Developing a Data-Driven Web Application for Workplace Wellness

Abstract: This paper details the creation and launch of a web application aimed at promoting wellness in the workplace through tailored mental health strategies. Developed during the Winter '24 Hackathon organized by Chegg Skills, this project utilized data analysis and a user-focused approach to offer practical insights and tools for better sleep and mental well-being. The application includes features such as personalized recommendations, interactive dashboards, and tailored coping methods, showcasing the importance of collaborative efforts from various disciplines in successfully bringing the product to life. This paper specifically focuses on the data analysis process that underpinned these features, showcasing the role of interdisciplinary collaboration in achieving a successful product launch.

Introduction

As mental health issues become more common in the workplace, organizations are increasingly looking for creative ways to enhance employee well-being. Factors like good sleep, effective stress management, and regular physical activity play a vital role in mental health, impacting productivity, job satisfaction, and overall wellness. This paper examines the development of the Workplace Wellness Web App, which was created during the Winter '24 Hackathon. The app combines data analytics with easy-to-use interfaces to provide enhanced mental health support for employees. The primary focus of this paper is on the data analysis process used to develop personalized health insights and recommendations, demonstrating how data-driven strategies can be leveraged to promote better mental health outcomes.

Methods

Data Collection and Preparation

The project started with gathering the "Sleep Health and Lifestyle Dataset," from Kaggle, which included various variables that were important for understanding overall wellness. This dataset had information on sleep duration, quality of sleep, stress levels, physical activity, and other key health metrics. The first task was to ensure the data was clean and accurate.

To achieve this, several steps were taken:

- Handling Missing Values: Missing data can skew results and lead to inaccurate analysis. However, no missing values were found in this dataset.
- Removing Duplicates: We removed duplicate entries to ensure that each individual was only counted once, which helped in maintaining the integrity of the data.
- Normalizing Data Formats: It was crucial to make sure all data was in a consistent format. We standardized formats for all variables to keep the data uniform and ensure that calculations were accurate.

```
# Split the 'Blood Pressure (systolic/diastolic)' column into two separate columns: 'Systolic' and 'Diastolic'
df0[['Systolic BP', 'Diastolic BP']] = df0['Blood Pressure'].str.split('/', expand=True)

# Convert the new columns to numeric types
df0['Systolic BP'] = pd.to_numeric(df0['Systolic BP'], errors='coerce')
df0['Diastolic BP'] = pd.to_numeric(df0['Diastolic BP'], errors='coerce')

# Drop the original 'Blood Pressure (systolic/diastolic)' column
df = df0.drop(columns=['Blood Pressure'])

# Create a new column for the arithmetic difference between 'Systolic BP' and 'Diastolic BP'
df['Pulse Pressure'] = df['Systolic BP'] - df['Diastolic BP']
```

```
df['BMI Category'] = df['BMI Category'].replace('Normal Weight', 'Normal')
df['Occupation'] = df['Occupation'].replace('Sales Representative', 'Salesperson')

df.drop('Person ID',axis=1, inplace=True)
df.head()
```

	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Heart Rate	Daily Steps	Sleep Disorder	Systolic BP	Diastolic BP	Pulse Pressure
0	Male	27	Software Engineer	6.1	6	42	6	Overweight	77	4200	None	126	83	43
1	Male	28	Doctor	6.2	6	60	8	Normal	75	10000	None	125	80	45
2	Male	28	Doctor	6.2	6	60	8	Normal	75	10000	None	125	80	45
3	Male	28	Salesperson	5.9	4	30	8	Obese	85	3000	Sleep Apnea	140	90	50
4	Male	28	Salesperson	5.9	4	30	8	Obese	85	3000	Sleep Apnea	140	90	50

By meticulously cleaning and preparing the dataset, we laid a strong foundation for the analysis and subsequent development of the app's features.

Exploratory Data Analysis

With a clean dataset in hand, we moved on to exploratory data analysis (EDA) to uncover patterns and relationships within the data. EDA is key for understanding the structure of the data and identifying important variables.

The EDA process involved:

- Pivot Tables: These were used to summarize the data and explore interactions between different variables. This helped us spot trends, such as differences in sleep duration based on stress levels.
- Statistical Tests: We conducted statistical tests, including two-sample t-tests, to compare averages between groups (like people with different sleep disorders). This allowed us to see if the differences between groups were statistically significant.
- Correlation Analysis: By calculating correlation coefficients, we were able to measure how strongly different variables were related, such as the connection between stress and sleep quality. These findings were crucial for creating personalized recommendations for the app.

