CASE STUDY

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betterhelp

INTRODUCTION

Betterhelp is an app that provides online therapy through live video, phone, or chat sessions with a licensed therapist. As a subscription service, it offers affordability and convenience compared to traditional in-person therapy, though it does not accept health insurance. BetterHelp, as a leading online therapy service, seeks to understand how users' digital habits and lifestyle choices impact their emotional well-being. In particular, the company aims to identify which age groups could benefit most from its services and how factors such as moderate social media use and regular physical activity relate to stress levels, happiness, and overall quality of life.
This project uses the "Social Media and Mental Health Care" dataset, which includes information on age, gender, screen time, sleep quality, stress levels, exercise frequency, and happiness. Through this analysis, the goal is to uncover patterns and correlations that will enable BetterHelp to design more effective strategies for reaching the groups that need support the most, promoting a personalized, evidence-based approach to improving users' emotional well-being.

Guiding questions...

- How does daily social media usage (screen time) relate to users' reported levels of happiness and stress?
- Do users who engage in regular physical activity report higher happiness levels compared to those who do not exercise frequently?
- Which age group shows the highest and lowest overall happiness or satisfaction scores?
- Is there a significant difference in stress or happiness levels between age groups with high versus low social media use?
- How can the insights from these relationships guide BetterHelp in developing targeted wellness features, such as online yoga or meditation programs?

SCENARIO

BetterHelp aims to evaluate new features that promote healthy habits and increase user satisfaction.
As part of this initiative, the company is considering introducing a virtual physical activity section, offering options such as online yoga or guided meditation classes, to encourage overall well-being. However, before implementing this new feature, the product team seeks to use data to verify whether users who engage in physical activity report higher levels of happiness or satisfaction compared to those who do not.
At the same time, the application also aims to identify which age group accounts for the highest product usage, in order to design personalized strategies that better support each user segment throughout their therapy or emotional well-being journey.

OBJECTIVES

- To analyze the correlation between daily screen time and reported happiness levels among users.
- To evaluate how regular physical activity influences stress and happiness levels.
- To identify which age groups show the highest and lowest happiness or satisfaction scores.
- To segment users based on age, screen time, and exercise frequency, in order to detect behavioral patterns that could guide product personalization.
- To provide data-driven recommendations for BetterHelp's product team regarding the implementation of virtual wellness features.

PREPARE DATA

For this project, We will be using the **"Social Media and Mental Health Balance"** dataset, available on Kaggle. This dataset provides information about users' social media usage patterns, screen time, physical activity, and self-reported mental health indicators such as happiness and stress levels. The dataset will be uploaded to a SQL(BigQuery) database, allowing it to efficiently query, filter, and aggregate the data to extract relevant insights for the analysis. Using SQL will also help ensure data integrity and reproducibility throughout the exploratory and correlation stages of this study.

VARIABLE	DESCRIPTION
User ID	Identifier
Age	Age
Gender	Category
Daily screen time	Usage
Sleep quality	Rest
Stress level	Pressure
Exercise frequency	Activity
Happiness index	Well being

Clean data...

Mental_Health_and_Social_Media_Balance_Dataset

In this project, the Mental Health and Social Media Balance dataset was first downloaded in CSV format and imported into google sheets for preliminary data cleaning. This process included identifying and handling missing values, correcting data inconsistencies, and ensuring that all numerical and categorical fields were properly formatted. After the dataset was cleaned and structured, it was uploaded to SQL (BigQuery), where the main analysis was conducted through a series of queries designed to extract insights aligned with the project's objectives.

ANALYSIS

The following section presents the data analysis process used to address the project's objectives. Each objective is explored through SQL queries executed in BigQuery, followed by the interpretation of the results and their implications for BetterHelp's wellness strategy.

