🧠 Mental Wellness Analysis – Visualization, Interactivity & Strategic Insights

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🎯 Analysis Objective

– Highlighting `major trends` in emotional and behavioral patterns over time

– Exploring relationships between `stress`, `sleep`, `exercise`, and `mood`

– Enabling the product and strategy teams to explore the data independently `through interactive visuals`

– `Providing clear recommendations` for developing a mental wellness app

📁 Step 1: Importing and Loading Libraries for Sample Data Display

We will import the `pandas` library to load the dataset, along with libraries such as `plotly` to create charts.

	Date	Mood Score	Sleep Hours	Exercise (min)	Social Interactions	Stress Level	Category	Type	Notes
0	2020-11-14	4	4.8	14	1	8	Recovery	Weekend	Busy day
1	2022-03-29	10	5.8	44	0	6	Peak	Sick Day	Distracted
2	2023-05-21	8	6.5	40	4	9	Low	Sick Day	Focused
3	2022-12-02	7	7.3	7	3	5	Recovery	Sick Day	Great mood
4	2020-10-16	7	9.0	36	3	7	Routine	Holiday	Felt productive

📌 Observation

The dataset contains 9 columns, named:

`Date`, `Mood Score`, `Sleep Hours`, `Exercise (min)`, `Social Interactions`, `Stress Level`, `Category`, `Type`, `Notes`.

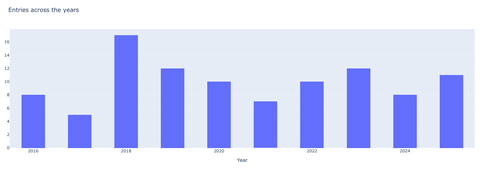
These columns will be used to formulate conclusions and insights throughout the mental wellness analysis.

📊 Step 2: Overview of Temporal Distribution

In this step, we will explore the overall structure of the dataset by analyzing the `distribution of entries across years`.

This will help us understand how the data is spread over time.

`Histogram:`



📌 Observation

The dataset includes entries from `2016` to `2024`, with visible fluctuations in yearly volume.
Years like `2018` and `2023` show the highest activity, while `2017` and `2021` are notably lower.

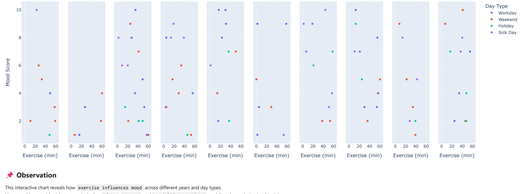
This distribution highlights `uneven engagement over time`, offering a useful baseline for identifying `behavioral trends` and guiding further analysis of `mood`, `stress`, `sleep`, and `exercise`.

📊 Step 3: Behavioral Analysis

In this step, we will investigate how lifestyle factors such as `Sleep Hours`, `Exercise`, `Stress Level`, and `Social Interactions` relate to `Mood Score`.

We will use a combination of `boxplots` and `scatter plots` to identify distribution patterns and potential correlations.
This will help us understand which behaviors are most strongly associated with emotional well-being, and how these relationships vary across different day types (`Type`).

`Boxplot ( Sleep Hours vs Mood Score )`



`Boxplot ( Stress Level vs Mood Score )`

`Scatterplot ( Exercise vs Mood Score )`

`Scatterplot ( Social Interactions vs Mood Score )`

📌 Observation

The behavioral analysis reveals key relationships between `Mood Score` and several lifestyle factors:

- The boxplots show that `Sleep Hours` and `Stress Level` vary significantly across mood levels.
  Higher mood scores tend to align with `longer sleep` and `lower stress`, especially on `Weekends` and `Holidays`.
- The scatter plots highlight positive correlations between `Exercise (min)` and `Mood Score`, with `lower stress` amplifying this effect.
  Similarly, `Social Interactions` appear to support better mood, particularly when paired with `adequate sleep`.

These patterns suggest that `sleep`, `exercise`, `stress management`, and `social connection` are strong behavioral drivers of emotional well-being.
They provide actionable insights for designing wellness app features that promote `restful routines`, `active lifestyles`, and `social engagement`.

📊 Step 4: Interactivity Layer

In this step, we will enhance the report with interactive features that allow users to filter the data by `Year`, `Category`, and `Type`.

We will also enable `hover tooltips` to display detailed insights for each entry, making the visualizations more informative and user-friendly.

This layer supports exploratory analysis and empowers product and strategy teams to investigate specific behavioral patterns.

📌 Observation

This interactive chart reveals how `exercise influences mood` across different years and day types.
Hover tooltips provide rich context, including `sleep`, `stress`, and `social interactions`, enabling deeper behavioral insight.
We observe tighter mood clustering on workdays, while holidays and sick days show greater emotional variability suggesting that structured routines `may stabilize mood responses to physical activity`.

📈 Step 5: Conclusions & Business Recommendations

Based on the interactive visualizations and behavioral breakdowns, we can now extract actionable insights and propose strategic directions for wellness optimization.

🎯 High-Mood Day Types

- **Weekends** and **Holidays** consistently show higher mood scores, especially when paired with moderate exercise and sufficient sleep.
- **Workdays** with structured routines and balanced activity also yield stable mood levels, particularly when stress is low.

⚠️ Stress-Reducing Combinations

- Days with **7+ hours of sleep**, **30+ minutes of exercise**, and **3+ social interactions** tend to correlate with lower stress levels.
- **Journaling** and **positive notes** (when present) often coincide with improved mood and reduced stress, suggesting emotional processing plays a role.

💡 App Feature Suggestions

- **Smart journaling prompts** based on mood and stress trends
- **Personalized nudges** for sleep hygiene, exercise, and social connection
- **Mood-linked sleep tracking** to detect patterns and suggest bedtime adjustments
- **Behavioral summaries** after each week to reinforce healthy habits

These recommendations support a proactive, personalized approach to mental wellness and can guide future app development or coaching strategies.