The insights gained during the EDA phase were used to develop the app's features, ensuring that the recommendations were based on real data.

Modeling and Hypothesis Testing

After the EDA, we moved to modeling and hypothesis testing to validate our findings and ensure our recommendations were backed by data.

- Two-Sample t-Tests: We used these tests to compare the means of different groups, such as those with varying levels of stress or different sleep disorders. This helped us confirm that the differences we observed were statistically significant and not just due to random chance.
- Hypothesis Testing: By testing hypotheses based on our EDA findings, we verified the relationships we identified. For example, we tested the hypothesis that higher stress levels correlate with lower sleep quality, and our results supported this hypothesis. This gave a strong basis for the app's recommendation system, ensuring that the guidance provided was grounded in solid data.

Data Analysis Techniques

1. Pivot Tables and Statistical Tests
    - Purpose: The main goal was to explore how different variables, such as stress levels, sleep disorders, sleep duration, and sleep quality, relate to each other and influence overall health.
    - Process:
        - Pivot Tables: These were used to summarize data and compute key statistics for different groups based on variables like stress level and sleep disorder. This method helped us quickly spot patterns and differences among various subgroups.
        - t-Tests: Two-sample t-tests assuming unequal variances were conducted to compare the means between groups (e.g., those with different stress levels or sleep disorders). This analysis helped determine if the observed differences were statistically significant, which informed the creation of targeted health recommendations.

t-Test: Two-Sample Assuming Unequal Variances

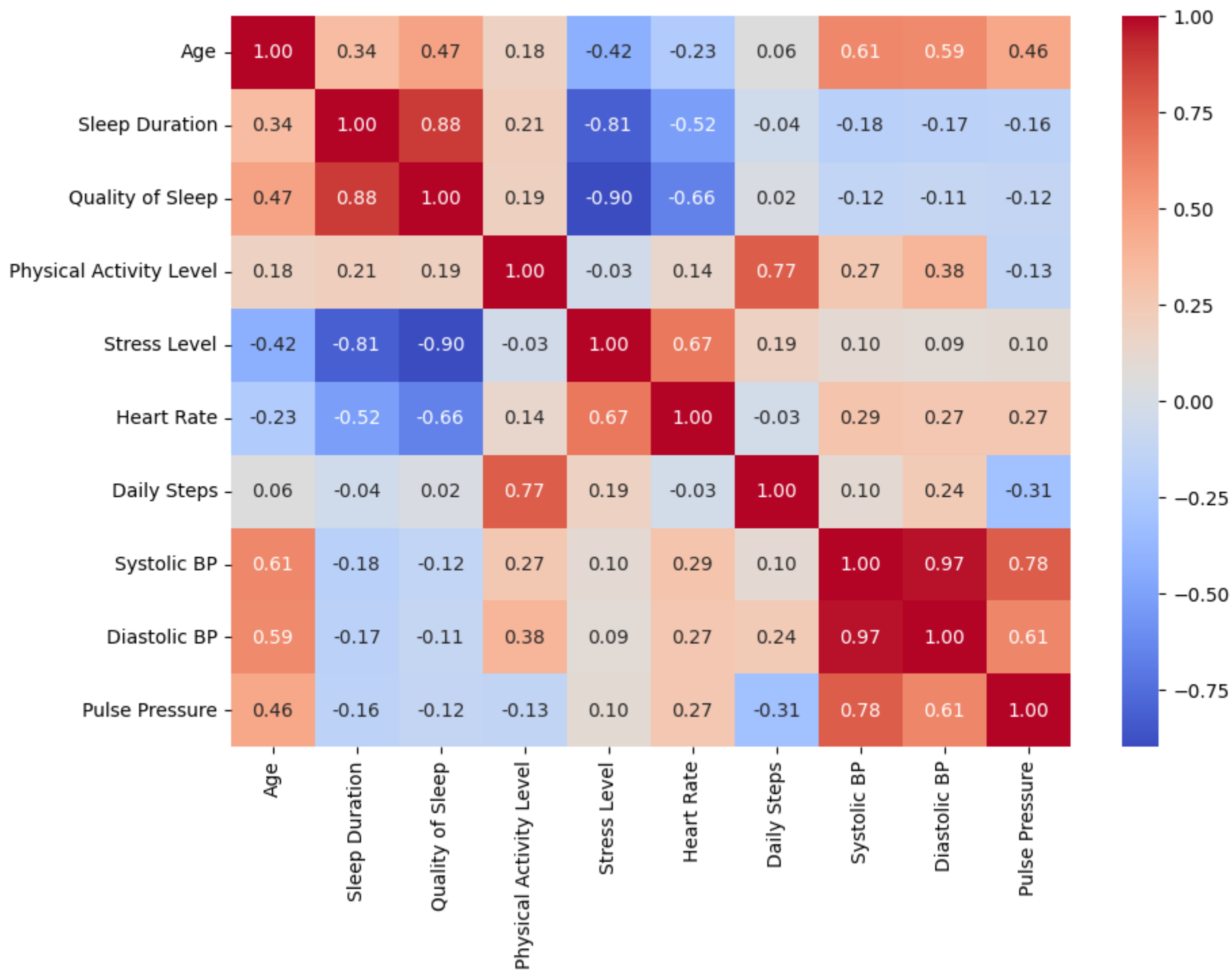
	Stress Level	
	≤ 7	*> 7*
Mean	7.38125	6.05
Variance	0.444630776	0.008333333
Observations	304	70
Hypothesized Mean Difference	0	
df	344	
t Stat	33.47376672	
P(T<=t) one-tail	1.5132E-110	
t Critical one-tail	1.649295214	
P(T<=t) two-tail	3.0264E-110	
t Critical two-tail	1.966884036	

