Lifestyle Factors Influencing Mental Health Among College Students in a High-Stress Research Program: A Mixed Methods Analysis

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Mental ill-health is a rising problem among U.S. adults, especially among college students. Concurrent declines in sleep quality and exercise raise concerns given that adequate sleep and exercise serve as protective factors for mental distress. A plethora of studies have measured lifestyle mental health approaches using self-reports rather than objective, psychophysiological devices. This study aims to explore that relationship in a sample of college students at a public education institution in New York enrolled in high-stress research programs. The primary research question this study aims to address is: What lifestyle factors are most associated with health and mental health? Participants completed a pre-assessment survey to gauge subjective mental health status, subjective health status and related variables before participation.Then, participants wore a MUSE S sleep headband and a Fitbit Charge 6 for 7 days and nights, using a daily survey to self-report their scores on various sleep and exercise measures. Finally, participants completed the post-assessment to assess changes in their health status, beliefs, and health behaviors throughout participation. Quantitative results indicated that median step count differed across subjective health status groups and that higher stepcount is moderately, positively correlated with sleep score ($r = 0.293$, $p = 0.036$). Qualitative results revealed that individuals who engaged in restorative-coping strategies reported improved well-being and that motivations for participating in health behaviors varied by altruistic versus self-exploratory intentions. Overall, findings supported prior research and demonstrated that targeted behavioral interventions in sleep and exercise can improve mental health. This approach underscores the importance of personalized, flexible health behavior strategies to promote well-being across diverse populations.

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1 Introduction

In recent years, rates of psychopathology have been rising among university students, with an average of 33.6% and 39.0% of students experiencing depressive and anxious symptoms, respectively (Li et al., 2022), including a notable rise in mental distress, which stands as one of the most pressing health challenges of the 21st century in the U.S. among both youth and adults (Choudhry et al., 2016). Reflecting this burden, high psychological distress affects 9% of students, exceeding the 3% observed in the general population (Oftedal et al., 2024). These rates emphasize the need to identify modifiable factors and the coping strategies students report using that may alleviate this burden.

Adequate sleep has been linked to greater emotional regulation, cognitive performance, and life satisfaction (Palmer & Alfano, 2017), while regular physical activity is associated with enhanced mood, vitality, and psychological flourishing (Biddle et al., 2019), highlighting the importance of these in our everyday lives, especially concerning mental health. However, much of the existing literature relies primarily on self-reported measures, which may be limited by recall bias and subjective reporting, illuminating the need for novel research to incorporate objective biological measures to more accurately capture sleep and exercise as they influence mental health outcomes. Further research also must consider specific social locations, such as minoritized status and socioeconomic status, among others, that may cause certain groups and individuals to be more at risk for experiencing mental distress and mental ill-health (CDC, 2025). Early health behaviors often have an impact on long-term outcomes, so it is crucial to encourage consistent sleep during adolescence and young adulthood to lead to improvements in long-term mental health outcomes.

1.1 Knowns and Unknowns

Due to the pervasiveness of mental distress — a subjective sense of discomfort, mental anguish, perceived lack of control, anxiety, or stress (CDC, 2025) — it is essential to address health behaviors such as sleep not only to reduce symptoms of distress but also to actively support well-being — defined as positive mood, life satisfaction, engagement, and meaning (Seligman, 2002). Research has shown that sleep quality and duration are significant predictors of mental health outcomes, and poor sleep hygiene is associated with increased mental distress (Dinis, 2018). Therefore, high-quality sleep and high exercise frequency may serve as protective factors for college students with low mental well-being, while poor-quality sleep and low exercise frequency would serve as risk factors. While we know the importance of sleep and exercise on mental distress, there is a lack of prior research specifically linking objective measures of these variables to it. Additionally, we do not know how these variables relate to an individual's goals, behaviors, beliefs, and sociodemographic factors, marking a significant area for further development.

An ecological model is essential for understanding healthy adolescent development, as it emphasizes the importance of considering cultural and environmental contexts and recognizes that healthy development is shaped by a dynamic interaction of risk and protective factors (Kia-Keating et al., 2011). Interventions that promote protective and promotive factors — such as high-quality sleep (Dinis, 2018) and regular exercise (Asmundson et al., 2013) — as well as reduce risk factors, may therefore contribute to improved mental well-being.

1.2 Research Aims

The primary gap is a methodological one, resulting from the limited number of studies that examine the biological data of participants' sleep throughout the night and their physical activity throughout the day. Although self-reported measures are a relatively effective method of analyzing sleep quality and physical activity, they assess subjective perceptions, whereas biological data such as brain waves and heart rate captured through wearable devices provide objective indicators aligned with different units of analysis, as emphasized by the National Institute of Mental Health's (NIMH) Research Domain Criteria (RDoC) framework (Michelini et. al., 2021). Incorporating both subjective self-reports and objective physiological measures enables a more comprehensive, multi-level approach to understanding lifestyle mental health and behavior across various domains. Thus, the aims of this study are to 1) utilize objective measures of sleep and physical activity to examine their frequency in a population of college students under high academic stress, and 2) look at the associations these frequencies have with individuals' beliefs, goals, behaviors, and sociodemographic factors. It is hypothesized that certain factors will be more associated with mental-wellbeing among college students. Thus, an exploratory approach was utilized due to the lack of research on this topic, as identified by these gaps. This study consists of a convergent parallel mixed methods design (Bishop, 2015). The primary research question this study aimed to address is: What **lifestyle factors** are most associated with **mental health?**

2 Methods

2.1 Participants and Sampling

The study was approved by the Institutional Review Board of a public higher education institution in New York. Research was conducted ethically to protect the rights, welfare, confidentiality, and privacy of participants. Also, participants were informed of the project and provided their consent before beginning the survey. Participants were eligible to participate if they were at least 18 years of age and were students at Binghamton University participating in a high-stress academic program, such as the First-Year Research Immersion (FRI) program or the Summer Research Immersion (SRI) program, or were peer mentors for one of these programs. Individuals were recruited either in person or virtually; they were shown either an informational presentation or an informational video, respectively, explaining the study and its purposes. They were informed of the requirements of participation, as well as the potential benefits and harms associated with participating. Potential participants were then given access to a Google form to provide consent and express interest if they still wished to participate in the study. Approximately 48 participants were included in the study, between both Summer and Fall recruitment periods.

Data were collected via survey using Qualtrics. Participants first completed a day one pre-assessment survey, around 15 minutes long, in which they self-reported data regarding their behaviors, beliefs, goals, and sociodemographics (Appendix A). They were then given a MUSE S sleep headband and a Fitbit Charge 6, wearable devices that physiologically measure sleep and physical activity, respectively. Participants wore these devices for a study period of seven days and seven nights. At the end of each day of physiological data collection, participants then completed a brief 5-minute Qualtrics survey where they transferred the data from their devices, as well as noted any stress or other non-measured variables that may have impacted their sleep and exercise that day. Finally, at the end of the week-long study period, participants completed a day seven post-assessment survey, around 15 minutes long, with questions similar to the pre-assessment survey to assess any changes in these variables that occurred over the study period.

2.2 Measures

2.2.1 Sleep Quality

Sleep data was collected physiologically through the use of the MUSE S headband. The headband monitors participants' sleep stages, time spent in each sleep stage, how quickly they fell asleep, time asleep, how frequently they woke up in the night, slow wave intensity, restoration points, sleep position, stillness, heart rate, and overall sleep score throughout their seven-day study period.

2.2.2 Physical Activity

For a physiological measure of physical activity, participants were asked to wear a FitBit Charge 6 during the day for seven days to monitor their step count, mileage, active zone minutes, energy burned (in calories), as well as record exercises (e.g., running, core training, cycling... 39 options). Through individual exercises saved to the Fitbit app, participants can measure their exercise time duration, active zone number, average heart rate, maximum heart rate, and energy burned while engaging in their individual exercise routines.

2.2.3 Mental and Physical Health Status

In the pre-assessment survey, participants' self-reported mental and general health status was collected as a sociodemographic variable. Participants were asked to rate either their mental health or their health in general, for mental health status and health status, respectively, on a five-point scale including options of "poor," "fair," "good," "very good," or "excellent."

2.2.4 Goals

Finally, to assess the health goals of participants, they responded to a series of open-ended questions, such as "Do you have a health goal you aim to achieve during your 7-day journey in this study? If yes, what is your specific goal?" in the pre-assessment survey and "Did you accomplish a specific health goal during your 7-day journey in this study? If so, what?" in the post-assessment survey. Additional open-ended questions were posed to assess why participants chose to participate in the study and what participants learned throughout the study, as well as any external causes they believe may have contributed to their sleep and physical activity results. These questions allowed for qualitative assessment of these aspects of participants' journeys throughout the study.

2.3 Data Analysis Plan

2.3.1 Quantitative

The data was analyzed using R to calculate descriptive statistical measures — including means, medians, standard deviations, and ranges — and create graphs and charts to assess relationships between MUSE S sleep scores, Fitbit Charge 6 step counts, and self-reported mental and physical health. Data was exported from the Qualtrics platform in numerical format and imported into Posit Cloud. R code provided in the data science workflow (Wickham & Grolemund, 2023) was modified to install R packages (see install.R) and import data (10.27.25.Day1_7.Clean.xlsx and daily_survey_clean.xlsx) using readr. After importing and cleaning, data from the two different surveys were merged using participant identifiers. Pre-assessment variables, including mental health status and general health status, were recoded into ordered factors. Composite lifestyle factors were then constructed by averaging each participant's sleep scores across six nights and step counts across seven days. These composite measures provided standardized indicators of sleep quality and physical activity for subsequent analyses. Cronbach's alpha was calculated for each composite score to ensure that the average was representative of participants' day-to-day scores.

Prior to inferential testing, composite sleep scores, composite step counts, and subjective health ratings were screened for normal and non-normal distributions using histograms, and participants' data were considered for exclusion if they did not consent, if they left 50% or more of the questions blank, or if they failed attention checks situated throughout the survey. Descriptive statistics such as mean and standard deviation were calculated for participants' sleep scores and step counts. Due to the non-normal distribution of the data as indicated by the histograms, nonparametric tests were incorporated where appropriate. Bivariate associations between step count and sleep score were assessed using both Pearson and Spearman correlations to capture all possible relationships, and a scatterplot with a regression line was used to visualize the association between these two lifestyle variables. Additional exploratory analyses plotted participants' daily sleep score and step count according to the day of the week on which they were observed to evaluate potential day-to-day differences.

To examine whether these lifestyle factors differed across self-reported mental and general health groupings, Kruskal-Wallis tests were planned to compare composite step counts and composite sleep scores across health categories. These analyses were supported by corresponding visualizations using box plots. All visualizations, including scatterplots and box plots were produced using ggplot2 within the tidyverse. The full analysis pipeline — including data cleaning, variable transformation, and statistical testing — was implemented within the Quarto document to ensure full reproducibility of the workflow.

2.3.2 Qualitative

The NVivo program was used to evaluate both the qualitative data acquired throughout the study in relation to specific variables. Data was tested for normal distributions. Only records from participants who provide informed consent were retained; all others were excluded during data cleaning. Using a directed content-analysis approach, each participant will be assigned a study ID and corresponding case/transcript file. Demographic data is then imported into Excel with the same file IDs. Once that is done, the study topic is tagged to facilitate code production within NVivo, followed by the content analysis coding approach. The transcript and classification sheet are then uploaded to NVivo and relevant information is entered into the appropriate code. The coding results will have a set number of files, representing the number of participants and references that include the required information. After all of the data has been entered into NVivo, it is exported to Excel. Sorting begins in Excel, with codes organized into separate labeled groups to generate categories. These categories are then imported into NVivo. Visual summaries such as word clouds, word trees, or project maps will be produced to illustrate key themes and relationships.

