How Digital and Lifestyle Behaviors Shape Wellness

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Why This Topic

Motivation

Problem
Screen time often treated as harmful

Gap
Different digital behaviors have different effects

Goal
Identify which behaviors matter for wellness and stress

Data Overview

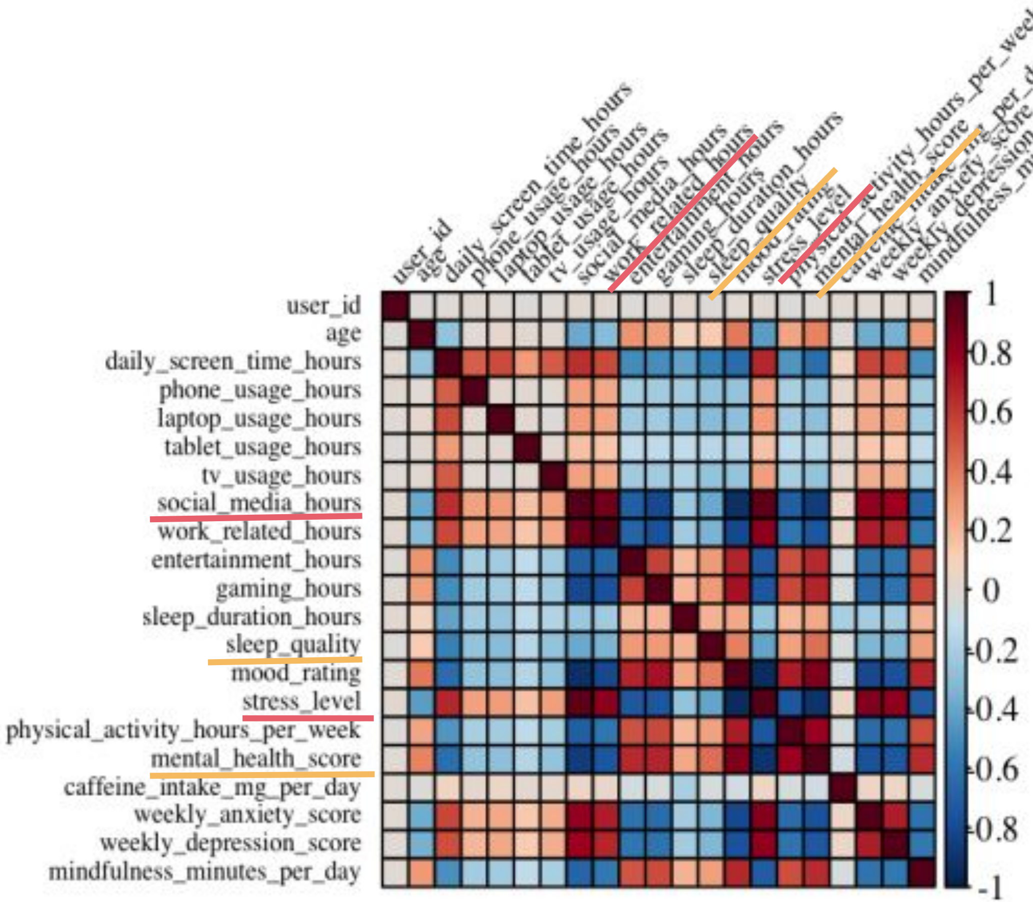
Dataset: 5,000 survey responses

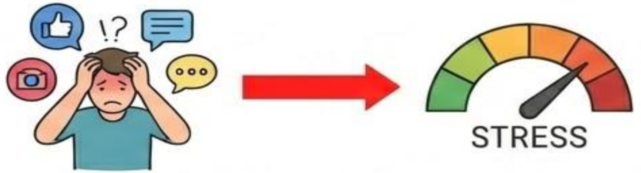
Digital
Social media, gaming, screen hours

Lifestyle
Sleep quality, activity, caffeine

Wellness
Mental health score, stress level

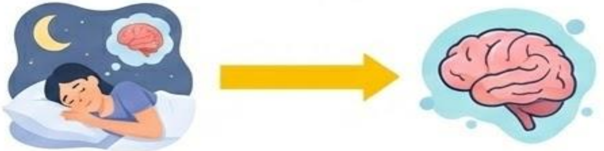
Correlation Matrix





Social media ↔ Stress

Strong Positive Correlation



Sleep quality ↔ Mental health

Strong Positive Correlation

Used to identify key predictors and avoid multicollinearity

Research Question 1: How are digital usage and lifestyle related to mental health scores and stress levels?