t-Test: Two-Sample Assuming Unequal Variances

	Sleep Disorder	
	No	*Yes*
Mean	7.625570776	6.870967742
Variance	0.950902769	1.788437369
Observations	219	155
Hypothesized Mean Difference	0	
df	265	

t Stat	5.988096927
P(T<=t) one-tail	3.44178E-09
t Critical one-tail	1.650623976
P(T<=t) two-tail	6.88356E-09
t Critical two-tail	1.968956281

2. Key Performance Indicators (KPIs) and Correlation Analysis
   - Purpose: The objective was to identify important variables that are associated with sleep duration and quality and understand how these variables interact with other health metrics. This is crucial for pinpointing factors that have a significant impact on sleep health.
   - Process:
     - Correlation Coefficients: We calculated these to assess the strength and direction of relationships between sleep metrics (such as duration and quality) and other factors, including stress level, heart rate, BMI category, sleep disorder, age, and physical activity.
     - Significance Testing: We evaluated the statistical significance of these correlations using p-values to identify which factors had meaningful relationships with sleep outcomes. This analysis played a key role in shaping the app's recommendation engine, ensuring that the advice provided was based on statistically significant data.



				Corr Coef		P-value (0.05)		
Target variables	Correlated variables	Data Type	Goal	Sleep Dur	Qual Sleep	Sleep Dur	Qual Sleep	Additional Observations
Sleep Duration	Stress Level	Numerical	Reduce	-0.81	-0.9			
Quality of Sleep	Heart Rate	Numerical	Reduce	-0.52	-0.66			
(corr coef: 0.88)	BMI Category	Categorical	Reduce			3.55E-13	9.26E-10	Obese people on average take about half the amount of daily steps Normal weight people take
	Sleep Disorder	Categorical	Reduce			1.63E-13	6.69E-12	People with no Sleep Disorders have overall better metrics than those who do
	Age	Numerical		0.34	0.47			
	Physical Activity Level	Numerical	Increase	0.21	0.19			
	Gender	Categorical				0.019	9.42E-09	Males on average have higher stress levels than Females
	Occupation	Categorical				1.02E-13	9.80E-41	Accountants, Engineers, and Lawyers have overall better metrics than Salespersons and Scientists

3. Analysis of Good Sleep Criteria
   - Purpose: The aim was to define what constitutes "good sleep" based on various metrics and provide actionable feedback to users based on their data.
   - Process:
     - Criteria Establishment: We set thresholds for what is considered good sleep quality and duration, as well as related health behaviors like stress levels and physical activity. These benchmarks were used to evaluate user data.
     - Feedback Provision: The app provided personalized feedback based on whether users met these criteria. For example, users who met the criteria received positive

reinforcement, while those who did not were given advice on how to improve their sleep habits and overall health.

4. Sleep Analysis Based on Sleep Duration
   - Purpose: The goal was to analyze data for individuals with different sleep durations and identify any outliers that might indicate unusual patterns or behaviors.
   - Process:
     - Descriptive Statistics: We calculated descriptive statistics such as mean, quartiles, and interquartile range (IQR) for variables like sleep duration, quality of sleep, physical activity, stress level, heart rate, and daily steps.
     - Outlier Detection and Recommendations: Outliers were identified for subsets of data based on these metrics, and customized recommendations were provided to help users understand how their sleep habits compared to the norm and what adjustments might be beneficial.

