupt sleep patterns, decrease time for physical activity and lead to social isolation, as increased time spent on phones results in people becoming distanced from their normal routines, prioritising an addiction to a screen over meaningful social interaction. Therefore, to optimize mental wellness, it is critical to cultivate a behavioral balance that promotes regular physical activity while consciously regulating screen time.

4.3. Marginal Effect of Sleep Hours

While many believe increasing the duration of sleep is enough to positively influence mental health, the regression model shows that it only has a minor positive influence, with a small coefficient (β = 1.47), compared to sleep quality's much larger coefficient (β = 18.15). Although chronic short sleep duration (e.g., less than six hours per night) is a known risk factor for mental distress, simply extending sleep time without improving its qualitative aspects yields limited benefits. Therefore, we can conclude that sleep duration may be important but not critical to one's mental health and other factors take increased precedence before it.

5. Analysis:

The regression model identified sleep quality as the most potent predictor of mental wellness, a finding strongly supported by contemporary research on the bidirectional link between sleep and emotional state. This relationship operates through multiple psychological and neurobiological mechanisms that create a self-reinforcing cycle between sleep quality and emotional well-being.

As Walker and van der Helm (2009) stated, sleep and emotion share a robust, reciprocal relationship that functions through specific brain mechanisms. According to their research, the prefrontal cortex—which is responsible for emotional regulation and executive functions—is particularly vulnerable to sleep deprivation. When individuals experience poor sleep quality, this impairment in prefrontal functioning leads to decreased emotional control and increased negative emotional responses. Furthermore, the amygdala, which processes emotional reactions, becomes hyperactive under conditions of sleep restriction, creating an imbalance that favors negative emotional processing over rational emotional regulation.

The neurochemical basis for this relationship is equally important. Goldstein and Walker (2014) explained that during deep sleep, the brain undergoes crucial restorative processes that reset emotional circuits and consolidate positive emotional memories. According to their findings, REM sleep specifically facilitates the processing of emotional experiences by weakening the neural connections associated with stressful memories while strengthening pathways related to adaptive emotional responses. This nightly recalibration of emotional brain circuits essentially allows the brain to "reset" its emotional baseline, making individuals more resilient to next-day stressors and better able to maintain positive emotional states.

Conversely, the influence of positive emotions on sleep architecture is equally significant. As demonstrated by Hoyniak et al. (2024) , positive affective states before bedtime contribute to smoother transitions into sleep and more stable sleep maintenance throughout the night. The researchers noted that individuals reporting higher positive mood during the day experienced shorter sleep latency—the time it takes to fall asleep—and fewer nighttime awakenings. This effect is mediated through both psychological and physiological pathways: positive emotions reduce pre-sleep cognitive arousal and worry, while also promoting parasympathetic nervous system activity that prepares the body for restful sleep.

The cyclical nature of this relationship creates either virtuous or vicious cycles in daily life. When individuals experience good sleep, they are better equipped to generate and maintain positive emotions during the day, which in turn prepares their neurophysiological systems for another night of quality sleep. Conversely, poor sleep initiates a downward spiral where impaired emotional regulation leads to increased stress and negative affect, which then further disrupts sleep patterns. This explains why sleep quality emerged as such a powerful predictor in our model—it represents not just a single variable, but a key node in a dynamic self-reinforcing system of mental wellness.

Additional research by Deliens et al. (2014) provides further mechanistic insight, showing that positive emotions specifically enhance sleep efficiency by reducing sleep-onset latency and increasing slow-wave sleep duration. Their experimental findings indicate that individuals who engage in positive emotion induction before bedtime show improved sleep architecture, including greater time spent in restorative deep sleep stages. This suggests that the relationship is not merely correlational but causal in both directions, with each element directly strengthening the other through measurable neurobiological pathways.

In similar analysis, reduction of screen time also is considered a significant factor in the overall improvement of a person's mental wellbeing. Santos et al. (2023) in their research on the effect of screen exposure on adolescents, found that two to four hours usage of TV daily was associated negatively with anxiety and self-esteem of the teen. Meanwhile, usage of smartphones throughout the week had positively correlated with problems of mental health, particularly any usage of social media. In today's time, where people's everyday social interactions have become increasingly limited to apps on the screen of their phones, it is noted that social media, rather than offering a rich robust environment for healthy connection and interaction, instead makes people feel lonelier and isolated which only further contributes to people's decline in mental health.

