ALBUKHARY INTERNATIONAL UNIVERSITY
SCHOOL OF COMPUTING AND INFORMATICS

Assignment 1 Task 2 (20%)

Mode: Pair

Own Fitness Tracker Data Visualization.

Course Code	**CCS3133**	Course Name	**Information Visualization**
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Assessment Marks:

No.	Criteria	Weight	Marks
1			
2			
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Comments:

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1.0 Introduction

With the digital age of health monitoring comes the need for information visualization for users in order for them to help interpret the personal health data generated through wearable monitors. Card et al. (1999) are of the view that a primary goal of information visualization is that it "amplifies cognition" by visualizing data such that patterns and insights can be more easily discerned. The more people use fitness trackers to monitor their health, the more visualization enables them to see trends in physical activity, sleep, and heart health that are difficult to identify with raw data. With health trackers such as Fitbit, Apple Watch, and other wearable devices gaining increasing usage, users are provided with day-to-day records of activity, heart rate, and sleep cycles, which must be decoded. Visualization bridges the gap between raw numbers and useful insights.

Chen (2010) points out that unlike scientific visualization, which often visualizes spatial or physical data, information visualization handles abstract, non-spatial data that needs to be translated into effective visual metaphors. This process is not merely technical; it is a mix of science, design, and human cognition to present data in a more understandable and usable way for decision-making. Gershon et al. (1998) assert that interactive visual interfaces can make users explore intricate datasets with ease, identify patterns, and arrive at insights that can inform behaviour change. For the use in tracking fitness, such interfaces can make users able to understand their health behaviours and make lifestyle adjustments.

The utility of information visualisation is also supported through activity in personal informatics systems. Keim (2002) emphasizes the benefit of visual analysis during an exploratory process of knowledge extraction from large and complex sets of data. Since wearable sensors monitor continuous health inputs, such as steps per day and heart rate, visualizations need to be generated in order to detect trends and outliers. Li et al. (2010) propose a stage model of personal informatics, where visualization helps users think about their data and evaluate progress towards health goals. Similarly, Choe et al. (2014) found that users of self-tracking devices consistently used visualizations for data interpretation with the aim of informing behaviour change.

Moreover, Kosara et al. (2003) highlight user interactive functions in visualizing information such as filtering, zooming, and dynamic querying, through which users can explore multiple dimensions of, as well as time scales in, the data. All such interactive functions can be particularly useful in personal health dashboards, as users will inevitably be keen on analyzing the relationship between sleep and steps, or identifying days of unusually high or low heart rates.

This project leverages these principles to visualize personal fitness tracker data collected from Fitbit over a one-month period. The intent is to demonstrate how interactive dashboards can make self-tracking data interpretable as well as actionable. With core methods of data visualisation, its users can learn daily physical activity trends, sleeping patterns, as well as heart rate-converting raw material to insights for healthier decision-making.

1.1 Problem Statement

The use of wearable health monitors such as Fitbit has created huge quantities of personal health data like steps, heart rate, and sleep recorded in real-time. While such monitors provide useful information, raw data in the shape of numbers is not being used because of its complexity of analysis as well as lack of meaningful presentation. CSV files cannot be read by non-technical users, nor can hidden patterns in numbers be recognized from numeric logs. Therefore, numerous individuals miss out on beneficial knowledge that can be used in maintaining their health, monitoring behavior, or identifying early warning signs of wellness issues.

Despite having such data available, little is presented in the form of tools where individuals can dynamically explore and analyze their health trends over time. The solution is presented through capturing the individual Fitbit data and bringing it into an interactive dashboard with the key health measures presented in an accessible, visual, user-driven way. The solution is designed in order for users to be more self-aware with enhanced capability for decision-making using information visualization methods.

2.0 Project Objectives

1. To engineer a structured and high-quality dataset from raw Fitbit activity, sleep, and heart rate records through comprehensive data preprocessing and integration techniques.
2. To conduct temporal and multivariate exploratory data analysis on step count, sleep duration, and cardiovascular patterns using visual analytics methods.
3. To design and implement an interactive dashboard in Tableau that enables dynamic, multi-dimensional exploration of personal fitness behavior.

2.1 Project Questions

1. How can raw Fitbit data be cleaned, integrated, and structured to support reliable personal health analysis?
2. What temporal trends and relationships can be identified across daily step counts, sleep duration, and heart rate patterns?
3. How can an interactive dashboard be designed to support meaningful exploration and interpretation of personal fitness data?

3.0 Literature Review

Fitness trackers generate a wide range of data, from simple step counts to complex metrics like sleep phases and heart rate variability. However, the sheer volume of data can be overwhelming if not presented effectively. Data visualization bridges this gap by transforming raw numerical data into meaningful and interpretable formats. Common methods like bar charts and line graphs are used to display daily step counts or weekly sleep patterns, making it easier for users to track progress (Chan et al., 2024; Alrehiely et al., 2018). Recent research also highlights the value of interactive visualizations, which allow users to explore historical data and compare metrics, enhancing engagement and understanding (Chan et al., 2024).

Different types of fitness data, such as physical activity and sleep metrics, require tailored visualization approaches. Physical activity data often uses simple bar and line charts, while sleep data is better represented through hypnograms or donut charts (Islam et al., 2022; Aravind et al., 2019). Studies have found that users prefer visualizations aligned with their specific fitness goals—such as weight loss, endurance training, or sleep improvement—underscoring the need for personalization (Alrehiely et al., 2018; Gouveia & Epstein, 2023).

Personalized visualizations further enhance motivation by making data more relatable and actionable. Styles like metaphoric displays or narrative formats cater to individual preferences and increase persuasiveness (Huang, 2022; Schneider et al., 2017). Emerging technologies such as artificial intelligence and machine learning now enable fitness apps to generate personalized workout plans and real-time feedback, adapting dynamically to user needs (Sah, 2024; Ignat et al., 2024).