We ran **two Multiple Linear Regression (OLS)** models:

1. **Model 1: Predicts mental health score using lifestyle + digital behavior variables.**

2. **Model 2 : Predicts stress level using different screen-time categories (social media, work-related, etc.).**

Model fit / significance

- **$R^2 = 0.8225$ model explains about 82% of variation in mental health scores.**
- **$p < 2.2e{-}16$. Shows overall model is significant**

```
> summary(lm_model1)

Call:
lm(formula = mental_health_score ~ age + entertainment_hours +
    gaming_hours + sleep_duration_hours + sleep_quality + mood_rating +
    physical_activity_hours_per_week + mindfulness_minutes_per_day,
    data = clean_data)

Residuals:
     Min       1Q   Median       3Q      Max
-21.7925  -3.7467   0.0336   3.8034  22.5391

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                      31.563160   1.142846  27.618  < 2e-16 ***
age                               0.026667   0.004973   5.363 8.56e-08 ***
entertainment_hours               1.506144   0.164858   9.136  < 2e-16 ***
gaming_hours                      0.936562   0.168969   5.543 3.13e-08 ***
sleep_duration_hours              0.381535   0.150177   2.541   0.0111 *
sleep_quality                     2.228866   0.128923  17.288  < 2e-16 ***
mood_rating                       1.952589   0.057625  33.884  < 2e-16 ***
physical_activity_hours_per_week  1.957856   0.048746  40.164  < 2e-16 ***
mindfulness_minutes_per_day       0.129696   0.013373   9.699  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.521 on 4991 degrees of freedom
Multiple R-squared:  0.8225,	Adjusted R-squared:  0.8222
F-statistic:  2892 on 8 and 4991 DF,  p-value: < 2.2e-16
```

Model 1: Key Drivers of Mental Health Scores

SLEEP QUALITY

SLEEP QUALITY

Better Sleep Quality
=
Higher Mental
Health Scores

PHYSICAL ACTIVITY (hours/week)

PHYSICAL ACTIVITY
(hours/week)

More Activity is
Strongly Linked to
Higher Mental
Health Scores

RECREATIONAL SCREEN TIME

MODERATE GAMING

May act as **Recovery/Coping,** not harm.

SOCIAL MEDIA

Dominant Driver of Stress in this Model.

Model 2 – Predicts Stress Level

🔴**Biggest stressor: social media hours (largest positive coefficient).**

+1 hour of social media is associated with about **+2.7 higher stress units** (largest coefficient

🟡**Work-related use slightly reduces stress mostly depends on the structure and productivity.**

Model fit / significance

- **Adj. R^2 = 0.9256 → explains about 93% of stress variation.**
- **Overall model is significant: $p < 2.2e{-16}$.**

```
> summary(lm_model2)

Call:
lm(formula = stress_level ~ gaming_hours + daily_screen_time_hours +
    social_media_hours + work_related_hours, data = clean_data)

Residuals:
     Min       1Q   Median       3Q      Max
-2.48866 -0.58508 -0.06799  0.53235  2.23906

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             -1.398248   0.106185 -13.168  < 2e-16 ***
gaming_hours             0.094403   0.027479   3.436 0.000596 ***
daily_screen_time_hours  0.148974   0.007939  18.766  < 2e-16 ***
social_media_hours       2.696408   0.025958 103.876  < 2e-16 ***
work_related_hours      -0.778843   0.032905 -23.670  < 2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7949 on 4995 degrees of freedom
Multiple R-squared:  0.9257,	Adjusted R-squared:  0.9256
F-statistic: 1.556e+04 on 4 and 4995 DF,  p-value: < 2.2e-16
```
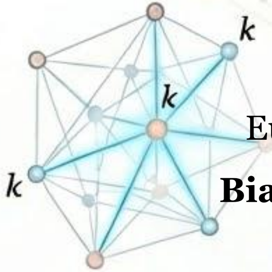

Can we predict stress level using digital behaviors?