2.3.3 Mixed Methods

This study used a convergent parallel design as its primary mixed methods design, in which we examine these variables both qualitatively and quantitatively simultaneously, and then integrate these analyses to come to a broader interpretation (Bishop, 2015). The main purpose of this mixed methods research is complementarity, as we will first identify which factors are associated with sleep and exercise quantitatively and then qualitatively examine why these factors came to be and how these factors matter (Javdani, 2015).

2.4 Load

```
library(tidyverse)
library(psych)
library(knitr)
library(tibble)
library(dplyr)
library(tidyr)
library(scales)     # for number formatting like comma()
library(english)    # to convert numbers to words
library(stringr)    # for text functions like str_c()
library(ggdist)

theme_set(theme_bw(base_family = "LM Roman 10"))

#source: Importing Data Once (Hei & McCarty, 2025): https://shanemccarty.github.io/FRIplaybook/
```

2.5 Import

```
library(readxl)
# Import Excel file
onesevendata <- read_excel(
    "10.27.25.Day1_7.Clean.xlsx",
```

```r
    col_names = TRUE)

onesevendata[onesevendata == -99] <- NA
onesevendata[onesevendata == -50] <- NA

##explanation: all -99 and -50 data will be treated as missing data
# View first 10 rows
head(onesevendata, 10)

#source: Importing Data Once (Hei & McCarty, 2025): https://shanemccarty.github.io/FRIplaybook/
```

```r
library(tidyr)

## Convert to wide format
wide_onesevendata <- onesevendata %>%
  pivot_wider(
    id_cols = PASSWORD,
    names_from = SURVEYDAY,
    values_from = c(`MENTALHEALTHSTATUS`, `HEALTHSTATUS`),
    names_glue = "{.value}_T{SURVEYDAY}"
  )

#source: https://dcl-prog.stanford.edu/list-columns.html
#source: Tidying your Data (McCarty et. al., 2025): https://shanemccarty.github.io/FRIplaybook/
#explanation: this allows data to be viewed with only one row per participant, allowing for wi
```

```r
library(readxl)
# Import Excel file
daily_survey_clean <- read_excel(
    "daily_survey_clean.xlsx",
    col_names = TRUE)

#source: Importing Data Once (Hei & McCarty, 2025): https://shanemccarty.github.io/FRIplaybook/
#explanation: all -99 and -50 data will be treated as missing data
```

2.5.1 Combining Daily Survey with Mental Health Status and Health Status

```r
library(readxl)
library(dplyr)


# Select only the variables you need from secondary dataset, then join
masterdata <- wide_onesevendata %>%
  left_join(
```

```
    daily_survey_clean %>% select("PASSWORD", "SLEEPSCORE_T1", "SLEEPSCORE_T2", "SLEEPSCORE_T3"
    by = "PASSWORD"
  )

#source: Tidying your Data (McCarty et. al., 2025): https://shanemccarty.github.io/FRIplaybook/
#explanation: join data from the day 1/7 survey to data fom the daily survey
```

2.6 Transform

```
library(dplyr)
library(ggplot2)

# Fix list columns in wide_onesevendata
library(dplyr)

wide_onesevendata <- wide_onesevendata %>%
  mutate(across(starts_with("MENTALHEALTHSTATUS_"),
                ~ as.numeric(as.character(sapply(., `[`, 1)))))

wide_onesevendata <- wide_onesevendata %>%
  mutate(across(starts_with("HEALTHSTATUS_"),
                ~ as.numeric(as.character(sapply(., `[`, 1)))))

#source: https://r4ds.hadley.nz/data-transform.html
#explanation: this makes it so that the list is viewed as numbers instead of characters
```

2.6.1 Recode Values

```
recode_labels <- function(x) {
  case_when(
    x == 1 ~ "Poor",
    x == 2 ~ "Fair",
    x == 3 ~ "Good",
    x == 4 ~ "Very Good",
    x == 5 ~ "Excellent",
    TRUE ~ NA_character_
  )
}

#source: https://fripublichealth.quarto.pub/zerosum/report-preview.html#introduction, r manual
#explanation: Assign labels to each response option for health status and mental health status
```

2.6.2 Composite Score for Sleep Scores

```r
library(psych)
SLEEPSCORE_keys <- list(
  SLEEPSCORE = c("SLEEPSCORE_T2", "SLEEPSCORE_T3", "SLEEPSCORE_T4", "SLEEPSCORE_T5", "SLEEPSCO
)

#source: Creating Composite Scorex from Multi-Item Measures (McCarty, 2025): https://shanemcca
#explanation: create keys for composite scoring, a list which tells R which survey questions be
#note: remove T1 because all NAs
```

```r
library(dplyr)

# Convert all SLEEPSCORE columns to numeric using dplyr
masterdata <- masterdata %>%
  mutate(across(starts_with("SLEEPSCORE_T"), ~ as.numeric(as.character(.))))

# Verify conversion
cat("Checking SLEEPSCORE column types:\n")
masterdata %>%
  select(starts_with("SLEEPSCORE_T")) %>%
  sapply(class) %>%
  print()

#source: https://r4ds.hadley.nz/data-transform.html
#explanation: convert character columns to numeric for composite scoring
```

```r
library(psych)

# Now use scoreItems with clean numeric data
SLEEPSCORE_scores <- scoreItems(SLEEPSCORE_keys, masterdata)

# Add composite score to dataframe
masterdata$SLEEPSCORE <- SLEEPSCORE_scores$scores[, "SLEEPSCORE"]

# View reliability statistics
SLEEPSCORE_scores




#source: Creating Composite Scores from Multi-Item Measures (McCarty, 2025): https://shanemcca
#explanation: use scoreItems to calculate composite scores and reliability statistics
```

2.6.3 Composite Step Count

```
library(psych)
STEPCOUNT_keys <- list(
  STEPCOUNT = c("STEPCOUNT_T1", "STEPCOUNT_T2", "STEPCOUNT_T3", "STEPCOUNT_T4", "STEPCOUNT_T5"
)

#source: Creating Composite Scores from Multi-Item Measures (McCarty, 2025): https://shanemcca
#explanation: create keys for composite scoring, a list which tells R which survey questions be
```

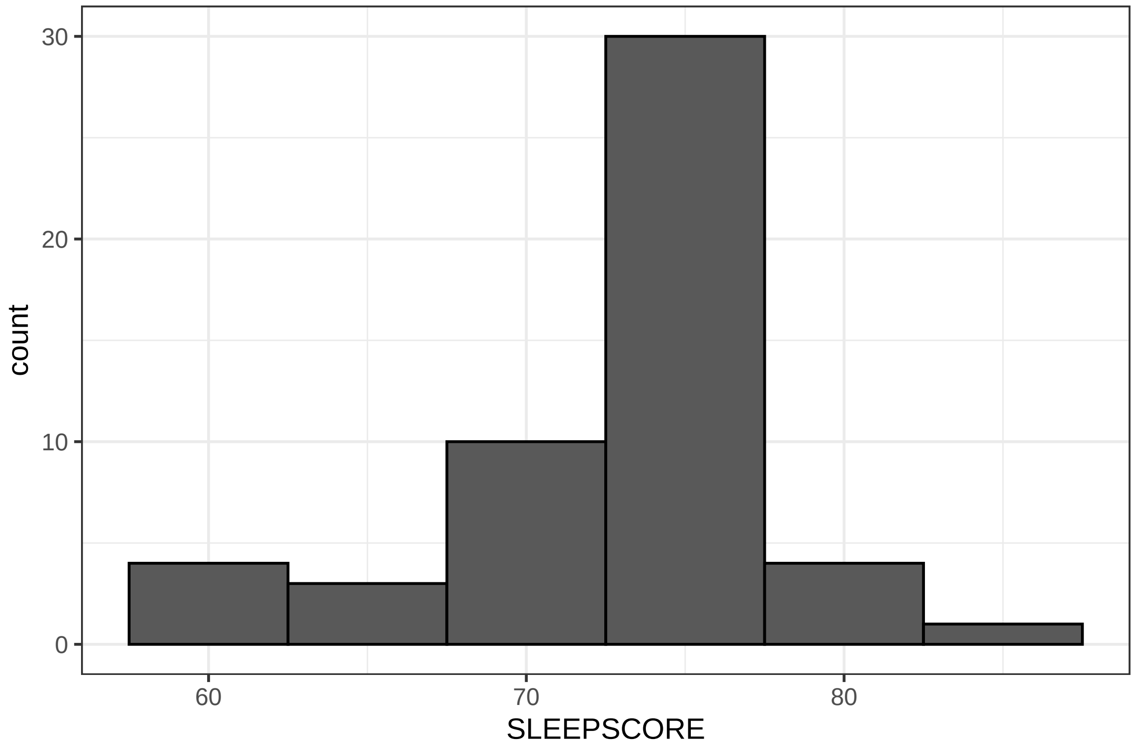
```
library(dplyr)

# Convert all STEPCOUNT columns to numeric using dplyr
masterdata <- masterdata %>%
  mutate(across(starts_with("STEPCOUNT_T"), ~ as.numeric(as.character(.))))

# Verify conversion
cat("Checking STEPCOUNT column types:\n")
masterdata %>%
  select(starts_with("STEPCOUNT_T")) %>%
  sapply(class) %>%
  print()

#source: https://r4ds.hadley.nz/data-transform.html
#explanation: convert character columns to numeric for composite scoring
```

```
library(psych)

# Now use scoreItems with clean numeric data
STEPCOUNT_scores <- scoreItems(STEPCOUNT_keys, masterdata)

# Add composite score to dataframe
masterdata$STEPCOUNT <- STEPCOUNT_scores$scores[, "STEPCOUNT"]

# View reliability statistics
STEPCOUNT_scores

#source: Creating Composite Scores from Multi-Item Measures (McCarty, 2025): https://shanemcca
#explanation: use scoreItems to calculate composite scores and reliability statistics
```