The first question we got to analize is **How does daily social media usage (screen time) relate to users' reported levels of happiness and stress?** in order to understand whether there is a relationship between the time users spend on their screens daily and their reported levels of happiness.
The following query groups users based on daily screen time and calculates their average happiness score.

```
-- RELATION BETWEEN screen_time & happiness_index
WITH screen_time_groups AS (
 SELECT
   user_id,
   screen_time,
   happiness_index,
   CASE
     WHEN screen_time < 2 THEN 'Low (<2h)'
     WHEN screen_time BETWEEN 2 AND 4 THEN 'Medium (2-4h)'
     ELSE 'High (>4h)'
   END AS screen_time_group
 FROM `klr-projects.better_help.mental_health`
)

-- AVG HAPPINESS
SELECT
 screen_time_group,
    AVG(happiness_index), 2) AS avg_happiness,
    COUNT(*) AS user_count
FROM screen_time_groups
GROUP BY screen_time_group
ORDER BY screen_time_group;

-- DIRECT CORRELATION
SELECT
 CORR(screen_time, happiness_index) AS correlation_screen_happiness
FROM `klr-projects.better_help.mental_health`;
```

VISIT QUERIES...

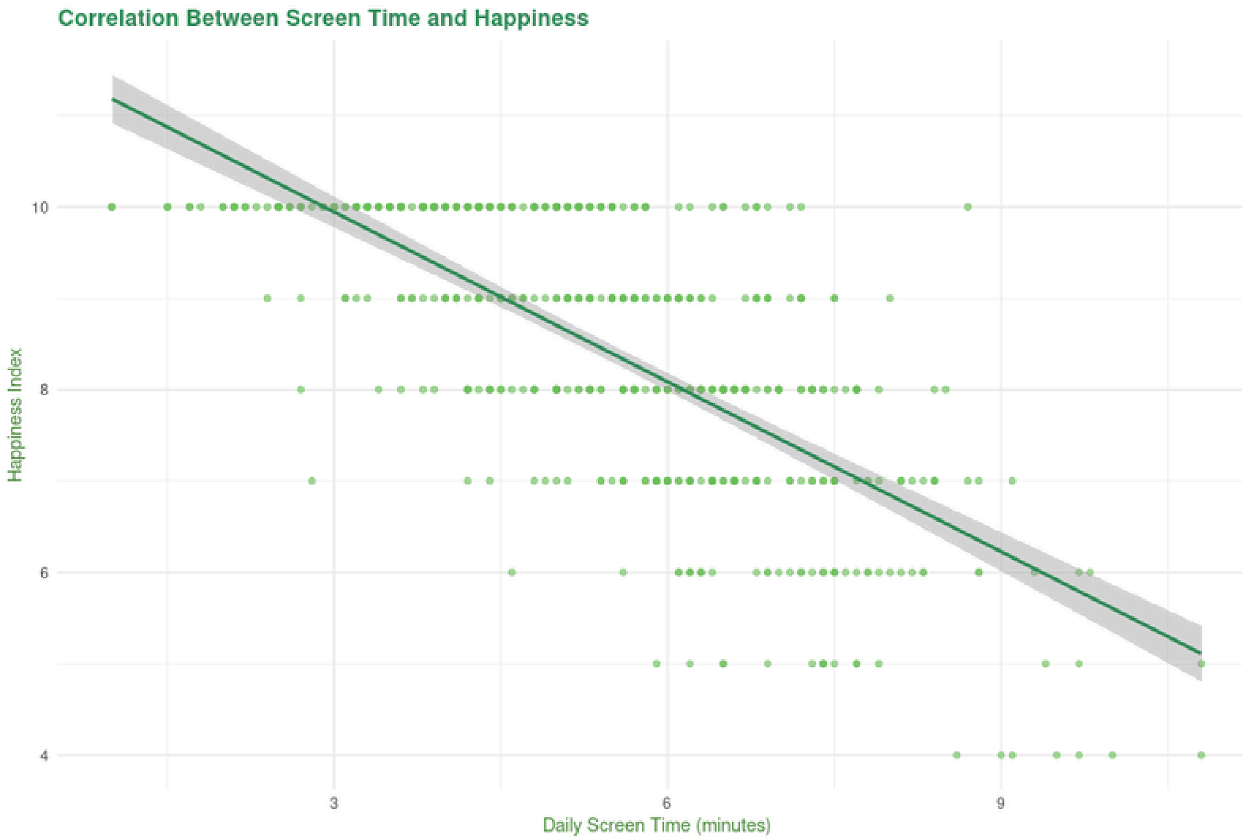
- RELATION BETWEEN SCREEN TIME & HAPPINESS/AVG HAPPINESS
- DIRECT CORRELATION SCREEN TIME & HAPPINESS

RESULTS...