Despite these advances, presenting complex, multivariate data remains a challenge. Fitness metrics often involve multiple interdependent parameters—such as heart rate variability (SDNN, RMSSD) and VO_2 max—that can overwhelm users if not visualized properly (Muñoz et al., 2015). High-dimensional data often requires reduction techniques like Principal Component Analysis (PCA) to simplify visualization while retaining critical information (Weaving et al., 2019; Hasugian et al., 2023). Combining simplified charts with brief text summaries can improve user comprehension (Alshehhi et al., 2023; Alshehhi et al., 2022).

Accessibility is another vital concern. Traditional graphs may not be accessible for users with visual impairments, cognitive difficulties, or older adults. Incorporating auditory and tactile feedback mechanisms could enhance inclusivity in fitness tracking apps (Jean et al., 2023).

Identifying the Research Gap:

While significant work has been done on visualization of fitness metrics like steps and sleep patterns, a notable gap remains in how to effectively visualize multiple fitness data types—such as sleep, heart rate, and step count—together in a single, interpretable format. Prior studies often treat these metrics in isolation and focus largely on personalization to enhance user engagement (Gouveia & Epstein, 2023). However, few have explored how integrated visualizations of multivariate fitness data can support users in identifying cross-metric patterns and making meaningful health decisions. Our project aims to fill this gap by designing combined visualizations of Fitbit data that present sleep, heart rate, and steps in a coherent and accessible way.

Incorporating Additional Relevant Literature:
A relevant study not covered earlier is Zhou et al. (2021), which analyzes user engagement with fitness tracking technologies through the lens of technological affordances. The study emphasizes that features such as interactivity, real-time updates, and customizable dashboards play a significant role in sustained user engagement. This suggests that future research should explore how to optimize these affordances through visualization, particularly for complex data types. Additionally, investigating how visual storytelling, adaptive layouts, and gamification elements influence user interpretation could open new avenues for enhancing user experience in fitness tracking applications.

4.0 Dataset Description

The dataset used in this project is sourced from FitBit Fitness Tracker Data and was originally published by Furberg et al, (2016) on Zenodo. The data was collected between March 12–May 12, 2016, via Amazon Mechanical Turk, where 30 eligible Fitbit users voluntarily shared personal tracker data. These records include minute-level and daily measurements across various fitness indicators such as physical activity, heart rate, and sleep.

For the purposes of this visualization project, we focused specifically on three core aspects: heart rate, sleep, and steps—chosen for their potential to reflect personal health trends and daily routines. The dataset was originally distributed in separate CSV files categorized by activity type. As part of preprocessing, relevant files were merged into a single structure, aligned by timestamps and user IDs, to enable a cohesive multivariable analysis.

Although the dataset is relatively small in scale (30 participants) and somewhat dated (collected in 2016), it provides valuable insight into personal health tracking behaviors and offers rich ground for visual exploration. Minute-level granularity, in particular, allows for fine-tuned temporal visualizations and behavioral pattern discovery. Basic cleaning procedures, such as null value removal and format harmonization, were also applied to ensure readiness for visualization.

5.0 Tools and Technologies

To support the creation of clear, engaging, and interactive visualizations, this project uses several tools and technologies designed for data analysis and information design:

- **Tableau**
  Tableau was the primary tool used to build visual dashboards. Its drag-and-drop interface and wide range of chart types made it ideal for quickly exploring relationships between heart rate, sleep, and step data. Tableau's filtering, interactivity, and storytelling features were also used to enhance user engagement.

- **Python (Kaggle)**
  Dataset merging and pre-processing was done using Python (Combining multiple CSVs).

These tools together enabled efficient cleaning, transformation, and visualization of multi-dimensional Fitbit data, supporting the project's goal of making personal fitness data more intuitive and visually insightful.

6.0 Methodology

This section outlines the step-by-step processes undertaken to prepare the Fitbit dataset and develop an interactive dashboard that visualizes daily activity, sleep, and heart rate patterns.

6.1 Data Preparation

The final CSV files included the dailyActivity_merged.csv, heartrate_seconds_merged.csv, and sleepDay_merged.csv. They are physical activity, sleep, and heartrate measurements in per-second scale.

The subsequent activities were followed in preparation of unified and analysis-ready dataset as shown in Figure 1.

6.1.1 Data Standardization

The first step involved normalizing all the three files for uniformity of formats for merging accurately. The Time, ActivityDate, and SleepDay fields were normalized as standard datetime.

6.1.2 Heart Rate Aggregation

The heart rate data which was measured per-second, was rolled-up into the average per-user daily measures of heart rate. The step of aggregating data both reduced the data volume as well as simplified the heart rate measure for visualization in the dashboard.

6.1.3 Merging Datasets

The three sets of data were then combined on shared fields (Id and ActivityDate) in order to merge them into one daily-level set. The combined set of data included key measures like calories burned, total steps, minutes asleep, and average daily heart rate.

6.1.4 Derived Metrics

A computed column for ease of reading and comprehensibility, named SleepHours, was derived where total sleep in minutes was converted into hours. It was easier to read when graphing sleep patterns.

6.1.5 Missing Value Handling and Outlier Removal

The cleaning of the data involved deleting rows with missing values in the fields of step count, sleep duration, and heart rate. Further, outliers were logically excluded for values too extreme or not reasonable. That is, steps over 30,000, sleeping duration less than 2 hours or more than 14 hours, and heart rate values below 40 or above 200 bpm were removed.

The end result of these steps was an integrated, high-quality set of clean daily-level step, sleep, and heart rate data. These data were used as input for the building of the visual analytics dashboard in the subsequent project phase.