2.6.4 Sleep Score Normality

```
# Convert SLEEPSCORE from list to numeric
library(dplyr)
```

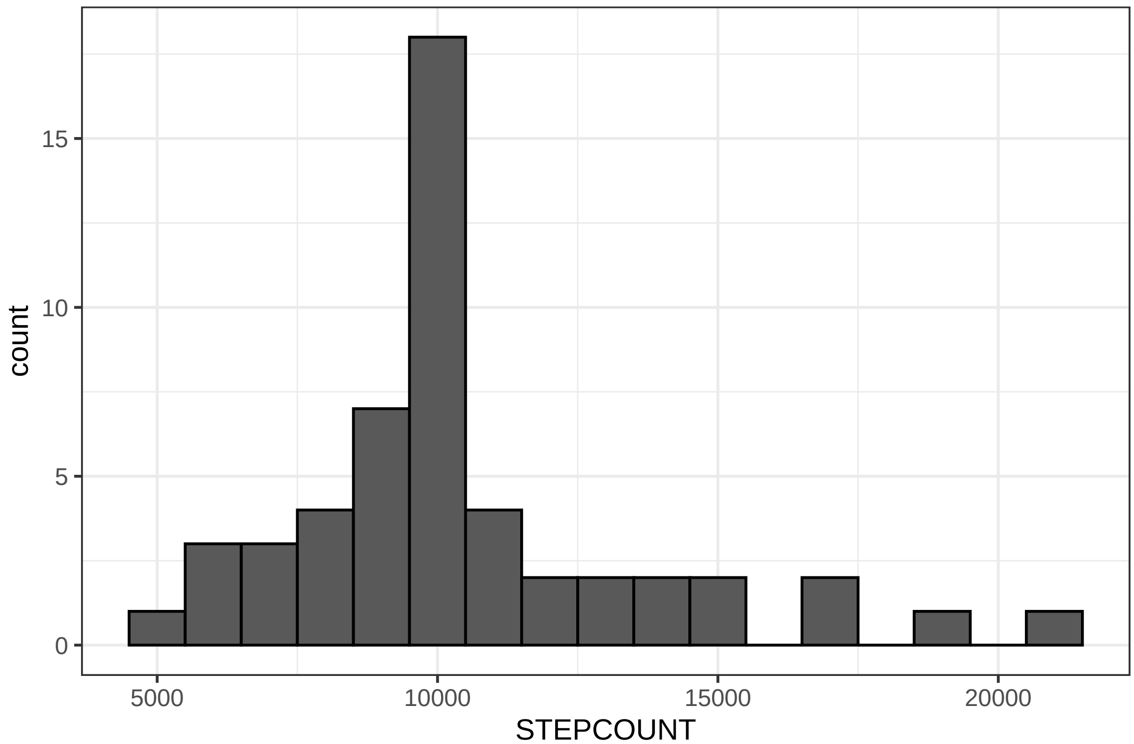
```
masterdata <- masterdata %>%
  mutate(SLEEPSCORE = as.numeric(as.character(sapply(SLEEPSCORE, `[`, 1))))

#check sleep score distribution
ggplot(masterdata, aes(x = SLEEPSCORE)) +
  geom_histogram(binwidth = 5, color = "black") +
  theme_bw()
```




```
#source: https://r4ds.hadley.nz/data-transform.html
#explanation: extract first element from list and convert to numeric
```

2.6.5 Step Count Normality

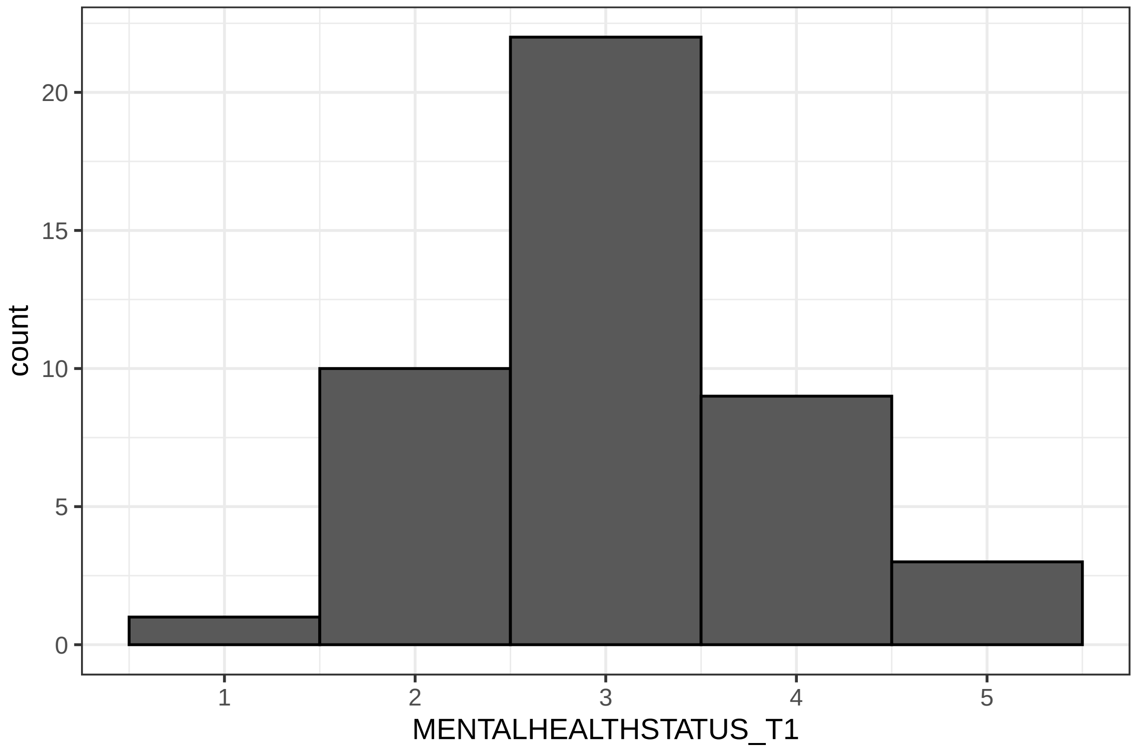
```
# Convert STEPCOUNT from list to numeric
library(dplyr)
masterdata <- masterdata %>%
  mutate(STEPCOUNT = as.numeric(as.character(sapply(STEPCOUNT, `[`, 1))))

#check step count distribution
ggplot(masterdata, aes(x = STEPCOUNT)) +
  geom_histogram(binwidth = 1000, color = "black") +
  theme_bw()
```




```
#source: https://r4ds.hadley.nz/data-transform.html
#explanation: extract first element from list and convert to numeric
```

2.6.6 Mental Health Status Normality

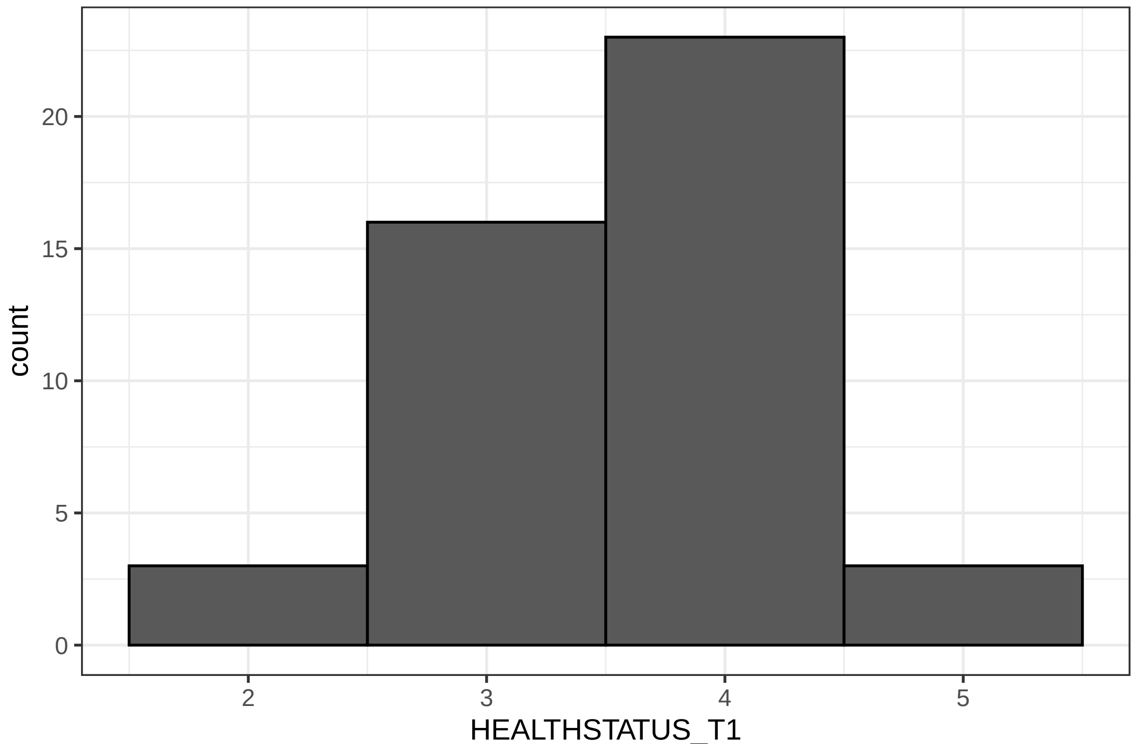
```
# Convert MENTALHEALTHSTATUS_T1 from list to numeric in masterdata
library(dplyr)
masterdata <- masterdata %>%
  mutate(MENTALHEALTHSTATUS_T1 = as.numeric(as.character(sapply(MENTALHEALTHSTATUS_T1, `[`, 1)

#check mental health status distribution
ggplot(masterdata, aes(x = MENTALHEALTHSTATUS_T1)) +
  geom_histogram(binwidth = 1, color = "black") +
  theme_bw()
```




```
#source: https://r4ds.hadley.nz/data-transform.html
#explanation: extract first element from list and convert to numeric
```

2.6.7 Health Status Normality

```
# Convert HEALTHSTATUS_T1 from list to numeric
library(dplyr)
masterdata <- masterdata %>%
  mutate(HEALTHSTATUS_T1 = as.numeric(as.character(sapply(HEALTHSTATUS_T1, `[`, 1))))

#check health status distribution
ggplot(masterdata, aes(x = HEALTHSTATUS_T1)) +
  geom_histogram(binwidth = 1, color = "black") +
  theme_bw()
```




```
#source: https://r4ds.hadley.nz/data-transform.html
#explanation: extract first element from list and convert to numeric
```

3 Results

3.1 Quantitative Results

3.1.1 Sociodemographics

Though demographics were not assessed for this report, all participants were undergraduate students at Binghamton University, with the majority of students being 1st- or 2nd-year First-year Research Immersion program (FRI) students, and the rest being 3rd- or 4th-year peer mentors for the FRI program. Approximately 10% of the ~600 students in the FRI program participated in the study, suggesting this sample should approximate Binghamton undergraduate students in the FRI program.

3.1.2 Step Count and Sleep Score

Composite sleep score collected by the MUSE over 6 nights was correlated with composite step count collected by the Fitbit Charge 6 over the same 7-day period. A Pearson correlation showed that the association was statistically significant ($r = 0.293$, $p = 0.036$) but modest, meaning that students who take more steps tend to have slightly higher sleep scores (Figure 1).