Row	screen_time_group	avg_happiness	user_count
1	High (>4h)	8.03	397
2	Low (<2h)	10	7
3	Medium (2-4h)	9.71	96

CORRELATION -0.70

- To get a better visualization of our correlation we transferred our data to R studio to do a Scatter plot graphic.



- The results suggest a negative correlation between screen time and happiness. Users who spend less than two hours on social media report higher happiness scores compared to those with over four hours of screen time.

After identifying that screen time has a negative impact on overall happiness levels, the next step is to explore how physical activity influences both happiness and stress. Understanding this relationship is crucial, as it can provide valuable insights into how healthy habits contribute to emotional well-being.

To investigate this, we conducted an analysis using the following query, designed to compare the happiness and stress scores of users who engage in physical activity versus those who do not.

This approach allows us to determine whether incorporating physical wellness features such as virtual yoga or meditation sessions could have a meaningful impact on users' emotional health and satisfaction with the app.

```sql
WITH activity_groups AS (
  SELECT
    user_id,
    age,
    screen_time,
    exercise_frequency,
    happiness_index,
    stress_level,
    CASE
      WHEN exercise_frequency = 0 THEN 'None'
      WHEN exercise_frequency BETWEEN 1 AND 2 THEN 'Low (1-2/week)'
      WHEN exercise_frequency BETWEEN 3 AND 4 THEN 'Medium (3-4/week)'
      ELSE 'High (5+/week)'
    END AS activity_level
  FROM `klr-projects.better_help.mental_health`
)

SELECT
  activity_level,
        AVG(happiness_index)  AS avg_happiness,
        AVG(stress_level)  AS avg_stress,
        COUNT(*) AS user_count
FROM activity_groups
GROUP BY activity_level
ORDER BY activity_level;
```

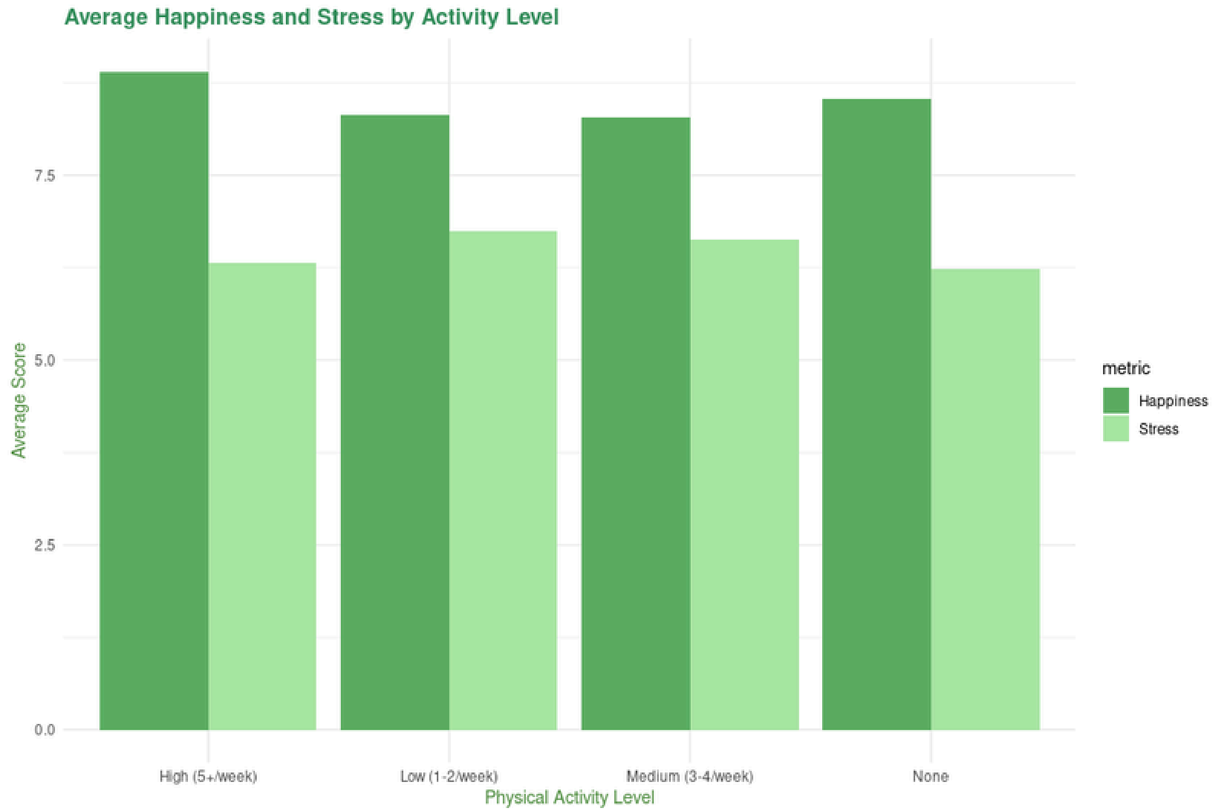
VISIT QUERY...