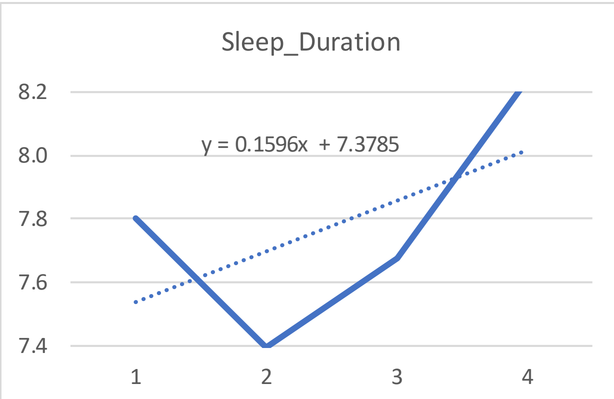
	Sleep_Duration	Quality_of_Sleep	Physical_Activity_Level	Stress_Level	Heart_Rate	Daily_Steps
Average	**7.7**	**8.1**	**65.3**	**4.3**	**68.7**	**6988.1**
Q0	7.1	7	30	3	65	3300
Q1	7.25	8	60	3	68	7000
Q2	7.7	8	65	4	68	7000
Q3	8.1	9	75	5	70	8000
Q4	8.5	9	90	6	86	10000
IQR	0.85	1	15	2	2	1000
LOWER BOUND	5.975	6.5	37.5	0	65	5500
UPPER BOUND	9.375	10.5	97.5	8	73	9500
Observations			*30 is an outlier for this subset*		*86 is an outlier for this subset*	*3300 is an outlier for this subset*

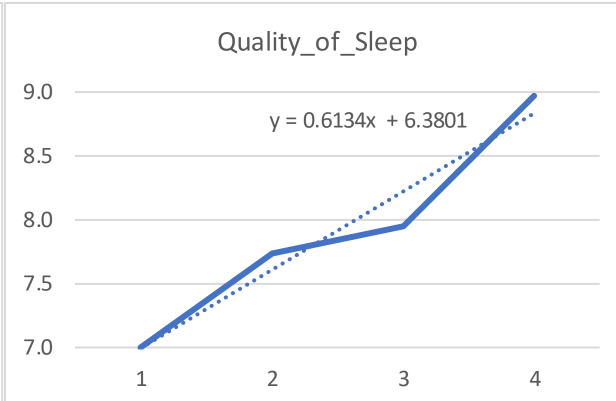
Recommendations:

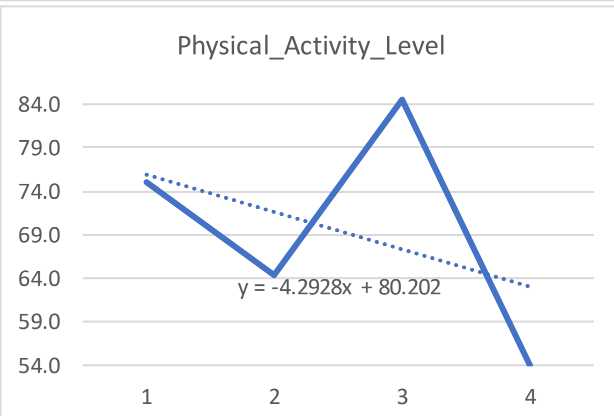
Message	**Sleep Duration**	**Quality of Sleep**	**Physical Activity Level**	**Stress Level**	**Heart Rate**	**Daily Steps**
"YOU ARE DOING GREAT!"	>= 7h 40min	>= 9	>= 70 min/day	<= 3	<= 68 bpm	>= 7000
"Those are some good numbers"	>= 7h 15min & < 7h 40min	8	>= 50 & < 70 min/day	4	> 68 & <= 70 bpm	>= 6000 & < 7000
"Still good numbers, but on the limit for good sleep"	>= 7h & < 7h 15min	7	>= 40 & <50 min/day	5	> 70 & <= 73 bpm	>= 5500 & < 6000
"YOU ARE BELOW RECOMMENDED VALUES FOR GOOD SLEEP"	< 7h	<= 6	< 40 min/day	>= 6	> 73 bpm	< 5500