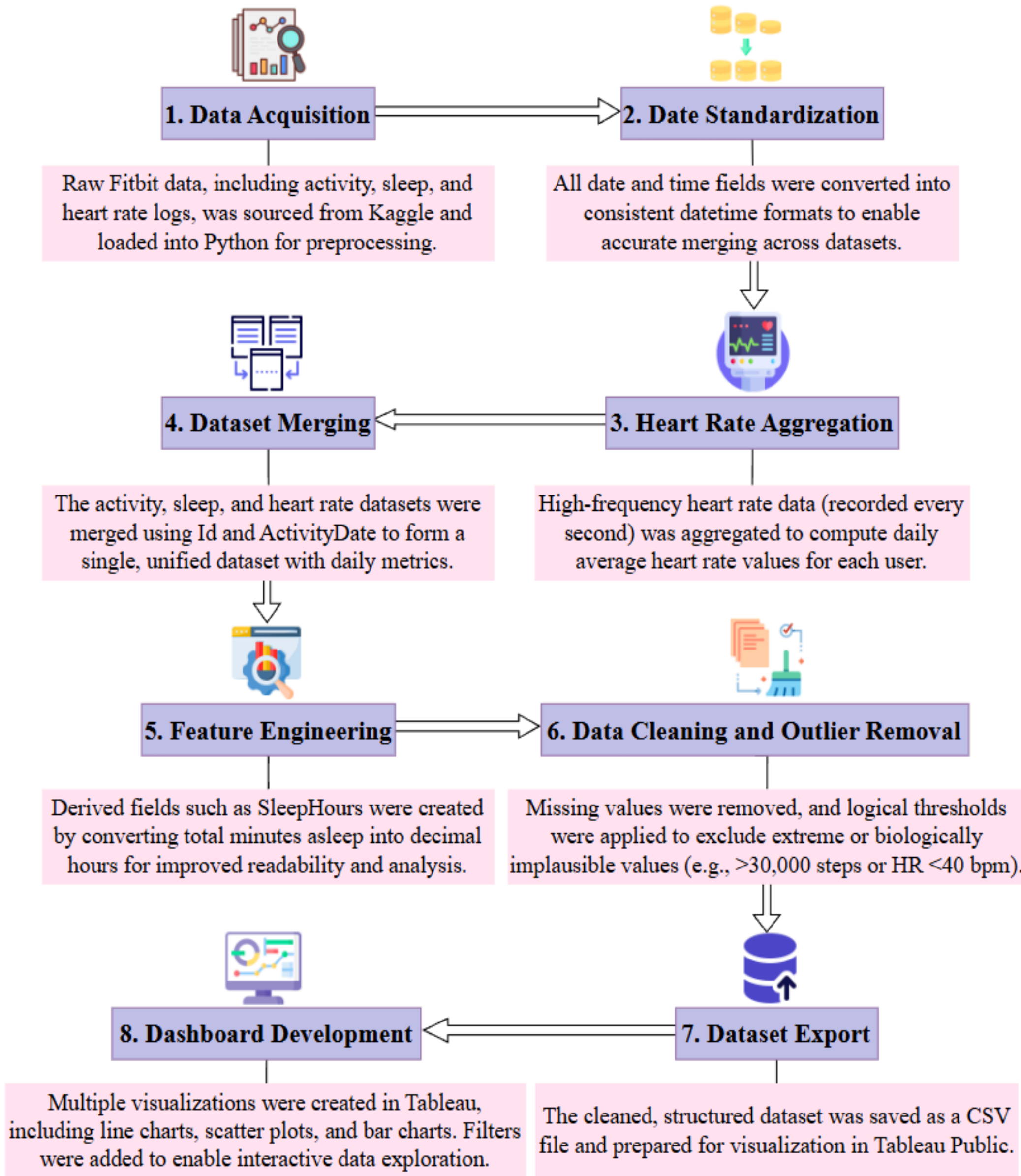

Figure 1. End-to-End Data Processing and Visualization Pipeline for Personal Fitness Dashboard.

6.2 Dashboard Workflow

After cleaning, the dataset was imported in Tableau Public, and the subsequent steps were performed in order to develop an interactive dashboard:

1. Data Import: Imported the fitbit_cleaned_dataset.csv file

2. Visualization Development:
   - Line Chart: Steps Per Day Over Time
   - Bar Chart: Sleep hours over time
   - Line graph: Average Heart Rate vs. Time
   - Scatter Plot: Steps vs. Sleep Hours
   - Bar Chart: Steps per Day
3. The interactive elements included activityDate filters for enabling date-based discovery.
4. Design Layout: The visualizations were structured in an understandable dashboard with labels and tooltips.
5. Export and integration: The completed dashboard was exported in order to be placed in the report appendix.

7.0 Visualizations and Analysis

The visualizations below were created through the use of Tableau Public to analyze personal fitness data on the basis of daily steps, sleeping time, and heart rate trends. Each chart is followed by an interpretation of what the findings reveal.

7.1 Daily Steps Over Time

- **Purpose:** To establish the range in the number of steps taken on a given day within the duration of 30 days and to determine trends in the level of physical activity.