3.1.2.1 Step Count and Sleep Score Scatterplot

```
library(ggplot2)
sleepstep_scatter <- ggplot(masterdata, aes(x = SLEEPSCORE, y = STEPCOUNT)) +
  geom_point(position = "jitter") +
  geom_smooth(method = "lm", color = "#cc397b", se = TRUE) +
  stat_summary(fun = mean, geom = "point", size = 3, color = "#4d1b7b") +
  xlab("Sleep Score (0-100)") +
  ylab("Step Count") +
  ggtitle("Association Between Sleep Score and Step Count") +
  theme_bw()

print(sleepstep_scatter)
```

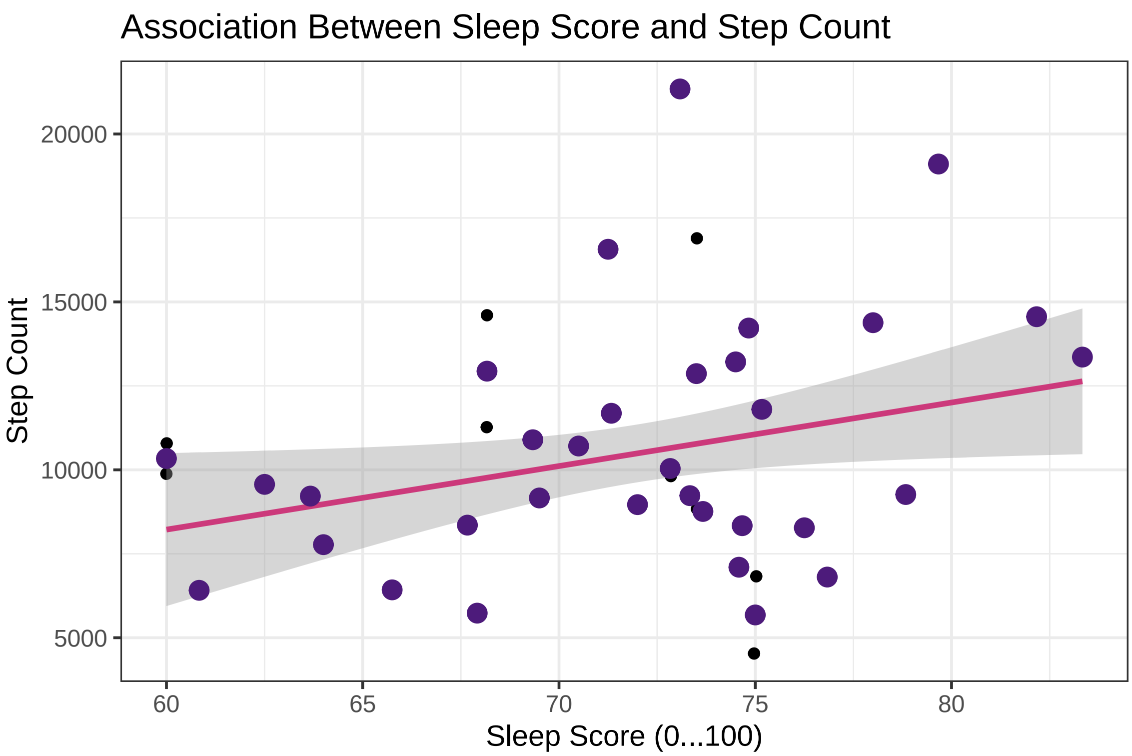


Figure 1: Figure 1. Relationship between daily step count and sleep quality. The scatterplot shows a slight positive association between step count and Muse S sleep score, suggesting that higher physical activity levels may be linked to marginally better sleep quality. The pink line represents the best-fit regression line with a shaded 95% confidence interval.

```
#source: datacamp
#explanation: scatter plot showing the relationship between composite sleep score and step cou
```

```
lm(formula = SLEEPSCORE ~ STEPCOUNT, data = masterdata)

print(sleepstep_scatter)
```

3.1.2.2 Step Count vs. Sleep Score Correlation

3.1.2.2.1 *Spearman*

```r
#correlation_SC_vs_SS_spearman
cor.test(masterdata$STEPCOUNT, masterdata$SLEEPSCORE, method = 'spearman')
```

```

	Spearman's rank correlation rho

data:  masterdata$STEPCOUNT and masterdata$SLEEPSCORE
S = 19730, p-value = 0.2639
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho 
0.1577799 
```

```r
#source: https://www.r-bloggers.com/2021/10/pearson-correlation-in-r/, https://www.onlinespss.c
#explanation: calculate Spearman correlation to view strength of relationship between variable
```

3.1.2.2.2 *Pearson*

```r
#correlation_SC_vs_SS_pearson
cor.test(masterdata$STEPCOUNT, masterdata$SLEEPSCORE, method = 'pearson')
```

```

	Pearson's product-moment correlation

data:  masterdata$STEPCOUNT and masterdata$SLEEPSCORE
t = 2.1637, df = 50, p-value = 0.03529
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.02141185 0.52368574
sample estimates:
      cor 
0.2926024 
```

```r
#source: https://www.r-bloggers.com/2021/10/pearson-correlation-in-r/, https://www.onlinespss.c
#explanation: calculate Perarson correlation to view strength of relationship between variable
```

3.1.3 Day vs. Sleep Score

A scatterplot was created to test the hypothesis that sleep score as collected by the MUSE would differ based on the night that the sleep data was collected. However, although minor day-to-day fluctuations were observed, no clear upward or downward trend emerged in overall sleep quality, and the line connecting the daily averages is relatively flat, indicating that sleep scores stayed fairly consistent throughout the week (Figure 2).

```
sleep_long <- masterdata %>%
  mutate(across(starts_with("SLEEPSCORE_T"), as.numeric)) %>%  # make all numeric
  pivot_longer(
    cols = starts_with("SLEEPSCORE_T"),
    names_to = "Day",
    values_to = "SleepScore"
  ) %>%
  mutate(Day = as.numeric(gsub("SLEEPSCORE_T", "", Day)))

#explanation: shift to long format so that day can be plotted on the x-axis
#source: Visualizing pre/post score (Sava, 2025): https://shanemccarty.github.io/FRIplaybook/vi
```

```
library(ggplot2)

sleepscore_day <- ggplot(sleep_long, aes(x = Day, y = SleepScore)) +
  geom_point(color = "#4D1B7B") +
  stat_summary(fun = mean, geom = "line", color = "#A68DBD") +
  xlab("Night of Sleep") +
  ylab("MUSE S Sleep Score") +
  ggtitle("Average Sleep Score by Day") +
  theme_bw() +
  scale_x_continuous(
    breaks = 1:7,
    labels = c(
      "Sunday",
      "Monday",
      "Tuesday",
      "Wednesday",
      "Thursday",
      "Friday",
      "Saturday"
    )
  )

#source: https://ggplot2.tidyverse.org/reference/index.html, https://r4ds.hadley.nz/ (ch5-12)
#explanation: plot day x sleep score relationship as a scatterplot with a line representing the

# Print and save to the plots folder
print(sleepscore_day)
```

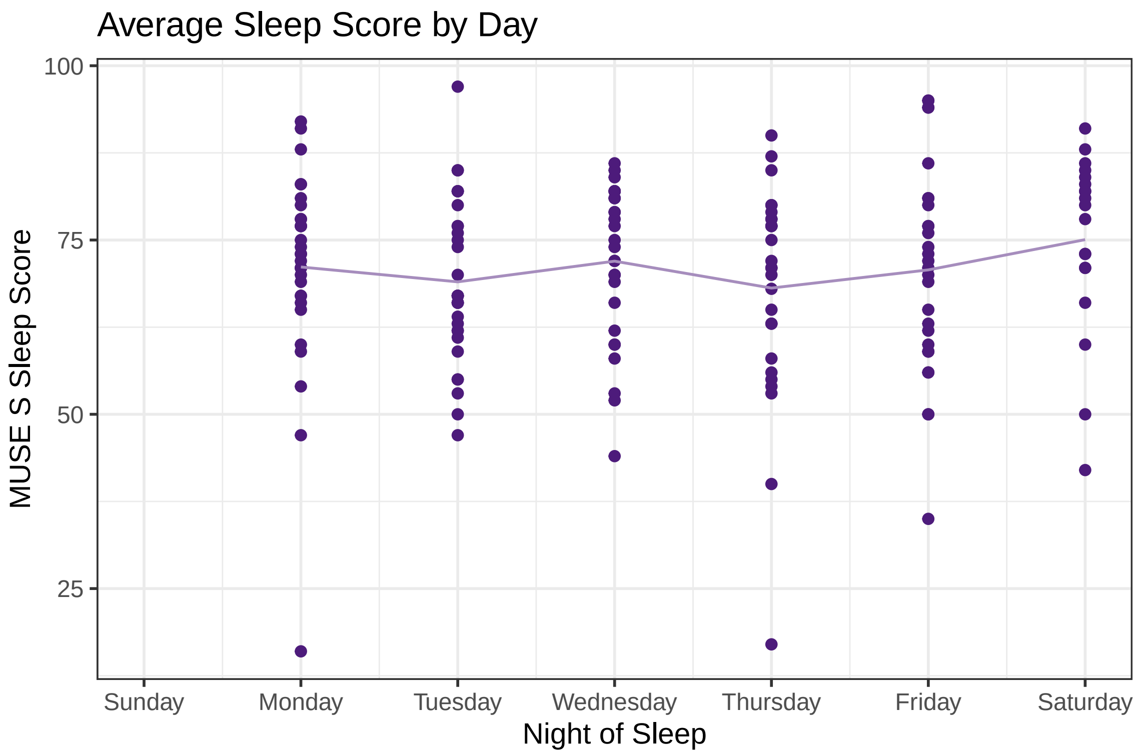


Figure 2: Figure 2. Average MUSE S Sleep Score Across Days of study participation. Sleep score was recorded on each day in reference to the score they achieved in their sleep from the night before. Average sleep scores remained relatively stable across Days 2 through 7 of data collection (participants did not wear their MUSE headbands before completing the first daily survey, so there is no data for Day 1). Although minor day-to-day fluctuations were observed, no clear upward or downward trend emerged in overall sleep quality.

3.1.4 Day vs. Step Count

Similarly, a scatterplot was created to test the hypothesis that step count as collected by the Fitbit Charge 6 would differ based on the day of the week that the exercise data was collected. Overall, variability is high across all days, with a connecting line showing slightly higher averages midweek and on Saturday compared to Monday and Sunday (Figure 3).

```
step_long <- masterdata %>%
  mutate(across(starts_with("STEPCOUNT_T"), as.numeric)) %>%  # make all numeric
  pivot_longer(
    cols = starts_with("STEPCOUNT_T"),
    names_to = "Day",
    values_to = "StepCount"
  ) %>%
  mutate(Day = as.numeric(gsub("STEPCOUNT_T", "", Day)))

#explanation: shift to long format so that day can be plotted on the x-axis
#source: #source: Visualizing pre/post score (Sava, 2025): https://shanemccarty.github.io/FRIpI
```

```r
library(ggplot2)

stepcount_day <- ggplot(step_long, aes(x = Day, y = StepCount)) +
  geom_point(color = "#cc397b") +
  stat_summary(fun = mean, geom = "line", color = "#f09cc1") +
  xlab("Day") +
  ylab("Fitbit Charge 6 Step Count") +
  ggtitle("Average Step Count by Day") +
  theme_bw() +
  scale_x_continuous(
    breaks = 1:7,
    labels = c(
      "Monday",
      "Tuesday",
      "Wednesday",
      "Thursday",
      "Friday",
      "Saturday",
      "Sunday"
    )
  )

#source: https://ggplot2.tidyverse.org/reference/index.html, https://r4ds.hadley.nz/ (ch5-12)
#explanation: plot day x step count relationship as a scatterplot with a line representing the

# Print and save to the plots folder
print(stepcount_day)
```