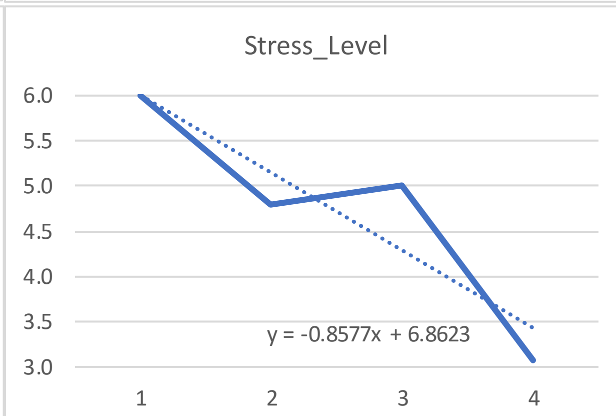
5. Age-Adjusted Analysis
   - Purpose: This analysis aimed to examine health metrics and sleep data across different age groups and adjust recommendations to be more relevant and effective for users of different ages.
   - Process:
     - Average Calculations: We calculated the average values of various metrics (like sleep duration, quality of sleep, physical activity) for different age groups to understand typical health behaviors in each group.
     - Trend Analysis: Slope calculations were used to analyze trends in these metrics across age groups, providing insights into how behaviors and health outcomes change with age.
     - Adjusted Recommendations: Based on the average health metrics and sleep data for each age group, we tailored recommendations to ensure they were appropriate and relevant for users of different ages.

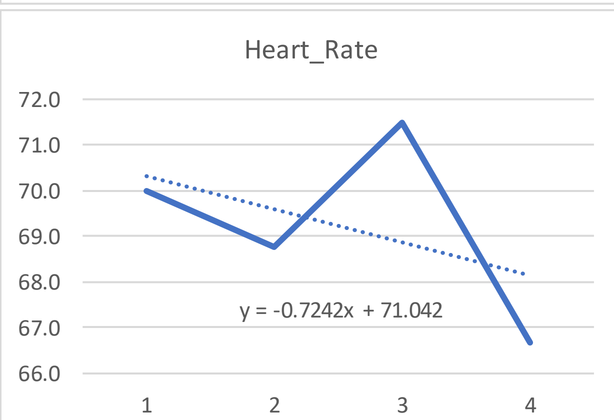
	Average						
Age	**Sleep_Duration**	**Quality_of_Sleep**	**Physical_Activity_Level**	**Stress_Level**	**Heart_Rate**	**Daily_Steps**	
20-29	**7.8**	**7.0**	**75.0**	**6.0**	**70.0**	**8000.0**	
30-39	**7.4**	**7.7**	**64.4**	**4.8**	**68.8**	**7378.8**	
40-49	**7.7**	**8.0**	**84.5**	**5.0**	**71.5**	**7395.3**	***(subset avg = 42)***
50-59	**8.2**	**9.0**	**54.0**	**3.1**	**66.7**	**6073.5**	
Slope	0.16		-4.3		-0.7	-576	
	10 min		-5 min/day		-1 bpm	-500 steps	