Longitudinal studies on a large sample of adolescents by Nagata et al. (2024) have only further proven long term effects of unregulated screen time and a person's mental well being. Their research showed important associations of DSM (Diagnostic and Statistical Manual of Mental Disorders) oriented symptoms, most notably depression and conduct symptoms, with increased exposure to screens. Consequently, unregulated screen time emerges as a modifiable risk factor for the development of mental health disorders in this vulnerable population.

Beside better sleep quality and limited screen time, the integration of physical activity and structured exercise into daily routines is linked to enhanced mental wellness. Mikkelsen et al. (2017) states that exercise acts as a physiological stimulus, triggering the release of endorphins and neurotransmitters like serotonin and dopamine, which directly improve mood and induce feelings of well-being. Beyond immediate effects, regular exercise has been noted to improve mental health in the long run as well. A review by Ruiz-Ranz and Asín-Izquierdo (2025) confirms that sustained physical activity is strongly associated with lower levels of anxiety, depression, and psychological distress in adolescent populations, a finding that is generalizable across age groups. This is supported by large-scale epidemiological studies, which, as discussed by Elbe et al. (2019), show a clear correlation between regular exercise and improved mental health outcomes in over 1.2 million individuals. Therefore, the habitual practice of physical activity serves as a key strategy for sustaining mental wellness throughout a person's lifespan.

6. Recommendations:

According to our model, sleep quality is the top contributor to the mental wellness index. Given the importance of contributors in shaping the wellness index, we aim to provide data-driven insights to support healthier, more balanced routines through the following recommendations.

We suggest that people have a routine of regular physical activity. According to Alhawwar et al. (2023), having regular physical activity can improve sleep quality, reduce sleep latency, and enhance overall sleep quality. Another study done by Santos et al. (2023) also suggests that having 4 to 7 physical activities every week can improve sleep quality. The study reveals that people who engage in physical activities are more likely to have lower Pittsburgh Sleep Quality Index (PSQI) scores, indicating better sleep quality. Although the variables of our model, Sleep Quality and Exercise Time, exhibit low multicollinearity, increasing exercise time may improve sleep quality and, ultimately, the wellness index. However, it is also worth noting that engaging in high-intensity physical activity in the evening or immediately before sleep may make it difficult to fall asleep. Dubinina et al. (2021) concluded that engaging in frequent and intensive physical activity both at and not at work can lead to insomnia. Therefore, people should maintain a regular physical activity routine at a moderate intensity.

According to our model and Chen et al. (2024), the longer the recreational or work-related screen time, the more likely people will have mental distress and poorer wellness. With reference to the Digital 2025 Global Overview Report, the average time spent using the internet on mobiles and computers (including laptops, desktops, or tablets) worldwide for people aged 16 or above is 6 hours and 38 minutes as of Q3 2024, with a trend of increasing. Due to digitalisation at work and school, people will inevitably spend hours on computers and or other digital devices. People may want to relax by scrolling through their phones after work or study. However, our model shows a negative correlation between the sleep wellness index and screen time. Therefore, we suggest reducing the time spent on the internet an hour before sleep. People can utilize leisure time for alternatives, such as reading books or doing yoga.

Therefore, in order to enhance the mental wellness index, people should prioritise establishing a routine of moderate physical activity and reducing pre-sleep screen time by alternative leisure.

7. Conclusion:

To conclude, in this study, we found out that small, consistent lifestyle habits have a significant impact on mental wellness. Maintaining good sleep quality by prioritizing sleep duration, maintaining regular physical activity, and controlling screen time on work-related and leisure activities to enhance mental health. The findings demonstrate that manageable actions can be taken by individuals to achieve a daily emotional balance improvement and reduce psychological distress. As mental health conditions continue to rise globally, our findings show that maintaining a good lifestyle habit offers a straightforward and easier approach to support mental wellness problems in the world.

References:

Alnawwar, M. A., Alraddadi, M. I., Algethmi, R. A., Salem, G. A., Salem, M. A., & Alharbi, A. A. (2023). The effect of physical activity on sleep quality and sleep disorder: A systematic review. *Cureus*, *15*(8), e43595. https://doi.org/10.7759/cureus.43595

Centers for Disease Control and Prevention. (2024, June 3). Mental health Chronic disease indicators. U.S. Department of Health & Human Services. https://www.cdc.gov/cdi/indicator-definitions/mental-health.html

DataReportal. (2025). Digital 2025: *Global overview report*. DataReportal. https://datareportal.com/reports/digital-2025-global-overview-report

Deliens, G., Gilson, M., & Peigneux, P. (2014). Sleep and the processing of emotions. *Experimental Brain Research*, *232*(5), 1403–1414. https://doi.org/10.1007/s00221-014-3832-1

