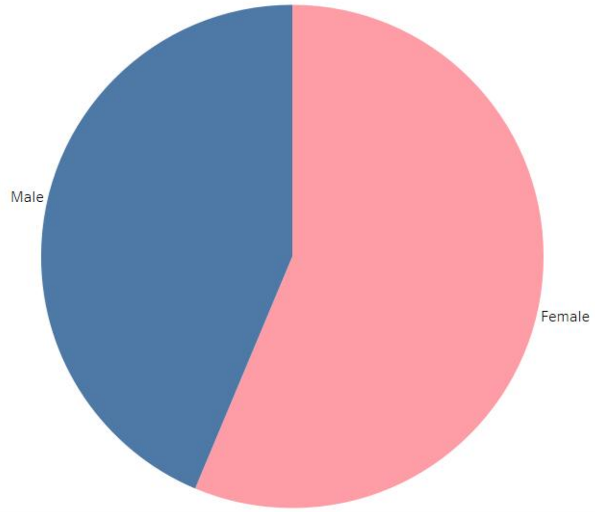
Dashboard 1: Responsive and Design of Dashboard

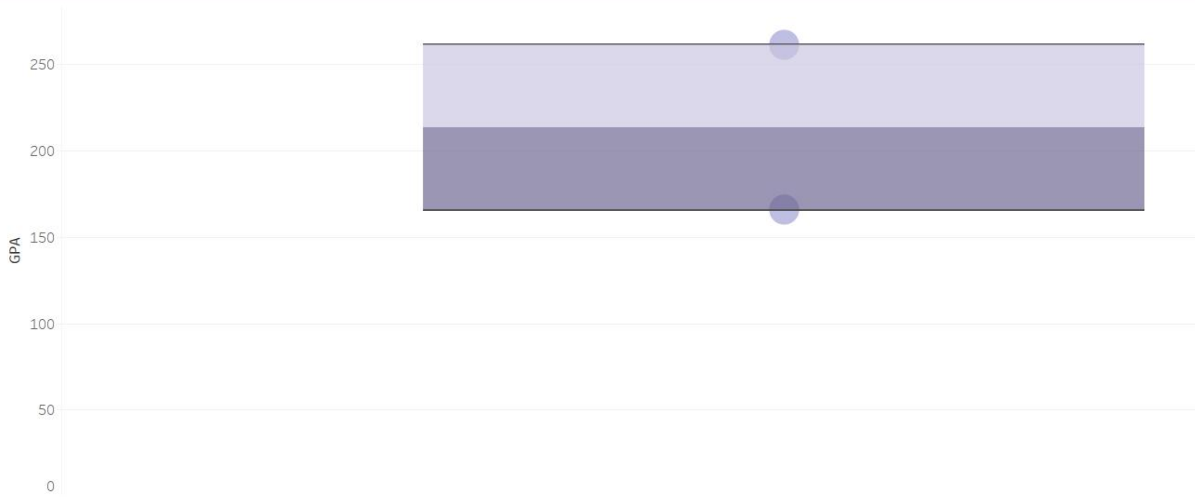
Gender Distribution

The visualization presents a categorical distribution of gender within the dataset using a proportional pie chart. It highlights a demographic skew, with female participants comprising a larger segment of the population relative to males. This gender imbalance may influence downstream analyses, such as behavioral trends or preference segmentation, and should be considered during inferential or predictive modeling stages.