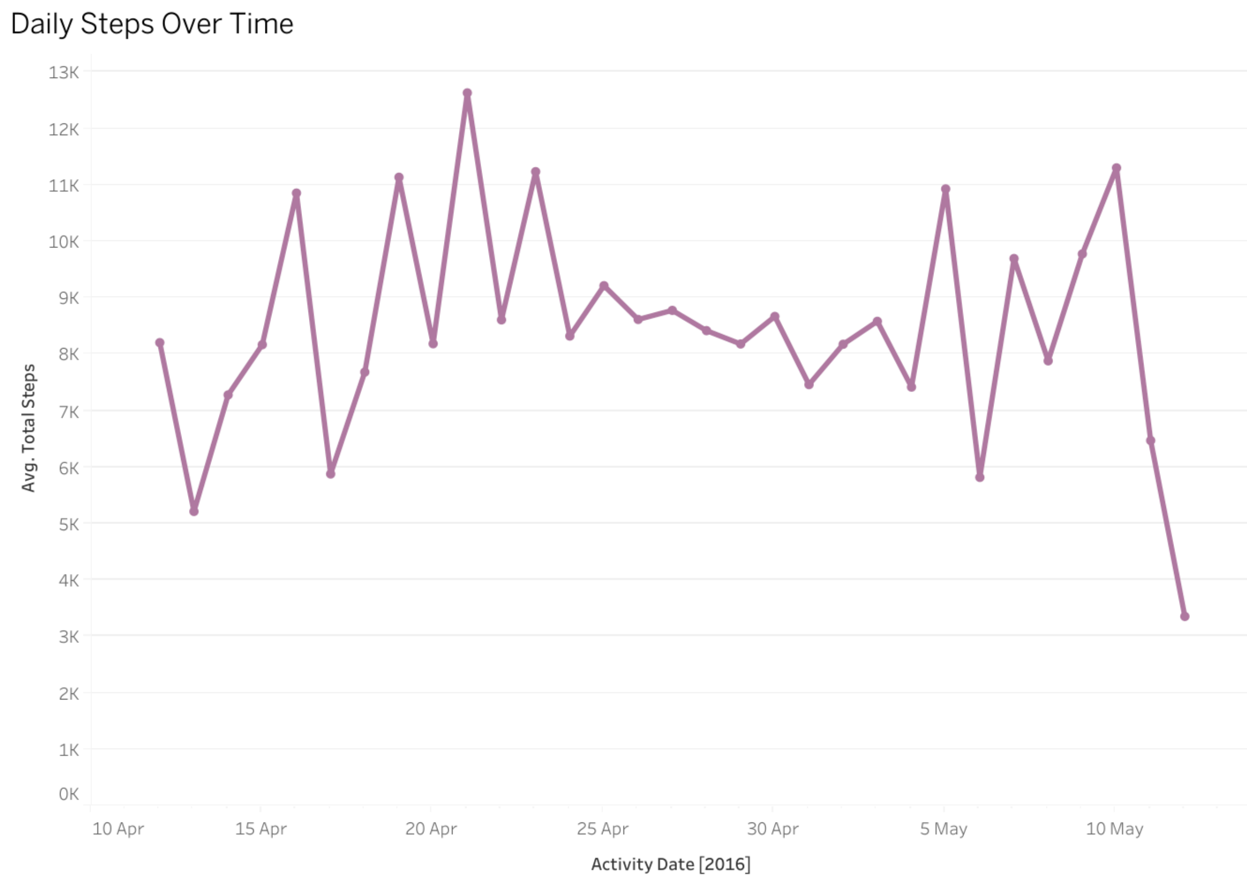

Figure 2. Line Chart of Daily Step Count (April 12 – May 12, 2016).

Analysis: Figure 2 chart illustrates the fluctuation in the number of steps taken per day for the sole month the Fitbit tracker recorded. The chart reveals a visible fluctuation in the level of activities as well as clear peaks and dips in steps.

Key Trends:

- High Activity Days: There are pronounced peaks in the daily average steps on some of the days in mid-April and early May when the daily average exceeded 10,000 steps. These could represent either periods of intensified physical activity or events that must have spurred the user to work out or move more (such as fitness competition, outdoor pursuits or sports vacations).
- Low Activity Days: There are also slight dips recorded on the 17th of April and the 11th of May when the step count drops below 5000. These dips are possibly due to rest days,

illness, or tracking interruptions. The trend portrays the user as being moderately to very active whereby the variance will occur in work-rest patterns, lifestyle, or routine.

Overall Insights:

- The user exhibits high to moderate levels for the month but the non-regular pattern of the data reveals physical activity to be regulated by work-rest cycles, individual routines or extraneous influences.
- The graph also prominently depicts the non-linearity of the user's activity, as days of intense activity are broken up by low activity or rest days that demonstrate the value of temporal data for determining overall activity patterns.

The graph displays how the physical activity of the user changes on a day-to-day basis and how temporal data is necessary to have an idea of the general trends of activity. It further shows that while the user is quite active, their daily steps are the result of a combination of lifestyle factors that are visualized clearly through this temporal data.

7.2 Sleep Hours Over Time

- **Purpose:** To track the user's sleeping duration for the duration of a 30-day period, observing trends, breaks or patterns in the sleeping pattern.

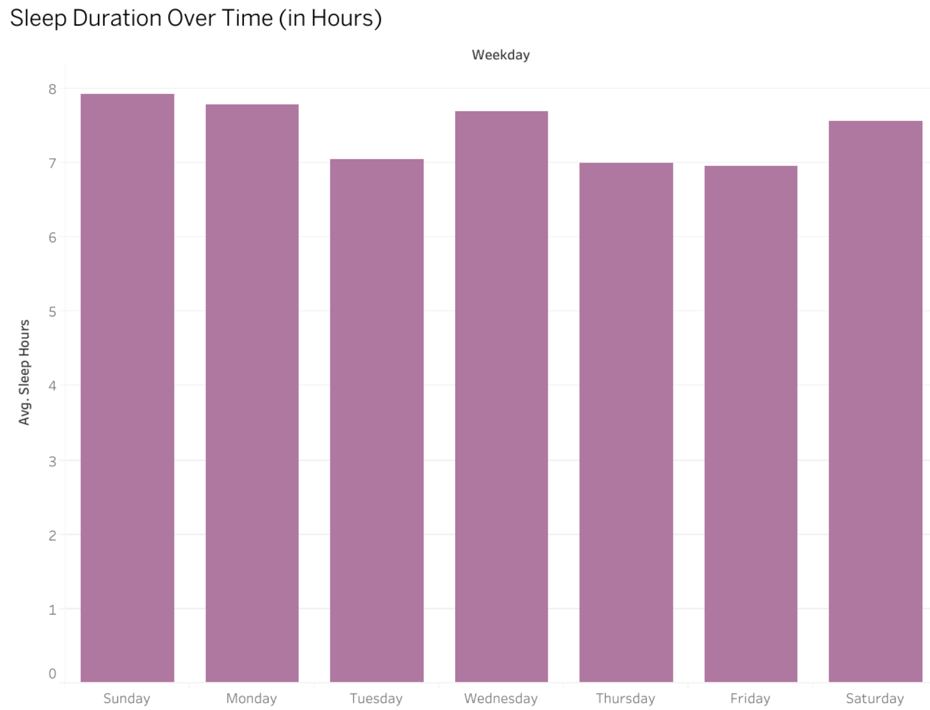

Figure 3. Bar Chart of Sleep Hours by Weekday (April 12 – May 12, 2016).