- CORRELATION PHYSICAL ACTIVITY & STRESS

RESULTS...

Row	activity_level	avg_happiness	avg_stress	user_count
1	High (5+/week)	8.90	6.31	42
2	Low (1-2/week)	8.32	6.74	223
3	Medium (3-4/week)	8.29	6.63	192
4	None	8.53	6.23	43

To enhance the clarity of our findings, we created a bar chart in R Studio, allowing for a more intuitive and visually engaging representation of the data. This visualization provides a clearer understanding of the patterns and relationships within the dataset, making it easier to observe variations in user behavior across different groups.



- While analyzing the relationship between physical activity, happiness, and stress levels, the results showed minimal variation across the general population. The differences between users with low, medium, and high exercise frequency were not as pronounced as initially expected. Therefore, the decision was made to further segment the analysis by age groups, allowing for a more detailed understanding of how physical activity influences emotional well-being within different segments. This additional breakdown provides a clearer visualization of potential behavioral patterns that may have been masked in the overall dataset.

To begin with our next steps, we first aim to identify which age groups show the highest and lowest happiness levels. The goal is to understand how happiness varies across age groups in order to better personalize the in-app experience. To gather this insight, we ran the following query:

```sql
WITH age_groups AS (
  SELECT
    user_id,
    age,
    happiness_index,
    CASE
      WHEN age BETWEEN 18 AND 25 THEN '18-25'
      WHEN age BETWEEN 26 AND 35 THEN '26-35'
      WHEN age BETWEEN 36 AND 45 THEN '36-45'
      ELSE '46+'
    END AS age_group
  FROM `klr-projects.better_help.mental_health`
)

SELECT
  age_group,
  ROUND(AVG(happiness_index), 2) AS avg_happiness,
  COUNT(*) AS user_count
FROM age_groups
GROUP BY age_group
ORDER BY age_group;
```

VISIT QUERY...

- AVG_AGE_HAPPINESS

RESULTS...

Row	age_group	avg_happiness	user_count
1	18-25	8.35	106
2	26-35	8.22	134
3	36-45	8.52	164
4	46+	8.37	96

- As shown in our chart, individuals between the ages of 26–35 exhibit the lowest happiness levels. With this data, we can better identify which demographic requires the most focus. However, it is also important to consider screen-time usage and activity levels across age groups. By analyzing these factors together, we can determine which types of physical classes to introduce in order to better meet user’s needs.

With the average happiness levels clearly segmented by age group, our next objective is to explore how social media usage influences emotional well-being across these segments. Specifically, we aim to determine whether notable differences in happiness and stress exist between age groups with high versus low social media engagement.
To uncover these behavioral patterns, we will run the following query. This analysis will allow us to better understand how digital habits interact with emotional wellness, guiding future recommendations and product features tailored to user needs.

```sql
WITH user_segments AS (
  SELECT
    user_id,
    happiness_index,
    CASE
      WHEN age BETWEEN 18 AND 25 THEN '18-25'
      WHEN age BETWEEN 26 AND 35 THEN '26-35'
      WHEN age BETWEEN 36 AND 45 THEN '36-45'
      ELSE '46+'
    END AS age_group,
    CASE
      WHEN screen_time < 2 THEN 'Low Screen'
      WHEN screen_time BETWEEN 2 AND 4 THEN 'Medium Screen'
      ELSE 'High Screen'
    END AS screen_group,
    CASE
      WHEN exercise_frequency = 0 THEN 'No Activity'
      WHEN exercise_frequency BETWEEN 1 AND 2 THEN 'Low Activity'
      WHEN exercise_frequency BETWEEN 3 AND 4 THEN 'Medium Activity'
      ELSE 'High Activity'
    END AS activity_group
  FROM `klr-projects.better_help.mental_health`
)

SELECT
  age_group,
  screen_group,
  activity_group,
  ROUND(AVG(happiness_index), 2) AS avg_happiness,
  COUNT(*) AS user_count
FROM user_segments
GROUP BY age_group, screen_group, activity_group
HAVING COUNT(*) > 5
ORDER BY age_group, screen_group, activity_group;
```

VISIT QUERY...