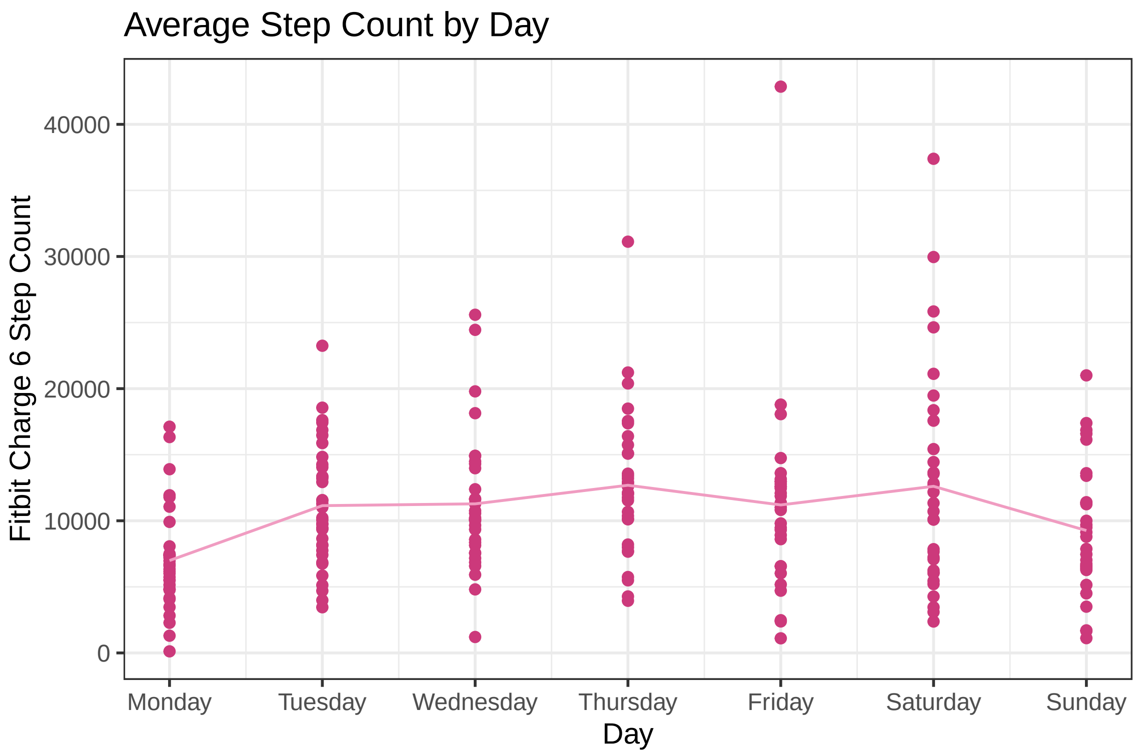


Figure 3: Figure 3. Average Fitbit Charge 6 step count by day. Individual daily step counts recorded by the Fitbit Charge 6 are displayed for each day of the week. The pink line represents the mean step count per day, showing slightly higher averages midweek and on Saturday compared to Monday and Sunday.

3.1.5 Step Count and Subjective Mental/Physical Health Status

Two Kruskal–Wallis tests were conducted to compare composite step counts, measured over a seven-day period with the Fitbit Charge 6, with participants' pre-assessment subjective ratings of mental and general health. Participants were placed into one of five groups based on their answer to the subjective mental or general health measure: Poor, Fair, Good, Very Good, and Excellent. The Kruskal–Wallis test comparing median step counts across general health status groups showed a statistically significant difference ($p = 0.023$; Figure 4), rejecting the null hypothesis that step count will not differ health status, and indicating that participants who reported better overall health tended to have higher composite step counts. However, the test comparing median step counts across mental health status groups indicated no statistically significant difference ($p = 0.082$; Figure 5). These findings fail to reject the null hypothesis, that step count will not differ across mental health status.

3.1.5.1 Step Count and Health Status

3.1.5.1.1 *Health Status vs. Step Count Box Plot*

```r
library(dplyr)
library(tidyr)
library(ggplot2)

# Check sample sizes and data distribution
samples.stepsXhealth <- masterdata %>%
  filter(!is.na(HEALTHSTATUS_T1) & !is.na(STEPCOUNT)) %>%
  group_by(HEALTHSTATUS_T1) %>%
  summarise(
    n = n(),
    mean = mean(STEPCOUNT),
    median = median(STEPCOUNT),
    sd = sd(STEPCOUNT),
    min = min(STEPCOUNT),
    max = max(STEPCOUNT)
  ) %>%
  # Add missing health status level (1: Poor)
  complete(HEALTHSTATUS_T1 = 1:5,
           fill = list(n = 0, mean = NA, median = NA, sd = NA, min = NA, max = NA))

## to check statistics used in the boxplot, remove # below
#samples.stepsXhealth

# Prepare data with all health status levels
plot_data <- masterdata %>% filter(!is.na(HEALTHSTATUS_T1) & !is.na(STEPCOUNT)) %>% mutate(HEAL
# Visualize the distribution with a boxplot to see outliers

plot.stepsXhealth <- ggplot(plot_data, aes(x = HEALTHSTATUS_T1, y = STEPCOUNT)) +
  geom_boxplot(fill = "#ef4f91") +
  geom_jitter(width = 0.2, alpha = 0.3) +
  ggtitle("Distribution of Step Counts by Health Status") +
  xlab("Health Status") +
  ylab("Step Count") +
  theme_bw() +
  scale_x_discrete( labels = c( "1 - Poor", "2 - Fair", "3 - Good", "4 - Very Good", "5 - Excel


print(plot.stepsXhealth)
```

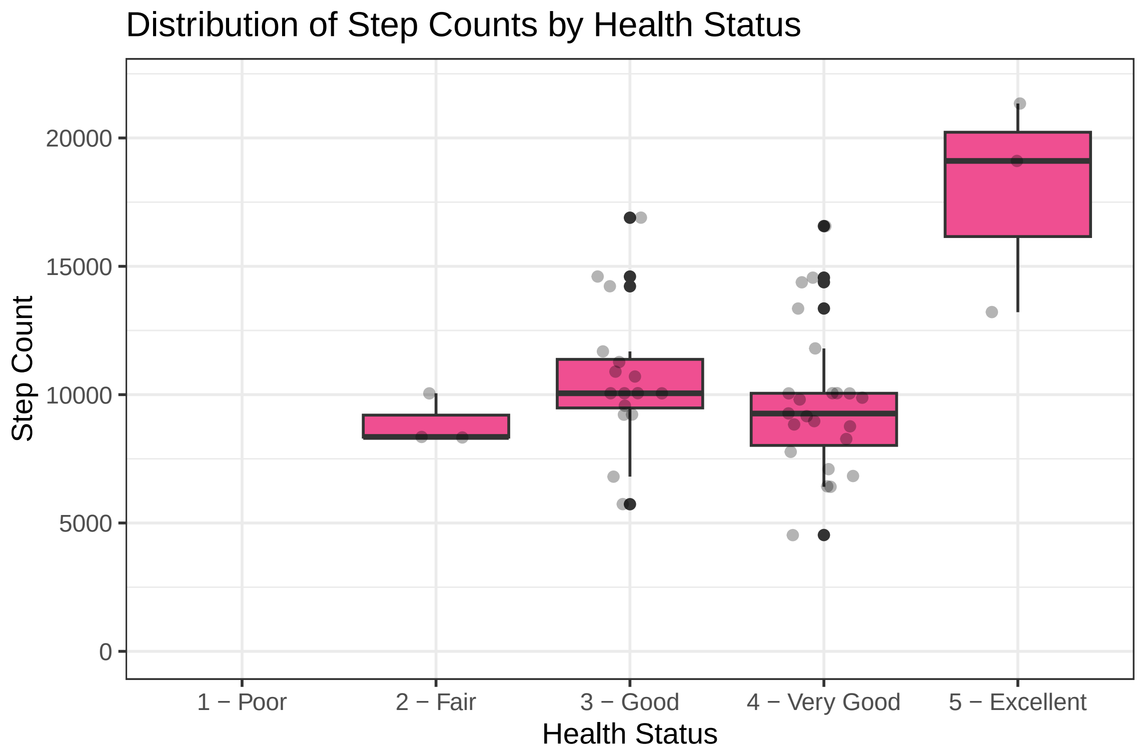


Figure 4: Figure 4. Distribution of daily step counts by self-reported health status. The boxplot presents the variation in participants' step counts across five levels of overall health, from Poor to Excellent. Median step counts increase with higher health ratings, with the highest activity levels observed among participants reporting Excellent health.

```
#source: https://ggplot2.tidyverse.org/reference/scale_discrete.html
#explanation: boxplot showing distribution of step counts with all health status categories inc
```

3.1.5.1.2 ***Kruskal-Wallis Test for Health and Step Count***

```
# kruskal-wallis test used for non-normal data and/or unequal group sizes comparing mean differ

library(dplyr)

# Prepare data
health_stepcount_data <- masterdata %>%
  filter(!is.na(HEALTHSTATUS_T1) & !is.na(STEPCOUNT))

# Perform Kruskal-Wallis test
kruskal.test(STEPCOUNT ~ HEALTHSTATUS_T1, data = health_stepcount_data)
```

```
    Kruskal-Wallis rank sum test
```

```
data:  STEPCOUNT by HEALTHSTATUS_T1
Kruskal-Wallis chi-squared = 9.5245, df = 3, p-value = 0.02307
```

```
# the p-value less than .05 demonstrates there are group differences

#source: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/kruskal.test
#explanation: non-parametric test for comparing multiple independent groups with unequal sample
```

3.1.5.2 Step Count and Mental Health Status

3.1.5.2.1 *Mental Health Status vs. Step Count Box Plot*

```
library(dplyr)
library(tidyr)
library(ggplot2)

# Check sample sizes and data distribution
samples.stepsXmentalhealth <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(STEPCOUNT)) %>%
  group_by(MENTALHEALTHSTATUS_T1) %>%
  summarise(
    n = n(),
    mean = mean(STEPCOUNT),
    median = median(STEPCOUNT),
    sd = sd(STEPCOUNT),
    min = min(STEPCOUNT),
    max = max(STEPCOUNT)
  ) %>%

  complete(MENTALHEALTHSTATUS_T1 = 1:5,
           fill = list(n = 0, mean = NA, median = NA, sd = NA, min = NA, max = NA))

## to check statistics used in the boxplot, remove # below
#samples.stepsXhealth

# Prepare data with all mental health status levels
plot_data <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(STEPCOUNT)) %>%
  mutate(MENTALHEALTHSTATUS_T1 = factor(MENTALHEALTHSTATUS_T1, levels = 1:5))

# Visualize the distribution with a boxplot to see outliers
plot.stepsXmentalhealth <- ggplot(plot_data, aes(x = MENTALHEALTHSTATUS_T1, y = STEPCOUNT)) +
  geom_boxplot(fill = "#ef4f91") +
  geom_jitter(width = 0.2, alpha = 0.3) +
  ggtitle("Distribution of Step Counts by Mental Health Status") +
  xlab("Mental Health Status") +
```

```r
  ylab("Step Count") +
  theme_bw() +
  scale_x_discrete(
    labels = c(
      "1 - Poor",
      "2 - Fair",
      "3 - Good",
      "4 - Very Good",
      "5 - Excellent"
    ),
     drop = FALSE
  ) +
  ylim(0, 22000)


print(plot.stepsXmentalhealth)
```