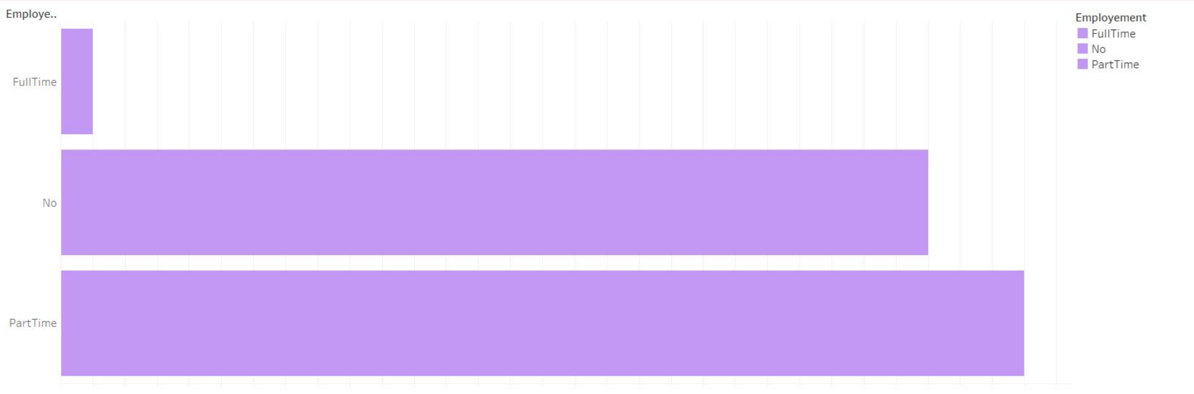
Gender Distribution

The box plot visualizes the distribution of GPA scores, providing a summary of the central tendency and variability within the dataset. The median GPA is 3.0, indicating the central value of the distribution. The interquartile range , spanning from the lower hinge (2.5) to the upper hinge (Q3 = 3.5), captures the middle 50% of observations. The lower whisker extends to 2.0 and the upper whisker to 4.0, representing the minimum and maximum values within 1.5 times the IQR. This distribution suggests a relatively symmetrical spread with no extreme outliers, supporting assumptions of normality for further statistical modeling or hypothesis testing.

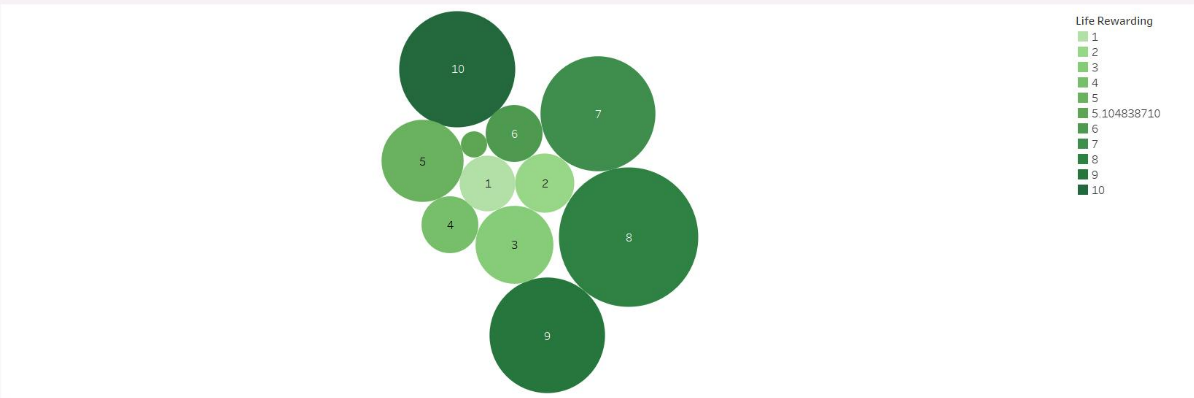


Gender Distribution

The horizontal bar chart illustrates the categorical frequency distribution of employment status among respondents. The categories—*FullTime*, *PartTime*, and *No*—are compared based on the count of individuals in each group. The majority of participants reported not being employed, followed by a substantial proportion engaged in part-time work, and a minority working full-time. This distribution indicates a workforce skewed toward non-employment or part-time roles, which could have implications for analyses related to financial stability, academic performance, or time availability in related datasets. The visualization effectively highlights class imbalance, which is critical for downstream tasks like classification modeling or stratified sampling.

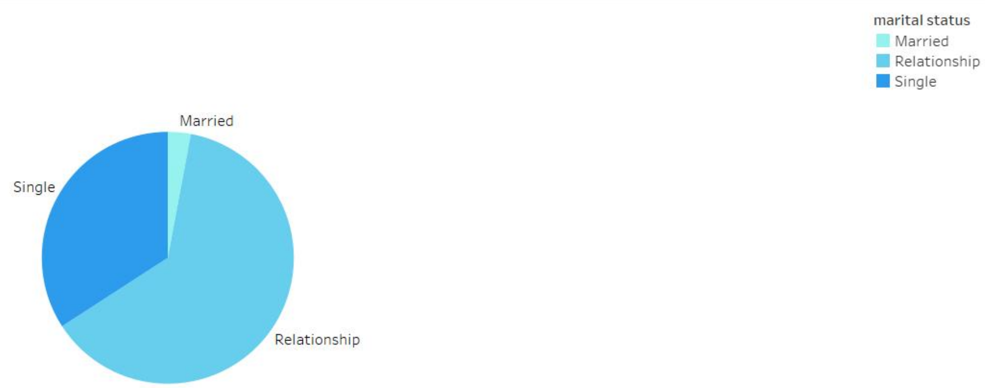


This bubble chart visualizes the frequency distribution of *LifeRewarding* ratings on a scale from 1 to 10. Each bubble represents a distinct rating value, with the size of the bubble proportional to the number of respondents selecting that rating. The larger bubbles for lower scores (e.g., 1 and 3) suggest that a significant portion of participants perceive their life as less rewarding, while higher scores (e.g., 9 and 10) are comparatively less frequent. The visual provides a quick and effective insight into the central tendency and skewness of subjective well-being, which can be critical for psychological or quality-of-life assessments in data-driven behavioral research.