Analysis: The line graph in Figure 3 now places the sleeping duration on the Y-axis while the weekdays are placed on the X-axis. The user's average duration of sleep oscillates between 6 to 8 hours, which is within the range of the healthy individual.

Key Trends:

- **Weekend Sleep Duration:** Both Saturday and Sunday have relatively longer average durations of sleep (> 7.5 hours). This suggests the user sleeps longer on weekends due to presumably having more free hours and recuperating from the workweek.
- **Weekdays:** Monday, Tuesday, Wednesday, Thursday, and Friday shows relatively regular sleep durations between 6 and 8 hours on average. The user has a relatively consistent routine even on weekdays.
- **No Major Disruptions**: There are no drops or interruptions as drastic to note in this case. There's a consistent pattern of the user's sleep with only minor fluctuations.

Overall Insights:

- **Weekend Rest:** The user appears to rest more on weekends and has a regular weekend recuperation pattern found in the majority of individuals.
- **Consistent Sleep Pattern:** There is no significant difference in the amount of sleep between weekdays, which reflects a good consistent pattern between workdays and weekends.

The graph illustrates that the user has a regular pattern of sleep for the entire week with little difference. The user sleeps a little more on the weekends but has a balanced and regular routine for the weekdays that generally indicates good sleep hygiene.

7.3 Average Heart Rate Over Time

- **Purpose:** This helps in identifying cardiovascular health trends, detecting unusual spikes or dips in heart rate, and potentially correlating them with physical activity, stress, or lifestyle changes.

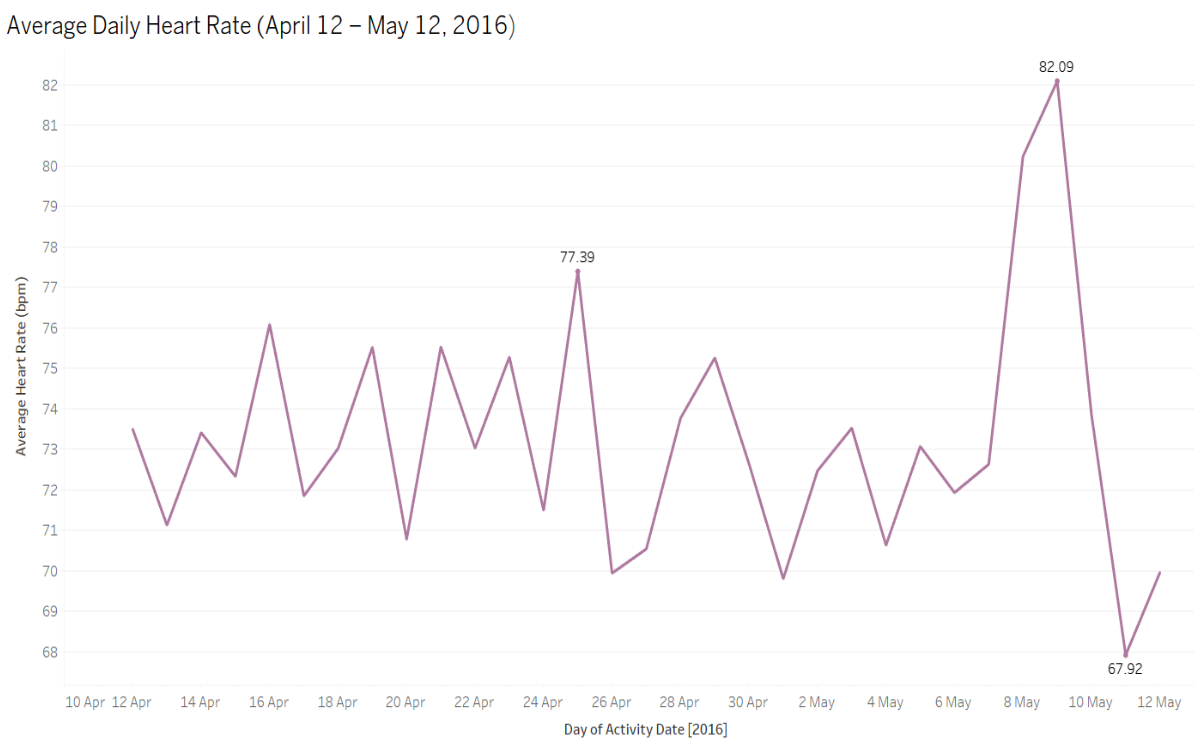

Figure 4. Line graph of Average Daily Heart Rate (April 12 – May 12, 2016).

Analysis: This line chart in Figure 4 displays the average heart rate (in bpm) on the Y-axis and the corresponding activity date on the X-axis, based on 31 days of daily recorded heart rate data. The continuous date axis allows for easy observation of both short-term fluctuations and broader trends over time. From visual inspection, heart rate values generally range between 69 bpm and 81 bpm, showing irregular peaks and dips throughout the month. These variations suggest dynamic cardiovascular responses that are likely influenced by differences in daily activities, rest patterns, or stress levels. The absence of a consistent linear trend implies that the user's heart rate is affected by varying lifestyle factors on a day-to-day basis.