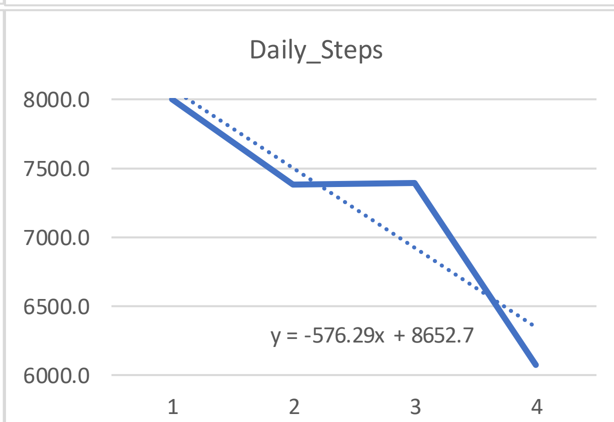












				Adjusted for Age groups		
Recommendations:	*Age 20-29*					
Message	Sleep Duration	Quality of Sleep	Stress Level	*Physical Activity Level*	*Heart Rate*	*Daily Steps*
"YOU ARE DOING GREAT!"	>= 7h 40min	>= 9	<= 3	*>= 80 min/day*	*<= 70 bpm*	*>= 8000*
"Those are some good numbers"	>= 7h 15min & < 7h 40min	8	4	*>= 60 & < 80 min/day*	*> 70 & <= 72 bpm*	*>= 7000 & < 8000*
"Still good numbers, but on the limit for good sleep"	>= 7h & < 7h 15min	7	5	*>= 50 & < 60 min/day*	*> 72 & <= 75 bpm*	*>= 6500 & < 7000*
"YOU ARE BELOW RECOMMENDED VALUES FOR GOOD SLEEP"	< 7h	<= 6	>= 6	*< 50 min/day*	*> 75 bpm*	*< 6500*
Recommendations:	*Age 30-39*					
Message	Sleep Duration	Quality of Sleep	Stress Level	*Physical Activity Level*	*Heart Rate*	*Daily Steps*
"YOU ARE DOING GREAT!"	>= 7h 40min	>= 9	<= 3	*>= 75 min/day*	*<= 69 bpm*	*>= 7500*
"Those are some good numbers"	>= 7h 15min & < 7h 40min	8	4	*>= 55 & < 75 min/day*	*> 69 & <= 71 bpm*	*>= 6500 & < 7500*
"Still good numbers, but on the limit for good sleep"	>= 7h & < 7h 15min	7	5	*>= 45 & < 55 min/day*	*> 71 & <= 74 bpm*	*>= 6000 & < 6500*
"YOU ARE BELOW RECOMMENDED VALUES FOR GOOD SLEEP"	< 7h	<= 6	>= 6	*< 45 min/day*	*> 74 bpm*	*< 6000*
Recommendations:	*Age 40-49*	*(subset average = 42)*				
Message	Sleep Duration	Quality of Sleep	Stress Level	*Physical Activity Level*	*Heart Rate*	*Daily Steps*
"YOU ARE DOING GREAT!"	>= 7h 40min	>= 9	<= 3	*>= 70 min/day*	*<= 68 bpm*	*>= 7000*
"Those are some good numbers"	>= 7h 15min & < 7h 40min	8	4	*>= 50 & < 70 min/day*	*> 68 & <= 70 bpm*	*>= 6000 & < 7000*
"Still good numbers, but on the limit for good sleep"	>= 7h & < 7h 15min	7	5	*>= 40 & <50 min/day*	*> 70 & <= 73 bpm*	*>= 5500 & < 6000*
"YOU ARE BELOW RECOMMENDED VALUES FOR GOOD SLEEP"	< 7h	<= 6	>= 6	*< 40 min/day*	*> 73 bpm*	*< 5500*
Recommendations:	*Age 50-59*					
Message	Sleep Duration	Quality of Sleep	Stress Level	*Physical Activity Level*	*Heart Rate*	*Daily Steps*
"YOU ARE DOING GREAT!"	>= 7h 40min	>= 9	<= 3	*>= 65 min/day*	*<= 67 bpm*	*>= 6500*
"Those are some good numbers"	>= 7h 15min & < 7h 40min	8	4	*>= 45 & < 65 min/day*	*> 67 & <= 69 bpm*	*>= 5500 & < 6500*
"Still good numbers, but on the limit for good sleep"	>= 7h & < 7h 15min	7	5	*>= 35 & < 45 min/day*	*> 69 & <= 72 bpm*	*>= 5000 & < 5500*
"YOU ARE BELOW RECOMMENDED VALUES FOR GOOD SLEEP"	< 7h	<= 6	>= 6	*< 35 min/day*	*> 72 bpm*	*< 5000*

Data Visualization and Insights

To showcase the findings from our data analysis, we created a detailed Tableau dashboard. This dashboard provides a visual overview of the relationships between various health metrics and sleep patterns, making it easy to see key trends and insights. The dashboard includes several charts and graphs:

- Sleep: Duration vs. Quality: This scatter plot displays how sleep duration (measured in hours per day) relates to the average quality of sleep (on a scale from 1 to 10). It shows that, generally, getting more sleep is linked to better sleep quality. This visualization helps identify the ideal amount of sleep for improved sleep quality.
- Sleeping Over 7 Hours: This line graph illustrates the average physical activity levels, heart rates, and daily steps for individuals who sleep more than seven hours, divided into different age groups (20-29, 30-39, 40-49, 50-59). It highlights how these health metrics change across different ages and their potential impact on sleep quality.
- Sleep vs. Age: A bar chart showing the average quality of sleep for various age groups. It reveals how sleep quality can vary with age, suggesting that different age groups might need tailored sleep advice.
- Sleep vs. Physical Activity Level: This horizontal bar chart compares the median sleep duration with different levels of physical activity (measured in minutes per day). It indicates that people who are more physically active tend to have better sleep, highlighting the importance of exercise for good sleep.
- Sleep vs. Stress Level: A bar chart illustrating the link between stress levels (rated from 1 to 10) and average sleep quality. The chart shows that higher stress levels often correspond to lower sleep quality, emphasizing the need for stress management to improve sleep.
- Sleep vs. BMI Category: This chart shows the median daily steps and average quality of sleep across different BMI categories (Normal, Overweight, Obese). It provides insights into how body weight may affect both physical activity and sleep quality.
- Sleep vs. Heart Rate: A bar chart comparing average sleep quality with median heart rate (beats per minute). It demonstrates that lower heart rates are usually associated with better sleep quality, pointing to a connection between heart health and sleep.
- Sleep vs. Gender: This chart displays the median stress levels and quality of sleep by gender, showing differences in stress and how it affects sleep quality between males and females.
- Sleep vs. Occupation: A bar chart presenting the median stress levels and quality of sleep for various occupations. It provides insights into how different job types might influence stress and sleep quality.
- Sleep vs. Sleep Disorder: This chart explores the median heart rate and quality of sleep for individuals with different sleep disorders (Sleep Apnea, Insomnia, None). It highlights how sleep disorders can impact sleep quality and overall health.