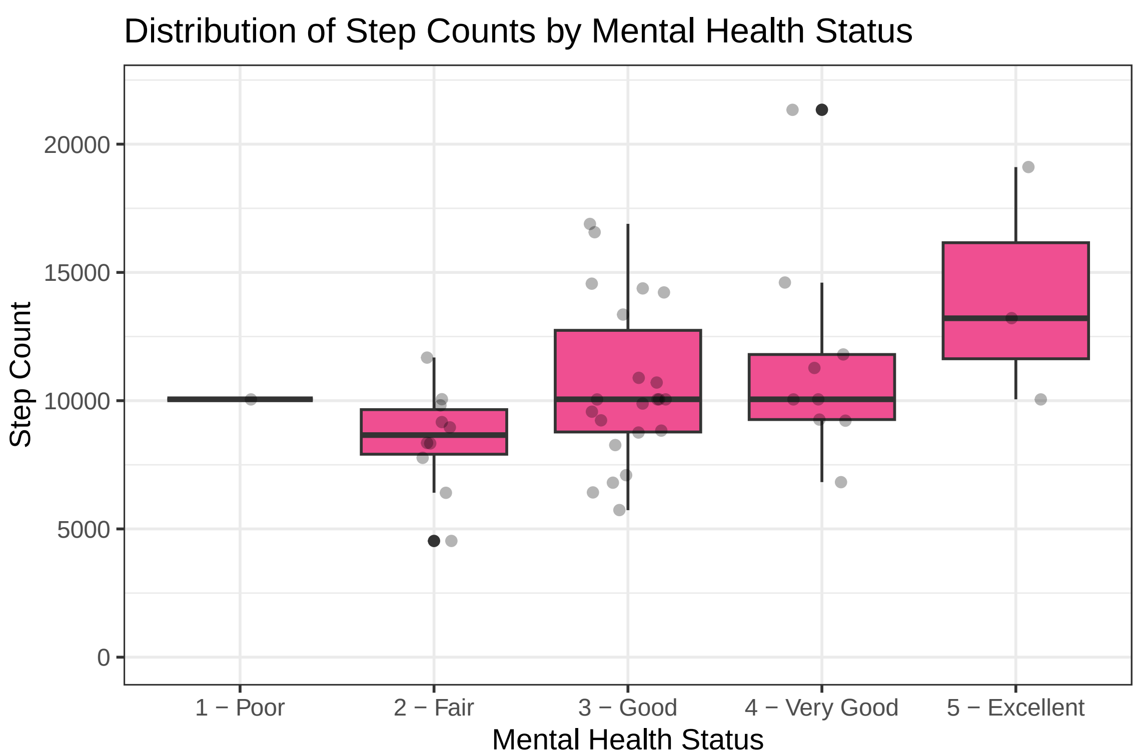


Figure 5: Figure 5. Distribution of daily step counts by self-reported mental health status. The boxplot illustrates how participants' daily step counts vary across five levels of mental health, ranging from Poor to Excellent. Median step counts generally increase with higher mental health ratings, suggesting that individuals reporting better mental health tend to be more physically active.

```
#source: https://ggplot2.tidyverse.org/reference/scale_discrete.html
#explanation: boxplot showing distribution of step counts with all mental health status catego
```

3.1.5.2.2 *Kruskal-Wallis Test for Mental Health and Step Count*

```r
# kruskal-wallis test used for non-normal data and/or unequal group sizes comparing mean diffe

library(dplyr)

# Prepare data
mentalhealth_stepcount_data <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(STEPCOUNT))

# Perform Kruskal-Wallis test
kruskal.test(STEPCOUNT ~ MENTALHEALTHSTATUS_T1, data = mentalhealth_stepcount_data)
```

```
	Kruskal-Wallis rank sum test

data:  STEPCOUNT by MENTALHEALTHSTATUS_T1
Kruskal-Wallis chi-squared = 8.2532, df = 4, p-value = 0.08273
```

```r
# the p-value greater than .05 demonstrates there are no group differences

#source: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/kruskal.test
#explanation: non-parametric test for comparing multiple independent groups with unequal sampl
```

3.1.6 Sleep Score and Subjective Mental/Physical Health Status

Additionally, two Kruskal–Wallis tests were conducted to compare composite sleep scores, measured over 6 nights of sleep by the MUSE headband, with participants' pre-assessment subjective ratings of mental and general health. Participants were placed into one of five groups based on their answer to the subjective mental or general health measure: Poor, Fair, Good, Very Good, and Excellent. The Kruskal–Wallis test comparing median sleep scores across general health status groups did not reveal a statistically significant difference ($p = 0.1724$; Figure 6). Similarly, median sleep scores did not differ significantly across mental health status groups ($p = 0.43$; Figure 7). These findings fail to reject the null hypothesis, that sleep score will not differ across mental and general health status.

3.1.6.1 Sleep Score and Health Status

3.1.6.1.1 *Health Status vs. Sleep Score Box Plot*

```r
library(dplyr)
library(tidyr)
library(ggplot2)

# Check sample sizes and data distribution
samples.sleepXhealth <- masterdata %>%
  filter(!is.na(HEALTHSTATUS_T1) & !is.na(SLEEPSCORE)) %>%
  group_by(HEALTHSTATUS_T1) %>%
  summarise(
    n = n(),
    mean = mean(SLEEPSCORE),
    median = median(SLEEPSCORE),
    sd = sd(SLEEPSCORE),
    min = min(SLEEPSCORE),
    max = max(SLEEPSCORE)
  ) %>%
  # Add missing health status level (1: Poor)
  complete(HEALTHSTATUS_T1 = 1:5,
           fill = list(n = 0, mean = NA, median = NA, sd = NA, min = NA, max = NA))

## to check statistics used in the boxplot, remove # below
#samples.stepsXhealth

# Prepare data with all health status levels
plot_data <- masterdata %>%
  filter(!is.na(HEALTHSTATUS_T1) & !is.na(SLEEPSCORE)) %>%
  mutate(HEALTHSTATUS_T1 = factor(HEALTHSTATUS_T1, levels = 1:5))

# Visualize the distribution with a boxplot to see outliers
plot.sleepXhealth <- ggplot(plot_data, aes(x = HEALTHSTATUS_T1, y = SLEEPSCORE)) +
  geom_boxplot(fill = "#A68DBD") +
  geom_jitter(width = 0.2, alpha = 0.3) +
  ggtitle("Distribution of Sleep Scores by Health Status") +
  xlab("Health Status") +
  ylab("Muse S Sleep Score") +
  theme_bw() +
  scale_x_discrete(
    labels = c(
      "1 - Poor",
      "2 - Fair",
      "3 - Good",
      "4 - Very Good",
      "5 - Excellent"
    ),
    drop = FALSE
  ) +
  ylim(0, 100)
```

```
print(plot.sleepXhealth)
```

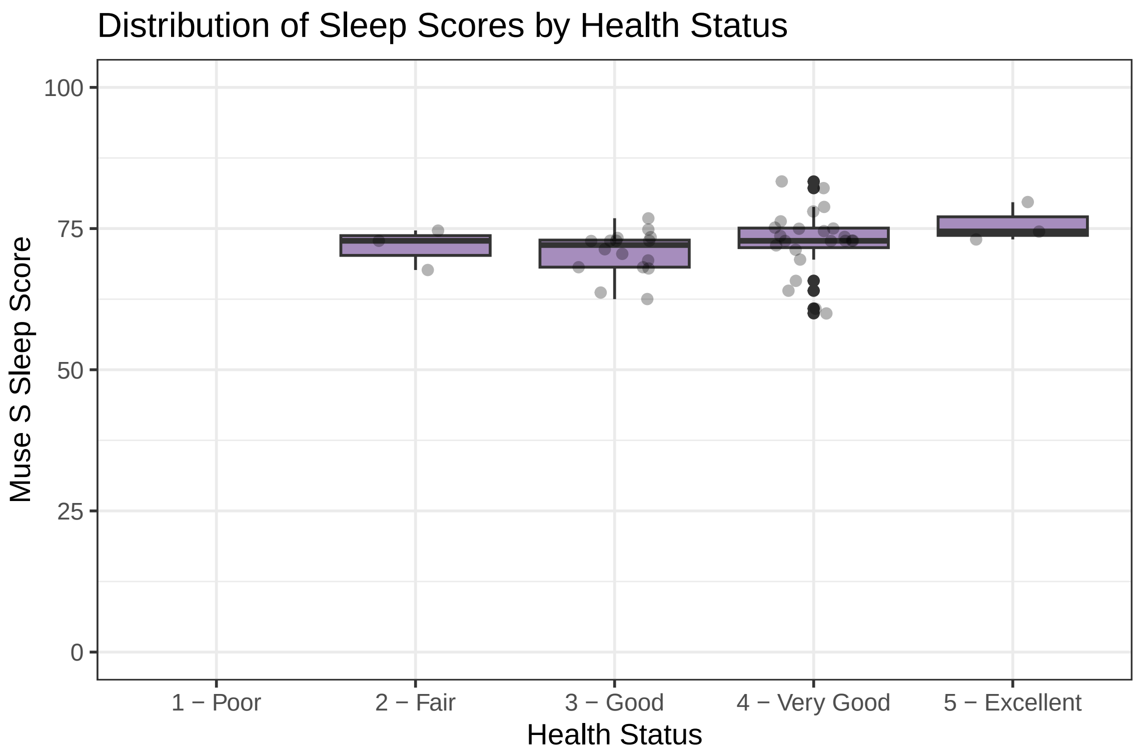


Figure 6: Figure 6. Distribution of Muse S sleep scores by self-reported health status. The boxplot shows how sleep quality, measured by Muse S sleep scores, varies across five levels of overall health ranging from Poor to Excellent. Median sleep scores remain relatively consistent across categories, with a slight upward trend among participants reporting Very Good and Excellent health.

```
#source: https://ggplot2.tidyverse.org/reference/scale_discrete.html
#explanation: boxplot showing distribution of sleep scores with all health status categories ir
```

3.1.6.1.2 ***Kruskal-Wallis Test for Health and Sleep Score***

```
# kruskal-wallis test used for non-normal data and/or unequal group sizes comparing mean diffe

library(dplyr)

# Prepare data
health_sleepscore_data <- masterdata %>%
  filter(!is.na(HEALTHSTATUS_T1) & !is.na(SLEEPSCORE))

# Perform Kruskal-Wallis test
kruskal.test(SLEEPSCORE ~ HEALTHSTATUS_T1, data = health_sleepscore_data)
```

```
    Kruskal-Wallis rank sum test

data:  SLEEPSCORE by HEALTHSTATUS_T1
Kruskal-Wallis chi-squared = 4.9917, df = 3, p-value = 0.1724
```

```
# the p-value greater than .05 demonstrates there are no group differences

#source: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/kruskal.test
#explanation: non-parametric test for comparing multiple independent groups with unequal sampl
```

3.1.6.2 Sleep Score and Mental Health Status

3.1.6.2.1 *Mental Health Status vs. Sleep Score Box Plot*

```
library(dplyr)
library(tidyr)
library(ggplot2)

# Check sample sizes and data distribution
samples.sleepXmentalhealth <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(SLEEPSCORE)) %>%
  group_by(MENTALHEALTHSTATUS_T1) %>%
  summarise(
    n = n(),
    mean = mean(SLEEPSCORE),
    median = median(SLEEPSCORE),
    sd = sd(SLEEPSCORE),
    min = min(SLEEPSCORE),
    max = max(SLEEPSCORE)
  ) %>%

  complete(MENTALHEALTHSTATUS_T1 = 1:5,
           fill = list(n = 0, mean = NA, median = NA, sd = NA, min = NA, max = NA))

## to check statistics used in the boxplot, remove # below
#samples.stepsXhealth

# Prepare data with all mental health status levels
plot_data <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(SLEEPSCORE)) %>%
  mutate(MENTALHEALTHSTATUS_T1 = factor(MENTALHEALTHSTATUS_T1, levels = 1:5))

# Visualize the distribution with a boxplot to see outliers
plot.sleepXmentalhealth <- ggplot(plot_data, aes(x = MENTALHEALTHSTATUS_T1, y = SLEEPSCORE)) +
  geom_boxplot(fill = "#A68DBD") +
```

```r
  geom_jitter(width = 0.2, alpha = 0.3) +
  ggtitle("Distribution of Muse S Sleep Score by Mental Health Status") +
  xlab("Mental Health Status") +
  ylab("Muse S Sleep Score") +
  theme_bw() +
  scale_x_discrete(
    labels = c(
      "1 - Poor",
      "2 - Fair",
      "3 - Good",
      "4 - Very Good",
      "5 - Excellent"
    ),
    drop = FALSE
  ) +
  ylim(0, 100)

print(plot.sleepXmentalhealth)
```