Key Insights:

- **General Stability with Fluctuations:** Most average heart rates fall between 70–77 bpm, indicating relatively stable cardiovascular health with day-to-day variation
- **Peak on May 9, 2016:** The heart rate spikes above 81 bpm, the highest value during the 31-day period, suggesting possible physical exertion or emotional stress.
- **Sharp Drop on May 10, 2016:** A significant decline to around 68 bpm occurs, potentially indicating recovery or a period of rest after the peak.
- **Mid-Month Consistency:** From April 18 to May 4, heart rate levels remain steady around 74–75 bpm, possibly due to routine habits like consistent sleep or exercise.
- **Contextual Relevance:** To gain deeper insights, these heart rate trends should be compared with other metrics like step count, calorie burn, or sleep patterns.

The chart suggests that the user maintains a generally stable average heart rate with moderate daily variation. A sharp peak on May 9 followed by a sudden drop on May 10 highlights days of potential stress and recovery, while the mid-month period reflects a stable pattern. These trends may indicate how lifestyle or environmental factors affect cardiovascular responses. To better understand such variations, integrating this data with sleep quality, step activity, or calorie expenditure can provide a more comprehensive view of the user's health and well-being.

7.4 Steps vs Sleep

- **Purpose:** This helps in identifying cardiovascular health trends, detecting unusual spikes or dips in heart rate, and potentially correlating them with physical activity, stress, or lifestyle changes.

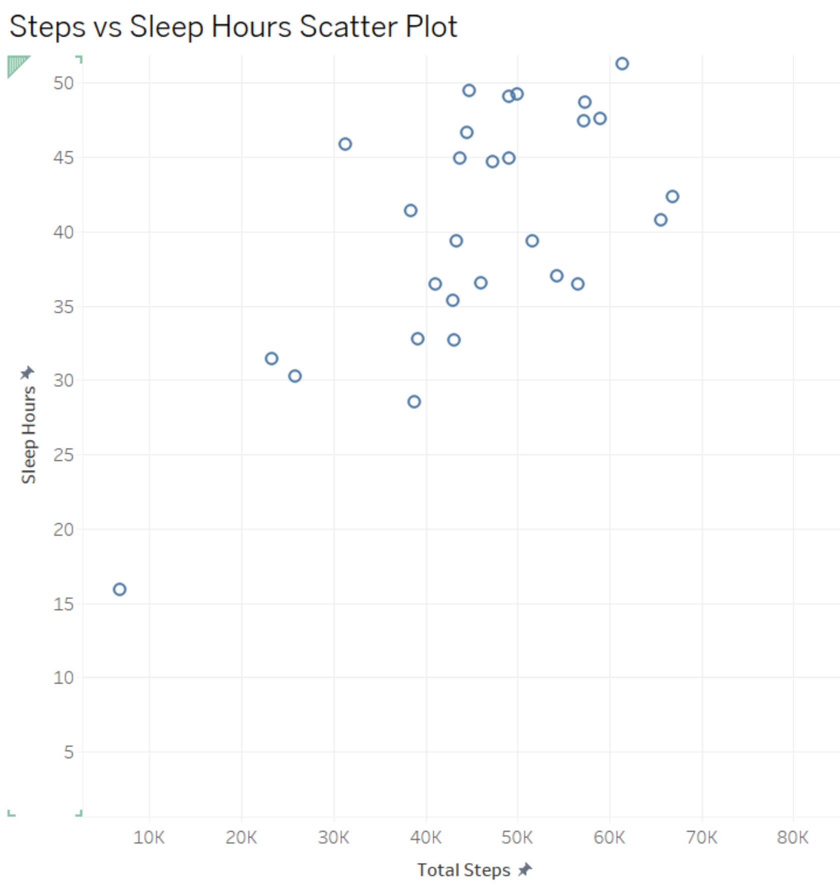

Figure 4. Scatter Plot for Steps over Sleep Hours (April 12 – May 12, 2016).

Analysis: Figure 5 presents a scatter plot of the user's total daily steps versus sleep hours, with each point representing a single day. The chart is used to examine whether there is any apparent relationship between the user's physical activity and their sleeping patterns.

Key Insights:

- **Mild Positive Relationship Observed:**
  There is a loose upward trend in the scatter plot, suggesting that on days with higher step

counts, the user tends to sleep more. However, the pattern is not strongly linear, indicating that sleep is influenced by other factors beyond physical activity alone.

- **Cluster of Balanced Days:**
  Most data points fall within the range of 40,000 to 60,000 steps and 35 to 50 hours of sleep (per week), suggesting a fairly balanced routine where high activity correlates with sufficient rest.
- **Presence of Outliers:**
  A few points deviate from the main cluster — for instance, a very low-step count paired with low sleep hours. These may represent abnormal days such as illness, travel, or disruptions in routine.
- **High Sleep with Moderate Steps:**
  Some data shows high sleep hours even with step counts below 40K, which implies the user sometimes prioritizes rest regardless of activity level — possibly during recovery days or weekends.

This plot helps to provide a broader view of how the user's physical activity might relate to their sleep habits. While an overall positive association is visible, sleep behavior appears to be only partly influenced by daily step count. For deeper insights, further analysis could include factors like day of the week, sleep quality, or stress levels.

7.5 Steps by Day of the Week

- **Purpose:** To compare the physical activity variation across the days of the week and to identify the trends in activities that are increasing or diminishing.