The Tableau dashboard allows users to easily explore the data and see the relationships between sleep and various health metrics. By visualizing these connections, we gain a clearer understanding of what factors contribute to good sleep and overall well-being. This information is crucial for creating personalized health recommendations that cater to users based on their unique characteristics such as age, gender, and occupation.

Feature Development

Using the insights from the data analysis, we developed several key features for the Workplace Wellness Web App:

- Personalized Health Insights: The app uses analyzed data to provide each user with tailored health insights, helping them understand their current health status and identify areas where they can improve.
- Data-Driven Recommendations: Based on identified patterns, the app offers personalized advice. For instance, users with high stress might get suggestions for stress-relief activities, while those with poor sleep might receive tips to improve sleep hygiene.
- Interactive Dashboards: To make the data easy to understand, we created interactive dashboards that visually show user metrics over time. These dashboards help users track their progress and make informed decisions about their health.

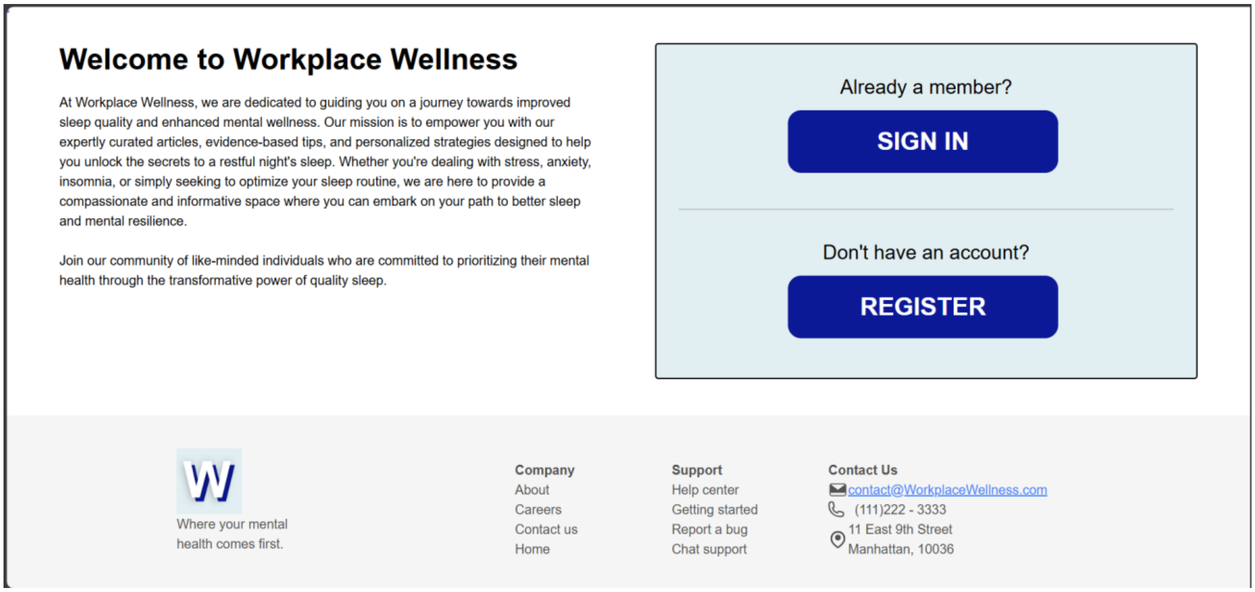
These features were designed to empower users by giving them the information and tools they need to manage their health effectively, ultimately enhancing their well-being.

Results

The creation of the Workplace Wellness Web App resulted in several key outcomes, demonstrating how effective data-driven strategies can be in offering personalized mental health support. These outcomes highlight the app's ability to engage users, provide meaningful insights, and deliver a positive experience.