Dubinina, E., Korostovtseva, L. S., Rotar, O., Amelina, V., Boyarinova, M., Bochkarev, M., Shashkova, T., Baranova, E., Libis, R., Duplyakov, D., Sviryaev, Y., Konradi, A., & Shlyakhto, E. (2021). Physical activity is associated with sleep quality: Results of the ESSE-RF epidemiological study. *Frontiers in Psychology, 12,* 705212. https://doi.org/10.3389/fpsyg.2021.705212

Elbe, A.-M., Lyhne, S. N., Madsen, E. E., & Krustrup, P. (2019). Is regular physical activity a key to mental health? Commentary on “Association between physical exercise and mental health in 1.2 million individuals in the USA between 2011 and 2015: A cross-sectional study,” by Chekroud et al., published in Lancet Psychiatry. J*ournal of Sport and Health Science, 8*(1), 6–7

Goldstein, A. N., & Walker, M. P. (2014). The role of sleep in emotional brain function. *Annual Review of Clinical Psychology, 10*(1), 679–708. https://doi.org/10.1146/annurev-clinpsy-032813-153716

Hoyniak, C. P., Vogel, A. C., Puricelli, A., Luby, J. L., & Whalen, D. J. (2024). Day-to-day bidirectional associations between sleep and emotion states in early childhood: Importance of end-of-day mood for sleep quality. *Sleep Health, 10*(3), 264–271. https://doi.org/10.1016/j.sleh.2024.03.007

Mikkelsen, K., Stojanovska, L., Polenakovic, M., Bosevski, M., & Apostolopoulos, V. (2017). Exercise and mental health. Maturitas, 106, 48–56. https://doi.org/10.1016/j.maturitas.2017.09.003

Nagata, J. M., Al-Shoaibi, A. A. A., Leong, A. W., Zamora, G., Testa, A., Ganson, K. T., & Baker, F. C. (2024). Screen time and mental health: a prospective analysis of the Adolescent Brain Cognitive Development (ABCD) Study. *BMC Public Health, 24*(1), Article 2686. https://doi.org/10.1186/s12889-024-20102-x

National Institutes of Health. (2005, June 13–15). NIH State-of-the-Science Conference statement on manifestations and management of chronic insomnia in adults. Journal of Clinical Sleep Medicine, 1(4), 412–421. https://jcsm.aasm.org/doi/pdf/10.5664/jcsm.26356

Ruiz-Ranz, E., & Asín-Izquierdo, I. (2025). Physical activity, exercise, and mental health of healthy adolescents: A review of the last 5 years. *Sports Medicine and Health Science, 7*(3), 161–172. https://doi.org/10.1016/j.smhs.2024.10.003

Santos, M., Sirtoli, R., Rodrigues, R., López-Gil, J. F., Martínez-Vizcaíno, V., Guidoni, C. M., & Mesas, A. E. (2023). Relationship between free-time physical activity and sleep quality in Brazilian university students. *Scientific Reports, 13*(1), 6652. https://doi.org/10.1038/s41598-023-33851-3

Santos, R. M. S., Mendes, C. G., Sen Bressani, G. Y., de Alcantara Ventura, S., de Almeida Nogueira, Y. J., de Miranda, D. M., & Romano-Silva, M. A. (2023). The associations between screen time and mental health in adolescents: a systematic review. *BMC Psychology, 11*(1). http://dx.doi.org/10.1186/s40359-023-01166-7

Walker, M. P., & van Der Helm, E. (2009). Overnight therapy? The role of sleep in emotional brain processing. *Psychological Bulletin, 135*(5), 731–748. https://doi.org/10.1037/a0016570

Appendix 1:

Variable Definition Table

Variable Name	Data Type	Description
user_id	Categorical	Unique identifier assigned
age	Numeric (integer)	Age of the participant
gender	Categorical	Gender identity
occupation	Categorical	The participant's current primary occupation
work_mode	Categorical	Work arrangement type (e.g., Remote, In-person, Hybrid).
screen_time_hours	Numeric (float)	Total average daily screen time in hours.
work_screen_hours	Numeric (float)	Average daily hours spent on screens for work
leisure_screen_hours	Numeric (float)	Average daily hours spent on screens for leisure
sleep_hours	Numeric (float)	Average daily sleep duration (in hours).
sleep_quality_1_5	Numeric (integer)	Self-rated sleep quality (1=Very poor, 5=Excellent).
stress_level_0_10	Numeric (float)	Self-reported stress level (0=No stress,10=extreme stress).
productivity_0_100	Numeric (float)	Self-reported productivity score
exercise_minutes_per_week	Numeric (float)	Average number of minutes spent exercising per week.
social_hours_per_week	Numeric (float)	Average number of hours spent in social interactions per week.
mental_wellness_index_0_100	Numeric (float)	index measuring mental wellness (0=Very poor, 100=Excellent).