Gender Distribution

The pie chart provides a categorical breakdown of respondents' marital status, segmented into *Single*, *In a Relationship*, and *Married*. The dominant proportion is represented by individuals identifying as *Single*, followed by those in a *Relationship*, with a minimal fraction marked as *Married*. This class imbalance is visually apparent and may introduce bias in demographic analyses or segmentation tasks. Such a distribution is critical to consider when modeling behaviors or preferences influenced by relationship status, and it underscores the importance of stratification or rebalancing techniques in statistical or machine learning workflows.



Dashboard 2: Dietary Habits and Preferences

The line chart illustrates the frequency distribution of participants' perceptions regarding the importance of daily calorie consumption, categorized as *Maybe*, *Not Important (NotImp)*, and *Very Important (VeryImp)*. The steep decline from *Maybe* to *NotImp* indicates a substantial drop in respondent count, followed by a marginal increase toward *VeryImp*. This trend suggests that while a significant portion of respondents are uncertain (*Maybe*) about the importance of calorie intake, fewer explicitly disregard it (*NotImp*), and only a slightly larger group strongly acknowledge its significance (*VeryImp*). Such insights can inform nutritional awareness strategies and guide targeted interventions in health behavior modeling or dietary education programs.

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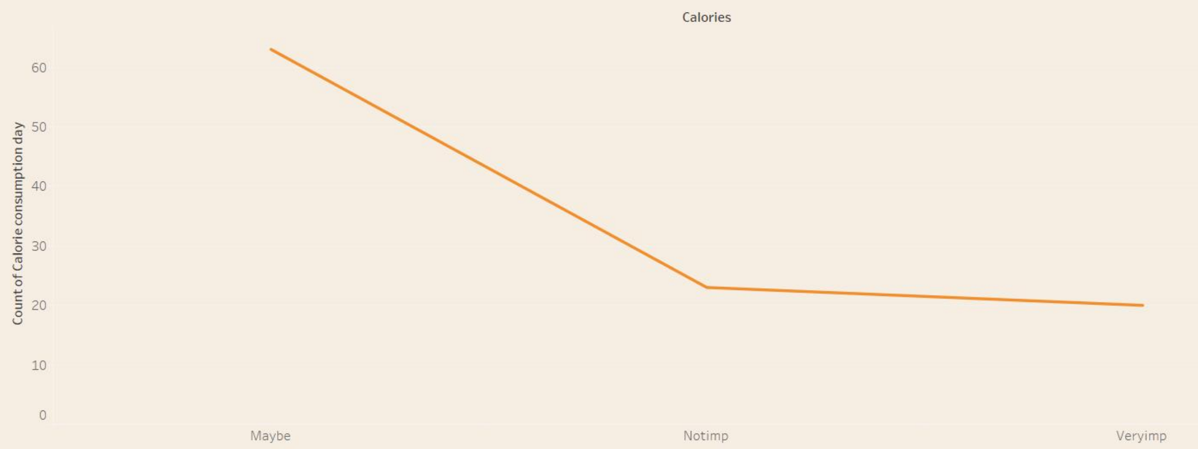
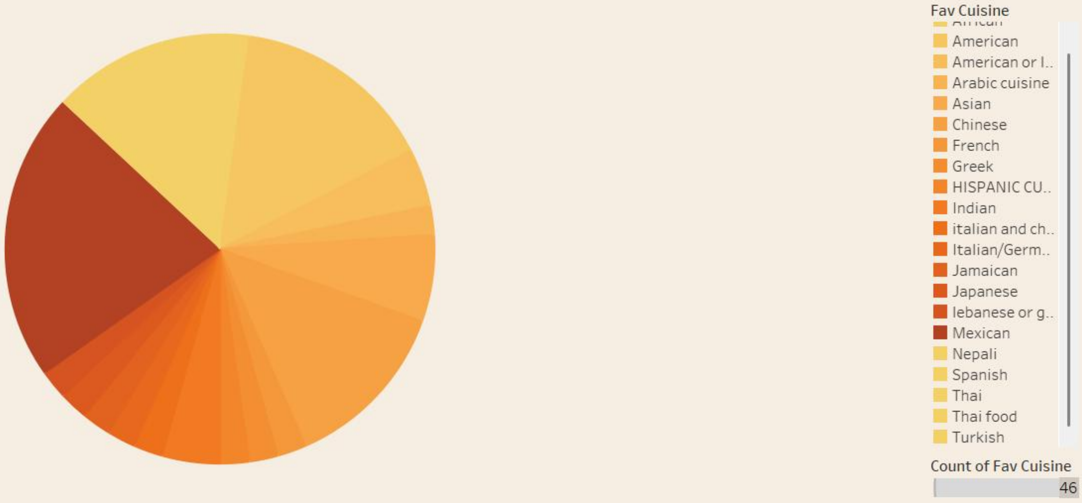
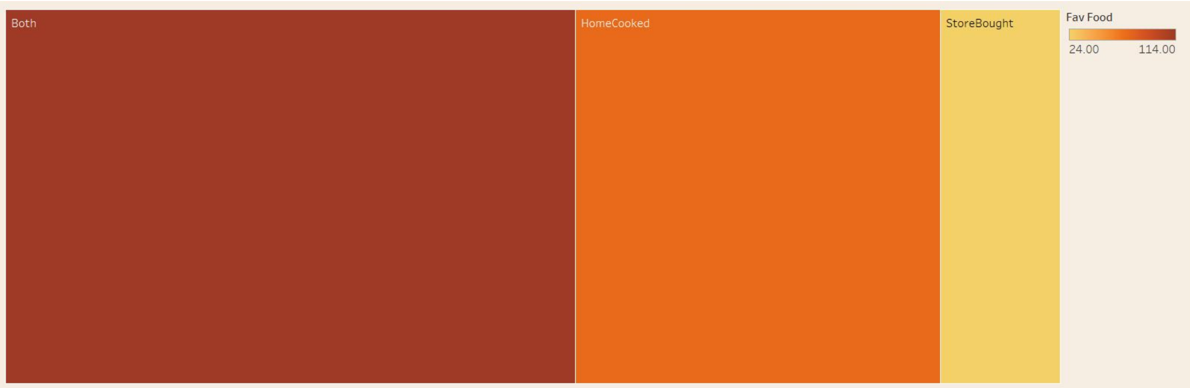