- SEG_AGE_SCREENTIME_EXERCISE

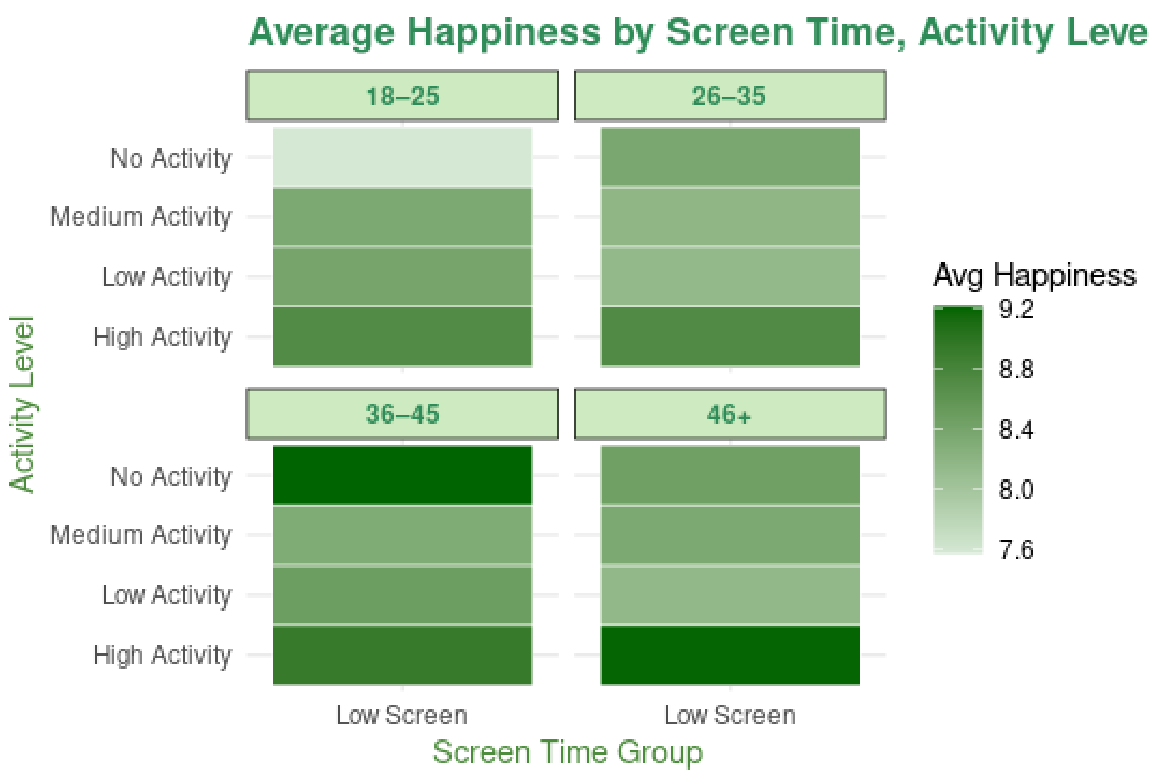
RESULTS...

When running this query, we sorted the average happiness field in ascending order to easily identify the age groups with lower happiness levels. This allowed us to clearly observe their screen-time patterns and physical activity levels, providing insight into how lifestyle behaviors may relate to emotional well-being.

Row	age_group	screen_group	activity_group	avg_happiness	user_count
1	26-35	High Screen	Medium Activity	7.73	45
2	46+	High Screen	Medium Activity	7.82	28
3	46+	High Screen	Low Activity	7.84	32
4	26-35	High Screen	Low Activity	7.85	46
5	36-45	High Screen	Medium Activity	7.94	50
6	18-25	High Screen	Medium Activity	8.1	29
7	18-25	High Screen	Low Activity	8.11	44
8	46+	High Screen	No Activity	8.11	9
9	26-35	High Screen	No Activity	8.2	10
10	26-35	High Screen	High Activity	8.25	8

Here, we observe the ten age segments with the lowest happiness levels. A notable pattern emerges across all of them: each group shows high screen time and low levels of physical activity. This consistent trend suggests a potential relationship between digital consumption habits, physical engagement, and emotional well-being.