Appendix 2:

Descriptive Statistics

```
>
> describe(data[, c("sleep_quality_1_5",
+                   "exercise_minutes_per_week",
+                   "work_screen_hours",
+                   "leisure_screen_hours",
+                   "sleep_hours",
+                   "mental_wellness_index_0_100")])
                            vars   n   mean    sd median trimmed   mad  min    max  range skew kurtosis   se
sleep_quality_1_5              1 400   1.40  0.65   1.00    1.27  0.00 1.00   4.00   3.00 1.54     1.71 0.03
exercise_minutes_per_week      2 400 109.81 70.01 103.00  106.87 72.65 0.00 372.00 372.00 0.42    -0.17 3.50
work_screen_hours              3 400   2.18  1.93   1.46    1.88  1.40 0.11  12.04  11.93 1.31     1.45 0.10
leisure_screen_hours           4 400   6.84  2.22   6.70    6.83  2.15 0.89  13.35  12.46 0.12    -0.13 0.11
sleep_hours                    5 400   7.01  0.85   7.03    7.01  0.92 4.64   9.74   5.10 0.04    -0.27 0.04
mental_wellness_index_0_100    6 400  20.33 20.38  14.80   17.22 19.57 0.00  97.00  97.00 1.22     1.14 1.02
```

Appendix 3:

R code

```
file_path <- "C:\\Users\\hinhi\\OneDrive - City University of Hong Kong - Student\\CityU year5 Sem 1\\Introduction to Data Science GE1356\\Group project\\datasets\\ScreenTime.csv"
file_path <- "C:\\Users\\User\\OneDrive - City University of Hong Kong - Student\\CityU year5 Sem 1\\Introduction to Data Science GE1356\\Group project\\datasets\\ScreenTime.csv"

data <- read.csv(file_path)

data$gender <- as.factor(data$gender)
data$work_mode <- as.factor(data$work_mode)
###
library(psych)

describe(data[, c("sleep_quality_1_5",
                  "exercise_minutes_per_week",
                  "work_screen_hours",
                  "leisure_screen_hours",
                  "sleep_hours",
                  "mental_wellness_index_0_100")])

##############################################

# model
model <- lm(
  mental_wellness_index_0_100 ~
    sleep_quality_1_5 +
    exercise_minutes_per_week +
    work_screen_hours +
    leisure_screen_hours +
    sleep_hours
  ,data = data
)
summary(model)

# Compare models with ANOVA
anova(model)
```

```
par(mfrow = c(2, 2))  # Arrange 4 plots in a grid
plot(model)

library(car)

vif(model)


#################
# Add interaction term to the model
model_interaction <- lm(
  mental_wellness_index_0_100 ~
    sleep_quality_1_5 * exercise_minutes_per_week +  # Interaction
    work_screen_hours +
    leisure_screen_hours +
    sleep_hours,
  data = data
)

#####################
summary(model_interaction)

#########################
model_exercise_sleep <- lm(
  sleep_quality_1_5 ~ exercise_minutes_per_week,
  data = data
)

#############
summary(model_exercise_sleep)
```

Appendix 3:

Model output

```
> summary(model)

Call:
lm(formula = mental_wellness_index_0_100 ~ sleep_quality_1_5 +
    exercise_minutes_per_week + work_screen_hours + leisure_screen_hours +
    sleep_hours, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-27.582  -6.155  -1.023   5.704  40.164

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               14.682125   5.494560   2.672 0.007850 **
sleep_quality_1_5         18.149824   0.959828  18.909  < 2e-16 ***
exercise_minutes_per_week  0.025031   0.007196   3.478 0.000561 ***
work_screen_hours         -3.457698   0.273683 -12.634  < 2e-16 ***
leisure_screen_hours      -3.682778   0.245347 -15.010  < 2e-16 ***
sleep_hours                1.465379   0.754184   1.943 0.052728 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.806 on 394 degrees of freedom
Multiple R-squared:  0.7713,    Adjusted R-squared:  0.7684
F-statistic: 265.8 on 5 and 394 DF,  p-value: < 2.2e-16
```

Appendix 4:

Appendix (Multicollinearity checking)

```
> vif(model)
        sleep_quality_1_5 exercise_minutes_per_week         work_screen_hours      leisure_screen_hours               sleep_hours
                 1.626780                  1.053091                  1.159280                  1.231977                  1.714927
>
```