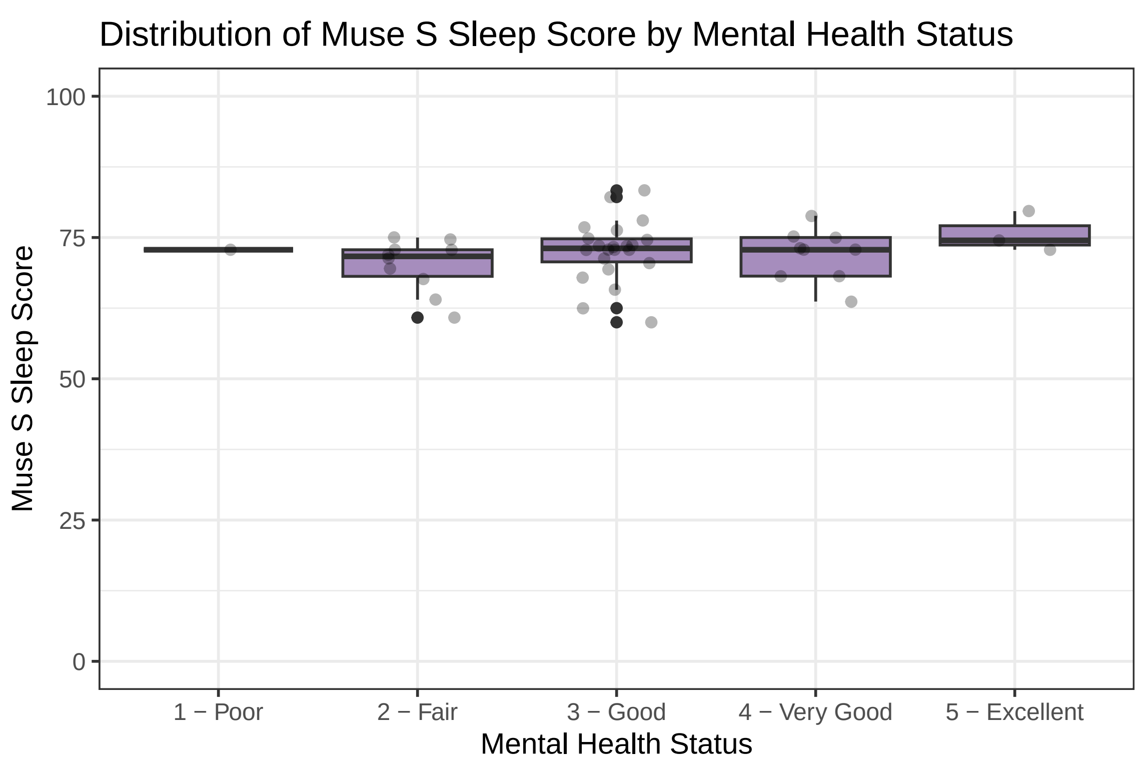


Figure 7: Figure 7. Distribution of Muse S sleep scores by self-reported mental health status. The boxplot displays how average sleep quality, as measured by Muse S sleep scores, varies across different levels of mental health. Participants with higher self-rated mental health (Very Good and Excellent) tend to show slightly higher median sleep scores compared to those reporting Fair or Good mental health.

```
#source: https://ggplot2.tidyverse.org/reference/scale_discrete.html
#explanation: boxplot showing distribution of sleep scores with all mental health status catego
```

3.1.6.2.2 *Kruskal-Wallis Test for Mental Health and Sleep Score*

```r
# kruskal-wallis test used for non-normal data and/or unequal group sizes comparing mean differ

library(dplyr)

# Prepare data
mentalhealth_sleepscore_data <- masterdata %>%
  filter(!is.na(MENTALHEALTHSTATUS_T1) & !is.na(SLEEPSCORE))

# Perform Kruskal-Wallis test
kruskal.test(SLEEPSCORE ~ MENTALHEALTHSTATUS_T1, data = mentalhealth_sleepscore_data)
```

```
    Kruskal-Wallis rank sum test

data:  SLEEPSCORE by MENTALHEALTHSTATUS_T1
Kruskal-Wallis chi-squared = 3.8263, df = 4, p-value = 0.43
```

```
# the p-value greater than .05 demonstrates there are no group differences

#source: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/kruskal.test
#explanation: non-parametric test for comparing multiple independent groups with unequal sampl
```

3.1.7 Descriptive Statistics

Variable	Mean	Median	SD	Min	Max
`Sleep Score`	72	72.83	4.95	60	83.33
`Step Count`	10489	10054	3201	4531	21341

3.2 Qualitative Results

3.2.1 Qualitative Findings - Strategy

Participants' descriptions of their experiences in a 7-day experience highlighted diverse strategies among coping with life stressors. These stressors have an influence on mental health and health status of an individual. Three primary coding categories emerged: Restorative States (i.e. exercise, sleep, mindfulness), Other Coping (i.e. avoidance or distraction), and Combination Coping. Data was drawn from open-ended responses to the "Day 1/7 Survey" prompt, "What specific activities do you do when you are under high stress to reduce your stress?" Overall, the findings reveal a range of stress coping strategies.

3.2.2 Restorative State Coping

Participants coded under Restorative States demonstrated engagement in adaptive coping, often describing stress-management behaviors that restore balance through physical activity, rest, or relaxation. For example, one participant shared "I love to go to the gym and workout to take my mind off of things. When it is warmer I go out and play spikeball or pickleball with my friends as well. I also may take a slight walk to reduce my stress" (ID 77). Another reflected, "Deep breathing, journaling, walking, running" (ID 49). Similarly, one participant notes, "Reading, meditation, exercise" (ID 56). These statements illustrate awareness of effective coping strategies and a willingness to engage in restorative behaviors, though the responses often reflect general habits rather than intentional, sustained coping practices. Overall, participants in this category exhibited adaptive but moderately consistent stress-regulation behaviors aligned with problem-focused coping.

3.2.3 Other Coping

The Other Coping Strategies category included behaviors that offered limited restoration and lacked intentional stress-regulation efforts. Participants in this category often described vague, passive, or distraction-based methods rather than active coping. For example, one participant shared "I like to go on tiktok or listen to music" (ID 13). Another explained, "I try to distract myself as best I can in the immediate situation. Though I do try to spend time with friends and talk through my experience. I also am an avid cleaner when I am in a stressful time (i.e. day before a test)" (ID 31). Similarly, one noted, "Watch a movie, talk with friends, listen to music on a walk" (ID 69). These responses reflect emotion-focused or avoidant coping, which may provide temporary relief but do not directly address the source of stress. Overall, participants in this category exhibited minimal engagement in adaptive coping behaviors, suggesting barriers to effective stress regulation or limited awareness of restorative strategies.

3.2.4 Combination Coping

Participants categorized under Combination Coping described using multiple strategies simultaneously to manage stress, often blending restorative behaviors with other reflective or leisure activities. These responses demonstrated flexible coping, reflecting both physical and emotional regulation. For example, one participant shared, "Play games, read, go for walks" (ID 45). Another wrote, "Distractions like spending time with family or friends, typically doing activities such as playing pickleball or going to eat with friends" (ID 42). Similarly, one described, "To reduce my stress I will do self care (skin care, long hot shower, clean my room) or I will sleep" (ID 48). These statements indicate an integrative approach to coping in which students draw from multiple domains (i.e. physical, cognitive, and social) to restore balance. This pattern reflects adaptive flexibility consistent with the Transactional Model of Stress and Coping, suggesting that many participants employ a combination of problem-focused and emotion-focused strategies to manage stress effectively.

3.2.5 Qualitative Findings - Control Goal

Three different goal orientations were evident in the reasons why participants participated in the study. The open-ended survey responses from participants in the study's "Day 1/7 Survey" were qualitatively coded to create three categories from the question "Why did you choose to participate in this study?" The three codes that emerged included: External Goal, Internal Goal, and No Goal. These three goal orientations collectively represent a motivational continuum ranging from externally driven to inwardly reflecting, resulting in a neutral or absent goal state. This distribution highlights how participants' initial motives influence their level of engagement and possibility for meaningful learning during a designed health journey.

3.2.6 External Goal

Participants who expressed external goals prioritized contributing to the study process or helping others seeking personal insights or behavioral effects. Their responses showed generosity or compliance-based motivation, rather than intrinsic self-improvement. For instance, participants wrote "Wanted to help out with your study" (ID 3), "To contribute to research" (ID 26), and "I want to help out the FRI people" (ID 38). Another participant mirrored the group mood, saying, "I chose to participate because we needed more participants" (ID 52). These statements suggest a sense of societal obligation, implying that for some, participation was motivated by external expectations rather than personal health goals.

3.2.7 Internal Goal

Participants who reported internal goals, on the other hand, stated reasons of participation focusing on self-awareness, health insight, and personal progress. These participants saw their participation as an opportunity for learning and self-reflection. For example, one participant indicated, "I wanted to get an accurate summation and analysis of my sleep" (ID 1), whereas another stated, "Due to me struggling with my mental health and wanting to find a possible solution" (ID 8). Others also indicated curiosity and self-directed learning: "I am excited to learn more about my habits" (ID 43), "I wanted to learn more about my sleep and exercise habits" (ID 51), and "To learn more about myself" (ID 67). Collectively, these replies indicate internal-goal participants started the study with a strong desire to obtain self-knowledge and potentially improve their well-being, indicating intrinsic involvement and self-motivation.

3.2.8 No Goal

Participants who did not identify a clear goal indicated a lack of intention or purpose in participation. Their comments frequently indicated casual interest or general engagement rather than specific goals. For example, several participants said, "It seemed cool" (ID 15), "I remember how annoying it is to find participants for experiments" (ID 40), and "I am generally interested in research" (ID 66). These statements indicate these individuals saw involvement as an activity, with no clear emphasis on personal learning or contribution.

3.2.9 Exploratory: Sleep Score

Sleep score, a numerical representation of a participant's sleep quality, was an essential component of this research study as this score gives a participant as well as research insight into how well an individual is sleeping and how they take sleep improvement. . Participants of the 7-day experience had the ability to track their sleep score through the wearable technology of MUSE S each night of their sleep. Sleep score consists of factors such as time it took a participant to fall asleep, total time asleep, how often a participant woke up, as well as sleep stages, such as time in deep sleep. The codes described above, restorative states and control of goal, have been compared to the measure of sleep score for exploratory purposes. The average sleep score among all participants was 71.73, according to quantitative analysis. Sleep score is scored out of 100, closer to 100 displaying a healthy, balanced night of sleep. If participants were below the sleep score average they were assigned "0." On the contrary, if participants of the 7-day study were above the sleep score they were assigned "1." Refer to Appendix D (Figures D7 and D8).

3.2.10 Exploratory: Goal Type

To understand health behaviors, another essential component of the study was exploring what goal types were mentioned qualitatively. The study was expressed to students for them to explore their health habits through a 7-day study period. With this being acknowledged, it was interesting to examine the frequency of participants mentioning a specific goal type. In response to the survey question "Do you have a health goal you aim to achieve during your 7-day journey in this study? If yes, what is your specific goal?" 3 codes emerged: exercise goal, sleep goal, and mental health goal. Refer to Appendix D (Figures D9, D10, D11).