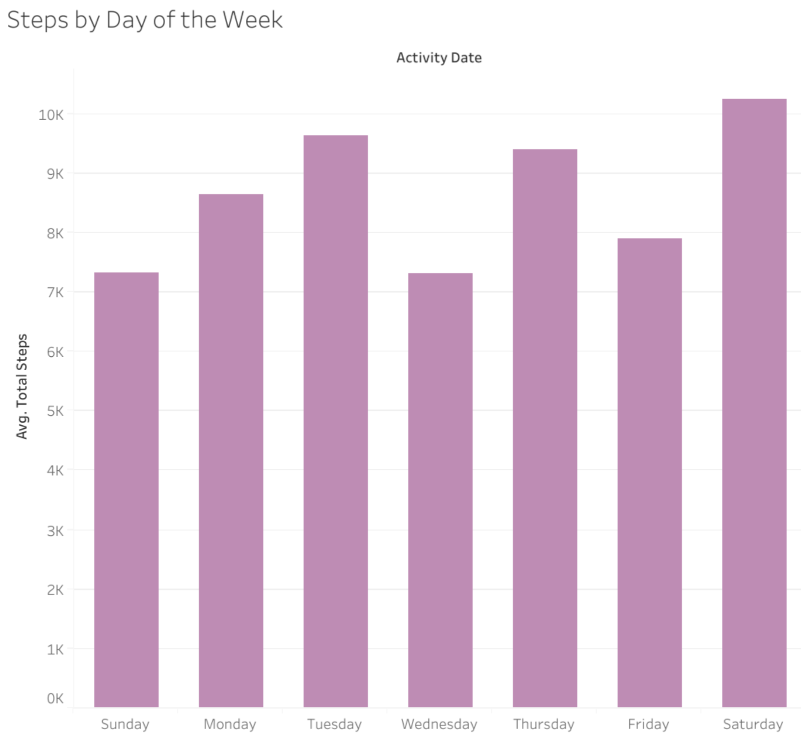

Figure 6: Bar Chart of Daily Step Counts by Day of the Week (April 12 – May 12, 2016).

Analysis: Figure 6 plots the user's daily average number of steps taken per day of the week in a bar chart. Contrary to some common weekly trends, there are no extreme spikes or troughs in the user's activity levels throughout the week.

Key Insights:

- **Moderate Activity Throughout the Week:** The user's steps are fairly high for all of the days, with a slight increase on Saturday and Friday when counts approached or even crossed 9,000 steps. This indicates the user following an active pattern in weekends due to acquiring more free time for physical fitness.
- **Weekday Consistency:** Weekdays (Mon to Thu) have a relatively consistent range of 6,000 to 7,000 steps for which there isn't a significant variation. It indicates that the user maintains a constant level of activity even on weekdays.
- **Tuesday and Wednesday Dip:** Tuesday and Wednesday both indicate the slightly reduced activity compared to other days at slightly below 7,000 steps. This may indicate the user to be less active in the middle of the week due to other reasons as well as workload or personal routines.

The chart suggests that the user maintains a moderate level of physical activity throughout the entire week, with weekends slightly more active. The consistency in weekday step counts suggests a stable routine, but mid-week days (Tuesday and Wednesday) show a subtle dip. By understanding this trend, the user can evaluate opportunities to improve or balance their physical activity across the entire week.

8.0 Challenges and Solutions

During this project, several challenges were encountered, including inconsistent data formats across multiple CSV files, missing values, and aligning different time-based records such as sleep and heart rate. The raw Fitbit data was complex and not user-friendly, requiring extensive preprocessing and cleaning using Python to merge datasets and remove inconsistencies. Another major challenge was visualizing multivariate data in a clear and engaging way that supports user interpretation. To address this, Tableau was used to build an interactive dashboard with dynamic filters and charts that allowed users to explore trends across sleep, steps, and heart rate. These solutions ensured the data was both accurate and accessible for meaningful health insights.

9.0 Conclusion and Future Work

Conclusion

The task involved developing and deploying an information visualisation dashboard for the data of Fitbit fitness trackers. It was essentially designed to provide insight into individual healthcare information through rigorous data preprocessing, exploratory data analysis, and visualising trends in the activities performed on a daily basis, sleeping patterns, and heart rate. We began by preprocessing and aggregating day activity data, sleep data, and heart rate data. The date formats were normalized, missing values dealt with, and outliers removed (for example, unrealistically high step counts or sleeping times). A new SleepHours feature was added for interpretability reasons and for ease of visualizations.

There were five important visualizations that formed the foundation of this dashboard. The Daily Steps Over Time chart, reflected the day-to-day fluctuation in physical activity levels, and there would be spikes on weekends or on highly active days as well as dips on rest days. This time-based plot exhibited the general oscillation of the user's activity level. The Sleep Hours Over Time chart, which was a grouped weekday bar chart, showed a clear trend of increased sleep on weekends and more consistent, moderate sleep during the workweek. This suggested a recovery-focused behavior typical of individuals balancing structured routines with personal well-being.

The Average Heart Rate Over Time graph showed physiological trends in the sense of recording fluctuations that can signify physical exertion, rest, or stress. It was compared with the activity data to give a better picture of how cardiovascular responses align with the common patterns of the day. Recurring patterns of activity also emerged in the Steps by Day of the Week bar chart in which the participant was most active on Saturdays but merely possessed average levels of the other days. Also, the Steps vs. Sleep Hours scatter plot yielded the multivariate view in which the physical activity and rest could intersect, and enabling the detection of possible correlations between high step counts and sleep duration.

Together, these visualizations achieved the three principal aims of the project: transforming the raw Fitbit data into a tidy and organized data set, performing temporal and multivariate analysis through the visual approach, and creating an interactive dashboard for dynamic examination. The dashboard provides a complete and personalized view of the user's habits, allowing for self-reflection and informed behavior management.

Future Works

While the current dashboard already includes robust analysis capabilities, there are several directions in which the project can be expanded. Subsequent releases might include metrics such as calories burnt, active minutes, or even a quality of sleep score to provide a more comprehensive personal health profile. Adding granularity in the form of an hour-by-hour trend, such as breaking the intensity of steps or heart rate variability by the hour could provide more insight into the user's behavior.

Additional long-term data collection and representation would support longitudinal analysis to the point that trends occurring in a seasonal cycle would be discernible, habit formation would be monitored, or long-term results of health would be determined. Personal reminders and goals would also support user participation in remaining on target for fitness goals. Predictive modeling would also predict low-activity days or detect early signs of fatigue as a result of analysis of current trends in the data.

Ultimately, the dashboard might be made larger to support multiple users to facilitate family unit or peer group comparative analysis for corporate employee wellness. Further expansion of the system would make the project a very helpful tool both for self-discovery and for proactive management of healthcare as well as for improving lifestyles.