KNN — Classification — Decision Tree

KNN

Euclidean distance

Bias VS. Variance

Initially k=5

Classification

High VS. Low Stress

80% Train / 20% Test

Standardized data

Decision Tree

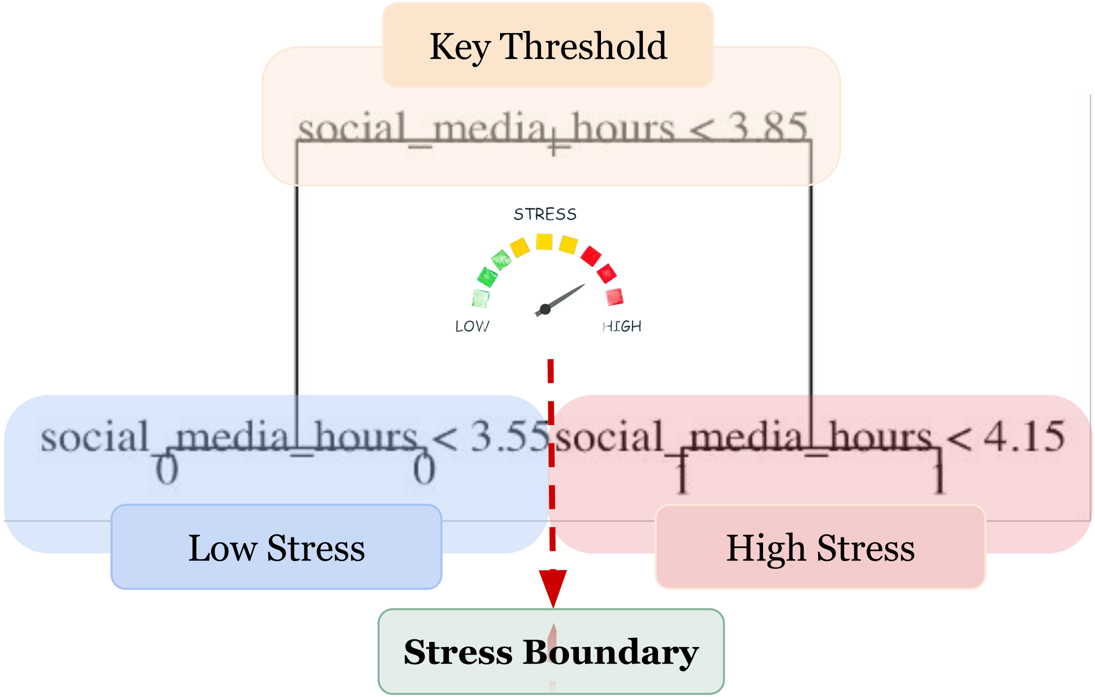
Classification tree

Minimize node impurity

KNN		Decision Tree
92.5%	**Test Accuracy**	96.6%
7.5%	**Error Rate**	3.4%
N/A (Distance-based)	**Strongest Predictive**	*social_media_hours*

Social Media Use Above 3.85 Hours is a Strong Predictor of High Stress

Data reveals a pronounced threshold effect where stress risk sharply increases after 3.85 hours.



From Effects to Personas:
Who Are the Users Behind the Patterns?

What we know

- Digital and lifestyle behaviors show **uneven effects** on wellness
- Social media stands out as a key stress-related behavior

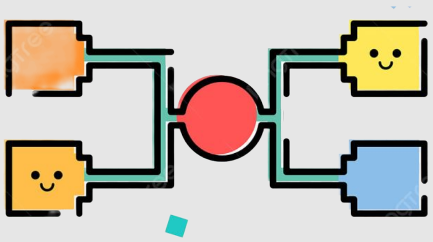
supervised

RQ1 - RQ2

What's missing

Results focus on **variables, not users**

We don't know **how behaviors merge in real life**



What we do next

- **Group** users by **digital usage behavior** patterns
- Identify **natural personas** without predefined outcomes

unsupervised

RQ3

Key Digital Usage Behaviors Used for Clustering

Overall Screen Exposure

- *daily_screen_time_hours*
- Overall level of daily digital engagement

Social Media Intensity

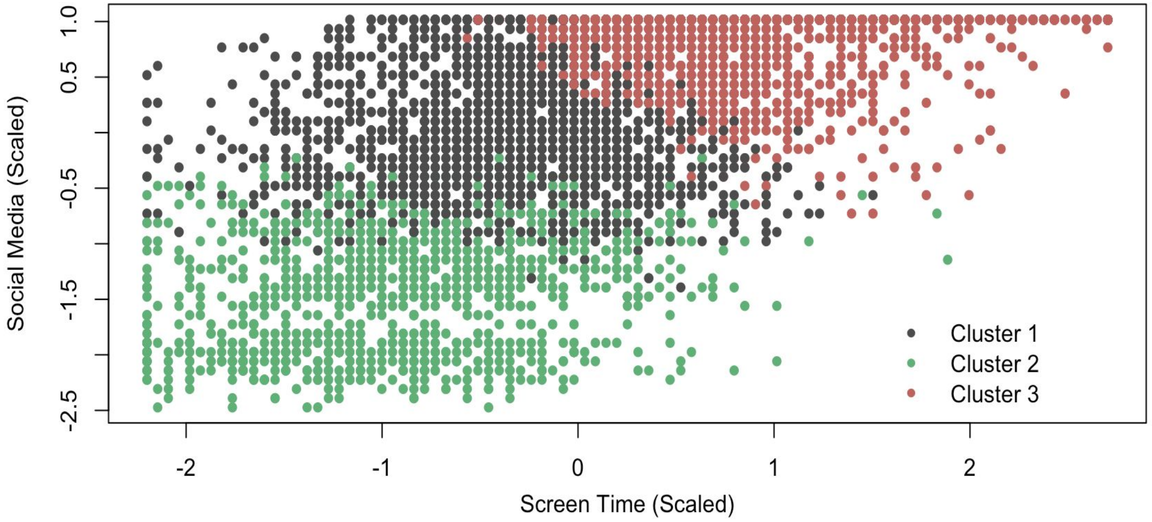
- *social_media_hours*
- Socially driven screen use and online interaction

Entertainment-Oriented Usage

- *gaming_hours*
- Entertainment-focused and recreational screen use

These dimensions describe how users allocate their digital time.
Different combinations of these behaviors naturally form distinct usage patterns.