1. Improved User Engagement:
    - Interactive Features: The app was designed with an intuitive interface that includes interactive components like dashboards, visualizations, and personalized prompts. These elements make it simple for users to navigate the app, monitor their health metrics, and stay involved in their wellness journey.
    - Customized Insights: By analyzing each user's data, the app delivers health insights that are tailored to their individual needs. For example, users receive specific feedback on their sleep patterns, stress levels, and physical activity. This personalized approach helps users feel more connected to their health management, encouraging them to engage more regularly.
    - Consistent Use: Thanks to the engaging design and relevant content, users are more likely to return to the app regularly. This consistent usage helps users track their progress over time and stay committed to the app's recommendations, leading to better health outcomes.
2. Actionable Insights:
    - Data-Based Feedback: A key feature of the app is its ability to provide practical advice based on a thorough analysis of user data. For instance, if a user is not getting enough sleep, the app might suggest changes like adjusting their bedtime routine or cutting down on caffeine.
    - Comprehensive Health Advice: The app looks beyond just sleep and takes other health metrics, such as stress levels and physical activity, into account. By integrating this data, the app offers well-rounded advice that covers multiple aspects of health, helping users make more informed decisions.
    - Empowering Users: The app gives users clear steps they can take to improve their well-being. This empowers them to make positive changes and encourages them to keep an eye on their progress.
3. Positive Feedback:

- Ease of Use: Users have reported that the app is user-friendly and easy to navigate, which is vital for keeping them engaged. They find the design straightforward and appreciate the interactive elements that help them understand their health data better.
- Relevant Recommendations: Feedback from users highlights the relevance and accuracy of the app's recommendations. Users value the fact that the advice is specifically tailored to their health data and personal circumstances.
- High Satisfaction: Overall, users are very satisfied with the app, noting its effectiveness in helping them understand their health better and make positive lifestyle changes. This positive response emphasizes the value of data-driven approaches in mental health support and shows how such tools can significantly benefit users.



Discussion

The development and success of the Workplace Wellness Web App illustrate the significant impact that data analytics can have on mental health and well-being in a professional setting. This project underscores the value of utilizing data-driven insights to create tools that not only promote mental health but also support overall wellness among employees.

By combining extensive data analysis with an intuitive, user-friendly design, the app is able to offer tailored mental health support that resonates with users. The data analysis process allowed us to identify key patterns and correlations between various health metrics, such as sleep quality, stress levels, and physical activity. These insights were then translated into actionable recommendations that users can easily understand and apply to their daily lives. This personalized approach is crucial, as it addresses the unique needs of each user, making the advice more relevant and effective.

Moreover, the project highlights the critical role of interdisciplinary collaboration in developing comprehensive health solutions. The app's success was not solely due to data analytics but also relied heavily on the combined expertise of various professionals, including data analysts, UX/UI designers, and software developers. Data analysts provided the insights needed to develop effective health recommendations, UX/UI designers ensured that the app was accessible and engaging for users, and developers built the technical infrastructure that made the app functional and reliable. This collaborative effort allowed the team to create a holistic solution that effectively meets the complex needs of its users, demonstrating the importance of integrating multiple skill sets to address multifaceted challenges.

The project also emphasizes the importance of creating user-centric designs in health applications. By focusing on ease of use and providing interactive features, the app encourages users to engage with their health data actively. This engagement is crucial for fostering long-term behavior change, as users who are actively involved in their health management are more likely to adopt and maintain healthier habits.

Conclusion

The Workplace Wellness Web App marks a significant advancement in the use of data analytics for supporting mental health in the workplace. By delivering personalized recommendations and actionable insights, the app empowers users to take proactive steps toward improving their mental well-being. This empowerment is key to fostering a healthier and more productive work environment, as employees who feel supported in managing their mental health are more likely to be engaged, satisfied, and effective in their roles.

This project, developed during a hackathon, serves as an exemplary model for future efforts aimed at leveraging data to enhance mental health outcomes. It demonstrates the transformative potential of data-driven solutions, particularly when they are designed with the user in mind and built upon a foundation of interdisciplinary collaboration. As the digital age continues to evolve, such innovative applications of data analytics will become increasingly important in addressing the growing mental health challenges faced by individuals in various settings.

The lessons learned from this project provide valuable insights for future initiatives. They underscore the importance of integrating data analytics with empathetic design and collaborative development to create tools that not only inform but also inspire users to take charge of their health. Moving forward, the principles and strategies employed in the Workplace Wellness Web App can be applied to a wide range of health-related applications, potentially revolutionizing how we approach mental health and well-being in both personal and professional contexts.

By focusing on data-driven, user-centered approaches, future projects can continue to push the boundaries of what is possible in digital health, ultimately contributing to a healthier, more resilient society.

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