- To gain a comprehensive view of all segments and better visualize the relationship between screen time and physical activity index, we created a heatmap in R Studio.



As we can see, excessive social media use combined with low physical activity is associated with lower happiness levels. This pattern is particularly evident among individuals aged 26–35, who exhibit noticeably lower well-being compared to other age groups.

VISIT R STUDIO CHARTS...

- BETTERHELP_RSTUDIO

INSIGHTS

- **Higher screen time is strongly associated with lower happiness** The data revealed a clear negative correlation between screen time and happiness. Users spending more than 4 hours per day on social media consistently reported lower well-being.
- **Physical activity alone does not guarantee higher well-being for all users** While activity levels showed some influence, differences in happiness and stress across activity groups were modest when looking at the whole population. This suggests that movement matters — but it's most impactful when paired with moderated screen time.
- **The 26–35 age group shows the lowest happiness levels** This demographic consistently reported lower emotional well-being and higher screen time, indicating a vulnerable group with elevated risk for digital fatigue and emotional strain.
- **Combined lifestyle factors matter more than individual habits** When screen time, age group, and physical activity were segmented together, the lowest happiness levels occurred in users who both spend high time on screens and have low physical activity levels, reinforcing that emotional health is shaped by interconnected behaviors.

CONCLUSION

This analysis highlights a meaningful relationship between digital habits, lifestyle behaviors, and emotional well-being among BetterHelp users. High social media usage — especially when paired with low physical activity — is associated with reduced happiness and increased stress, particularly in individuals aged 26–35.
Although physical activity alone did not drastically shift overall stress or happiness scores across the entire population, its positive impact emerged more clearly when analyzed alongside screen-time behavior and age segments. This suggests that a balanced digital-wellness approach, rather than a single-factor intervention, may be the most effective strategy for supporting mental health.
Overall, these findings reinforce the importance of encouraging mindful technology use and promoting healthy lifestyle routines to enhance user well-being and engagement.

RECOMMENDATIONS

1. Targeted well-being programs for the 26–35 age group
Develop personalized interventions focused on digital balance and emotional support, such as:

- Stress-management workshops
- Guided mindfulness series
- Personalized in-app reminders for healthy digital habits

2. Launch in-app wellness integrations
Introduce features that support movement and emotional regulation, such as:

- Virtual yoga sessions
- Meditation and breath-work exercises
- Stretch breaks and mobility prompts

3. Build behavior-driven nudges
Use behavioral insights to encourage balance by:

- Notifying users after extended screen-time periods
- Rewarding consistent physical activity
- Recommending short mental-restore activities during high usage times

4. Multi-factor well-being dashboard
Create a dashboard where users can track:

- Screen time
- Mood trends
- Physical activity
- Stress levels.

5. Continue segmentation-based research
Explore additional user dimensions such as:

- Work vs. student populations
- Relationship status
- Sleep quality clusters
- to further tailor user experience and support programs.

PRODUCT IMPACT

Based on this analysis, I recommend piloting a targeted Digital Balance & Wellness Program for users aged 26–35. The feature would trigger personalized prompts and short wellness sessions (meditation, stretch breaks, breathing exercises) after extended screen time, encouraging healthier emotional habits and improving long-term engagement.
This data-driven approach aims to increase user happiness, reduce stress fatigue, and strengthen retention by promoting mindful technology use.

SUMMARY...

Category	Key Takeaway
Biggest finding	Higher screen time = lower happiness
Key vulnerable group	Users ages **26–35**
Physical activity	Helps most when combined with lower screen time
Critical behavior insight	Digital habits + movement predict emotional well-being
Product opportunity	**Wellness + screen-time prompts** for at risk users
Suggested feature	Virtual yoga & meditation + screen-balance nudges
Expected business impact	↑ Retention, ↑ Satisfaction, ↑ Healthy emotional habits
Success metrics	Engagement uplift, happiness score trends, feature adoption rate

Delivering emotional well-being requires addressing digital balance and physical wellness no therapy alone.
This project demonstrates how behavioral data can guide personalized mental-wellness experiences, empowering BetterHelp to support users not just emotionally, but holistically.