Beyond Screen Time: Three Digital Usage Personas



KEY TAKEAWAY:

Digital engagement is defined by **modality** (Social vs. Gaming) rather than just **intensity**, distinguishing specific 'Gamer' niches from 'Social-driven' usage.

Cluster 1: Moderate Users

- **The Average Profile**
- Balanced usage; no extreme behaviors.

Daily Screen Time	Social Media	Gaming
4.3h	3.3h	1.5h

Cluster 2: Gamer Niche

- **Low Engagement, Specific Interest**
- Lowest total screen time, but highest gaming

Daily Screen Time	Social Media	Gaming
3.4h	1.6h	**2.5h**

Cluster 3: Heavy Social Users

- **The High-Risk Group**
- Driven by intense Social Media
- Correlates with high stress levels.

Daily Screen Time	Social Media	Gaming
6.6h	**4.3h**	1.1h

Key Findings: The Tipping Point

🔴 3.85 Hours / Day

🚨 Social Media

Strongest predictor of high stress

↓

High stress predictor

🎮 Gaming

Higher mental health scores

💤 Sleep quality

↓

More important than duration

Conclusion: Relationships to Patterns

Key Implications

🧠 **Core insight**
Digital behavior type > total screen time

🎮 **Main risk driver**
Social media — the strongest stress indicator

🎯 **Actionable takeaway**
Focus on Digital Hygiene to reduce toxic scrolling + allow restorative use

Limitations & Future Direction

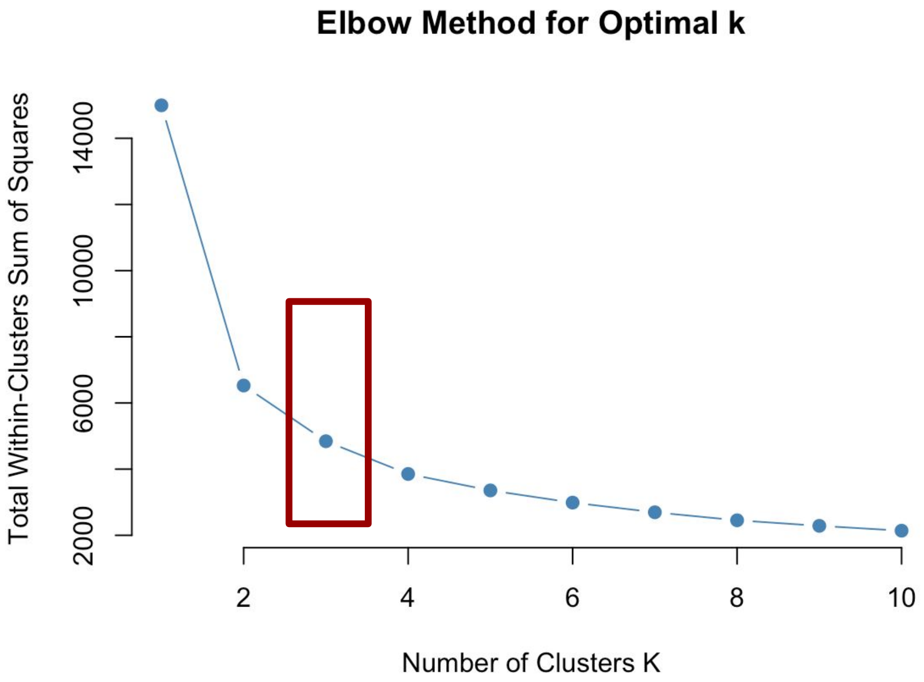
⚠️ **Scope**
Results show associations, not causal effects

⚠️ **Data limitation**
Findings rely on self-reported behavior

🚀 **Next step**
Validate results using objective device logs and APIs

Appendix

RQ3 - Clustering



Appendix

RQ3 - Clustering

Cluster	Daily Screen Time (h)	Social Media (h)	Gaming (h)
Cluster 1	4.3	3.3	1.5
Cluster 2	3.4	1.6	**2.5**
Cluster 3	**6.6**	**4.3**	1.1