10.0 References

Link to dataset: https://www.kaggle.com/datasets/arashnic/fitbit

1. Alshehhi, Y. A., Abdelrazek, M., & Bonti, A. (2022). Needs and Challenges of personal data visualisations in Mobile health Apps: User Survey. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2209.00838
2. Alshehhi, Y. A., Abdelrazek, M., Philip, B. J., & Bonti, A. (2023). Understanding User Perspectives on Data Visualization in mHealth Apps: A survey study. *IEEE Access*, *11*, 84200–84213. https://doi.org/10.1109/access.2023.3302325
3. Alrehiely, M., Eslambolchilar, P., & Borgo, R. (2018). *Evaluating different visualization designs for personal health data*. 205. https://doi.org/10.14236/EWIC/HCI2018.205
4. Aravind, R., Blascheck, T., & Isenberg, P. (2019). *A Survey on Sleep Visualizations for Fitness Trackers*. 85–87. https://doi.org/10.2312/EURP.20191152
5. Card, S. K., Mackinlay, J., & Shneiderman, B. (Eds.). (1999). Readings in information visualization: using vision to think. Morgan Kaufmann.
6. Chan, G., Nwagu, C., Odenigbo, I., Alslaity, A., & Orji, R. (2024). The Shape of Mobile Health: A Systematic Review of Health Visualization on Mobile Devices. *International Journal of Human-Computer Interaction*, 1–19. https://doi.org/10.1080/10447318.2024.2313282
7. Chen, C. (2010). Information visualization. Wiley Interdisciplinary Reviews: Computational Statistics, 2(4), 387–403. https://doi.org/10.1002/wics.101

8. Choe, E. K., Lee, N. B., Lee, B., Pratt, W., & Kientz, J. A. (2014, April). Understanding quantified-selfers' practices in collecting and exploring personal data. In Proceedings of the SIGCHI conference on human factors in computing systems (pp. 1143-1152).
9. Epstein, D. A., Ping, A., Fogarty, J., & Munson, S. A. (2015, September). A lived informatics model of personal informatics. In Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing (pp. 731-742).
10. Gershon, N., Eick, S. G., & Card, S. (1998). Information visualization. Interactions, 5(2), 9–15. https://doi.org/10.1145/274430.274432
11. Gouveia, R., & Epstein, D. A. (2023). This Watchface Fits with my Tattoos: Investigating Customisation Needs and Preferences in Personal Tracking. *https://dl.acm.org/doi/10.1145/3544548.3580955*, 1–15. https://doi.org/10.1145/3544548.3580955
12. Hasugian, P. M., Mawengkang, H., Sihombing, P., & Efendi, S. (2023). Review of High-Dimensional and Complex Data Visualization. *https://ieeexplore.ieee.org/document/10364377*, 1–7. https://doi.org/10.1109/icosnikom60230.2023.10364377
13. Huang, X. (2022). Data Visualization Design Strategies for Promoting Exercise Motivation in Self-Tracking Applications. *ACM International Conference on Design of Communication*. https://doi.org/10.1145/3513130.3558981
14. Ignat, B., López B, H., Mahmoud, R. A., M.H.S.M, H., Pulasinghe, K., & Krishara, J. (2024). AI-Driven Personalized Fitness Coaching with Body Type-Based Workout and Nutrition Plans and Real-Time Exercise Feedback. *International Journal of Preventive*
15. Islam, A., Aravind, R., Blascheck, T., Bezerianos, A., & Isenberg, P. (2022). Preferences and Effectiveness of Sleep Data Visualizations for Smartwatches and Fitness Bands. *CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3501921
16. Jean, P., Murphy, E., & Bates, E. (2023). Accessibility of health Data Representations for Older Adults: Challenges and Opportunities for design. In *Communications in computer and information science* (pp. 486–493). https://doi.org/10.1007/978-3-031-35992-7_65
17. Kosara, R., Hauser, H., & Gresh, D. L. (2003). An interaction view on information visualization. Eurographics 2003 - State of the Art Reports, 123–137.

18. Keim, D. A. (2002). Information visualization and visual data mining. IEEE Transactions on Visualization and Computer Graphics, 8(1), 1–8. https://doi.org/10.1109/2945.981847
19. Li, I., Dey, A., & Forlizzi, J. (2010, April). A stage-based model of personal informatics systems. In Proceedings of the SIGCHI conference on human factors in computing systems (pp. 557-566).
20. *Medicine and Health (IJPMH)*, *5*(1), 17–23. https://doi.org/10.54105/ijpmh.e8176.05011124
21. Muǫoz, J. E., Badia, S. B. I., Rubio, E., & Cameirɰo, M. S. (2015). Visualization of multivariate physiological data for cardiorespiratory fitness assessment through ECG (R-peak) analysis. https://pubmed.ncbi.nlm.nih.gov/26736281/, 390–393. https://doi.org/10.1109/embc.2015.7318381
22. Sah, D. (2024). Unveiling the Power of Personalization in Health and Fitness Apps. *International Journal for Research in Applied Science and Engineering Technology*. https://doi.org/10.22214/ijraset.2024.64980
23. Schneider, H., Schauer, K., Stachl, C., & Butz, A. (2017). *Your data, your vis: Personalizing personal data visualizations* (pp. 374–392). Springer, Cham. https://doi.org/10.1007/978-3-319-67687-6_25
24. Weaving, D., Beggs, C., Dalton-Barron, N., Jones, B., & Abt, G. (2019). Visualizing the complexity of the Athlete-Monitoring Cycle through Principal-Component analysis. *International Journal of Sports Physiology and Performance*, *14*(9), 1304–1310. https://doi.org/10.1123/ijspp.2019-0045
25. Zhou, X., Krishnan, A., & Dincelli, E. (2021). Examining user engagement and use of fitness tracking technology through the lens of technology affordances. *Behaviour and Information Technology*, *41*(9), 2018–2033. https://doi.org/10.1080/0144929x.2021.1915383