4 Discussion

These mixed-methods study the lifestyle factors of sleep and exercise associated with mental and physical health among college students. The findings revealed a correlation between step count and sleep score as well as a correlation between step count and subjective health status. The study also found that the use of restorative states may be effective to manage stress-level, and internal goals will allow for a self-exploratory health journey as opposed to external goals. These results support the original hypothesis that certain lifestyle factors are more influential to improve mental health with a focus on health intervention. When interpreted through the Transaction Model of Stress, these findings suggest coping is a dynamic process influenced by individual perceptions of stressors and control. Additionally, through Self-Determination Theory, these findings suggest how motivation, control beliefs, and coping strategies interact to influence well-being results. These results align with efforts to shift psychology away from pathologizing mental ill-health and toward the study of positive institutions (Seligman, 2002). They support prior work linking lifestyle habits to mental health in college students (Dinis, 2018) and extend this literature by examining how modifications in sleep and exercise relate to mental health.

4.1 Discussion: Quantitative

This study examined relationships between self-reported mental and general health status and composite scores of two biometric measurements, one of step count and one of sleep quality, over a seven day period. Although step count and sleep quality are widely recognized as important contributors to health and wellbeing, the findings from the Kruskal–Wallis analyses suggest that these relationships may differ in strength depending on the type of health (mental vs. general) assessed.

No statistically significant differences in composite sleep scores were observed across either mental or general health status groups, indicating that subjective perceptions of health status were not reflected in differences in average sleep quality. Unfortunately, due to the limits of the study in including only current or former participants in a research program, as well as the small sample size, the analyses may have lacked power to detect small to moderate differences.

However, a statistically significant difference did emerge in step count across general health status groups, with participants who reported better overall health having higher median step counts. This result suggests that self-reported general health may be more closely tied to activity levels than to sleep quality, reflecting the importance of an active lifestyle in positive health perception.

Importantly, step count and sleep score were positively correlated ($r = 0.29$, $p = .035$), indicating that participants who were more physically active also tended to report better sleep quality. This moderate, statistically significant association highlights the potential interdependence between daily movement and restorative rest which is consistent with previous findings that regular physical activity contributes to improved sleep efficiency and duration (Alnawwar et al., 2023). Together, these results suggest that while self-perceptions of health may not consistently predict sleep quality, objective activity levels are both associated with general health perceptions and linked to better sleep outcomes. Overall, the findings support the idea that physical activity serves as a behavioral bridge between perceived and physiological wellbeing.

4.2 Discussion: Qualitative

This study examined how individuals have strategies to deal with stress and their motives for participating in a week-long health journey. The qualitative findings identified three main coping categories, Restorative States, Other Coping, and Combination Coping, as well as three motivational orientations, External, Internal, and No Goal. Participants identified a wide range of stress-management strategies, including restorative activities like exercise and sleep, as well as distraction-based coping such as using social media or watching television. Furthermore, the reasons for research involvement revealed various levels of intentionality and self-awareness, with those reporting internal goals exhibiting stronger intrinsic motivation and reflection.

The findings add to the current knowledge on coping strategies and health ideals in college students, who are regularly exposed to academic, social, and personal pressures (Misra and McKean, 2000). Prior research has demonstrated that young adults use both problem-focused and emotion-focused coping techniques (Folkman & Lazarus, 1984), but the current study goes beyond this by revealing how participants frequently combine these strategies in dynamic, individualized ways. The findings show that coping is a dynamic, context-dependent set of activities impacted by motivation, self-awareness, and perceived control.

4.3 Hypotheses Addressed

It was expected and hypothesized that lifestyle factors with a focus on health intervention may be more associated with improving well-being than non-lifestyle factors with no focus on health intervention. The main quantitative results of the study include: median step count differs across subjective health status groups and a higher step count is correlated with a higher sleep score. The main qualitative results of this study include: individuals who cope with restorative states to manage stress levels will have improved well-being as opposed to individuals who do not cope with restorative states to manage stress levels and individuals who participate in a health journey vary on their level of self-commitment, differing by altruistic, generous intentions to take part in a health journey and differing by self-exploration and behavioral investigation to take part in a health journey. The hypothesis may be supported through these findings, confirming that lifestyle factors that focus on health intervention may be more associated with improving well-being. This confirmation is apparent on the quantitative side through exercise frequency relating to sleep quality, in turn improving well-being. This confirmation is apparent on the qualitative side through the displayed impact of restorative states on coping strategy and the mention of self-exploration for goal setting of a health journey.

4.4 Theoretical Findings

The findings are consistent with the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984), which suggests that coping is a dynamic process influenced by individual perceptions of stressors and control. Participants who utilized restorative or combination coping indicated adaptive self-regulation congruent with problem-solving tactics, whereas those in the Other Coping category exhibited emotion-focused or avoidant approaches.

Furthermore, the findings might be understood via the lens of locus of control research, which distinguishes between participants who believe outcomes are internally controllable and externally dictated (Rotter, 1966). Participants who set internal objectives and used restorative coping patterns tended to have a higher internal locus of control, assuming active responsibility for stress management. Those with external goals or passive coping practices, on the other hand, demonstrated a stronger external locus of control, relying on external circumstances or others for comfort. This finding emphasizes how perceived stress control affects both coping style and motivation to improve oneself.

Finally, our findings support the ideas of Self-Determination Theory (Deci & Ryan, 2000), which distinguishes between intrinsic and extrinsic motivations. Internal-goal participants displayed intrinsic motivation by seeking personal progress and understanding, whereas externally driven participants engaged in more compliance-based activities. These theories demonstrate how motivation, control beliefs, and coping strategies interact to influence well-being results.

4.5 Evidence-Based Conclusions: Mental Health Status

The findings from both sets of data show a clear link between coping strategies, control goals, and overall mental health. Participants who employed restorative or combination coping strategies reported good to very good mental health, implying that engaging in restorative practices or combining several coping mechanisms promotes psychological well-being. This is consistent with

Folkman and Moskowitz's (2004) findings, which stressed that adaptive coping methods, particularly those requiring emotional control and positive reappraisal, are associated with better mental health outcomes. Meanwhile, those who used different coping strategies had a broader variety of mental health outcomes, demonstrating that flexibility in coping can still be advantageous based on individual circumstances and environmental demands.

In terms of control goals, both internal goals and external goals were linked to better mental health outcomes, with the majority of individuals in these groups reporting good mental health. Individuals with internal goals had slightly higher variety, with some expressing very good to excellent mental health, which could represent the deeper sense of fulfillment and self-determination associated with intrinsic drive. This research lends credence to Ryan and Deci's (2000) Self-Determination Theory, which holds that pursuing genuinely driven goals, those that correspond with personal values and growth, improves psychological well-being. Even people who did not have specified goals had generally good mental health, indicating that, while goal-setting can improve well-being, it is not the only determinant of beneficial outcomes.

Overall, these findings demonstrate that adaptive coping mechanisms and meaningful goal orientation assist individuals to maintain good mental health. Approaches that combine restorative practices with clearly defined, genuinely driven goals appear to promote more psychological balance and resilience, highlighting the role of self-regulation and purposeful direction in fostering mental health.

4.6 Evidence-Based Conclusions: Health Status

The combined results show a clear link between individual's coping strategies, goal orientations, and overall health state. Across all coping categories, the majority of participants reported good to very good health, with restorative and other coping techniques receiving particularly high health status. Participants who used restorative states reported higher health status, with more than 78% describing their health as good or very good. Similarly, those who used alternative coping approaches reported the largest proportion of "very good" health (63.6%), implying that adaptive and flexible coping benefits not only mental wellness but also overall physical health. The combination coping group also had favorable results, demonstrating that incorporating several tactics can assist maintain balance and resilience.

When it comes to goal orientation, those with both internal and external goals were more likely to report high or excellent health. Those with internal goals had a fair distribution across "good" and "very good" health categories, confirming the notion that intrinsic motivation, based on personal growth and autonomy, contributes positively to overall well-being. This is consistent with Ryan and Deci's (2000) Self-Determination Theory, which argues that intrinsic objectives promote overall health through psychological fulfillment. Meanwhile, participants with external goals had better health ratings, indicating that achievement-oriented or outcome-based motives can also boost well-being when pursued appropriately. Even those who reported no explicit goals had generally good health, albeit somewhat lower on average, showing that purpose and self-direction can improve, but are not essential for, beneficial health outcomes.

Overall, the data show that adaptive coping strategies and intentional goal orientation promote both mental health status and health status. The data supports Taylor and Stanton's (2007) conclusion that efficient coping promotes greater physiological control and resilience to stress. Similarly, Cohen et al. (2016) discovered that stress management and coping skills improve health by reducing physiological strain and increasing recovery. These findings support the notion that engaging in restorative, flexible coping and pursuing meaningful goals, particularly those driven by internal motivation, can improve both mental and physical health outcomes.

4.7 Strengths and Limitations

The findings support previous research that emphasizes the significance of self-regulation, autonomy, and perceived control in health habit change. Interventions aimed at improving health may benefit from building both an internal locus of control and intrinsic motivation, so encouraging intentional and self-directed coping behaviors. Overall, the study adds to the emerging understanding that adaptive stress regulation is both behavioral and motivational, influenced by how people perceive control, purpose, and personal agency in their well-being. This study prioritized the use of biological data collected by wearable technology over the use of self-reported data in an attempt to get the most accurate possible measurement. This study was designed to address the methodological gap in the literature by pairing self-reported, subjective health measures with the MUSE-S and FitBit devices in order to capture physiological sleep quality and step count aligned with the NIMH's RDoC framework (Michelini et. al., 2021). Due to the nature of the study in only including participants from a research program requiring an application and selection, the sample size is both limited and homogeneous. Additionally, there is the potential for social desirability bias, as the study design required participants to self-report both their responses to various survey questions and their physiological sleep and exercise data. It is possible that the data participants reported is not reflective of their true beliefs or are not the actual results measured by their wearable devices.

4.8 Impact and Future Work

This study used a health behavior design centered on sleep and exercise interventions to show how targeted behavioral approaches may improve individual mental health. This intervention's design has the potential for greater implementation in public health since it emphasizes the need for personalized health behavior adjustment. From the perspective of public health, increasing engagement with health interventions requires promoting mental well-being. The study may be easier to move through the stages of transformation when self-tracking tools are combined with mental health resources like mindfulness training or reflective journaling. Recognizing that health behavior demands and outcomes differ amongst individuals, this paradigm emphasizes the importance of flexible solutions for improving health knowledge and promoting positive lifestyle changes across varied groups in the United States.

The trend seen in the Kruskal-Wallis test comparing median step count and group mental health status indicates possible differences that may be seen in a larger sample, as the p-value is only slightly above 0.05. Therefore, with continued exploration and measurement of stepcount and subjective mental health status, a correlation may be found between median step count and group mental health status.

The future direction of the study for someone in the field of public health or in the next First-Year Research Immersion cohort to build on this research is to examine how students progress through the stages of change over time and whether mental well-being predicts advancement between stages, an immediate next step would be to expand this study longitudinally, perhaps for a few weeks rather than a 7-day experience. This may be a notable course of action as one week for a university student may be different than another week for a university student with varying academic pressures, social events, and personal responsibles overall creating a difference in experience and availability. Furthermore, having a larger sample size for this study may improve general quality of research. A larger sample size for this study design may be achieved through a select process of various samples of students. For instance, instead of just opening the study to students within a stress-inducing research program, the study may be open to college athletes, commuter students, international students, and other various distinct categories in which results may be drawn. The study may also explore differences among age among these categories of students, indicating differences between underclassmen and upperclassmen in undergraduate education.

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