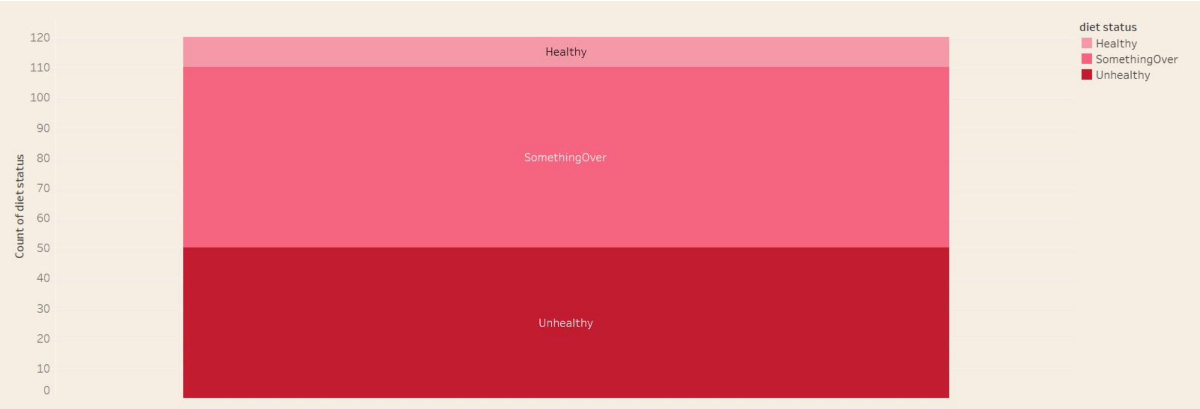
The pie chart presents the distribution of participants based on the cuisine they grew up with, serving as a categorical summary of cultural food preferences. The dominant category is *American cuisine*, accounting for the vast majority (103 responses), indicating a strong cultural prevalence. Other cuisine categories such as *Mexican/Spanish* and additional minor groups occupy significantly smaller proportions, highlighting a class imbalance. This skewed distribution is crucial for interpreting downstream analyses related to dietary habits, cultural food influences, or taste preference modeling, and may necessitate stratified sampling or reweighting techniques in predictive modeling scenarios.



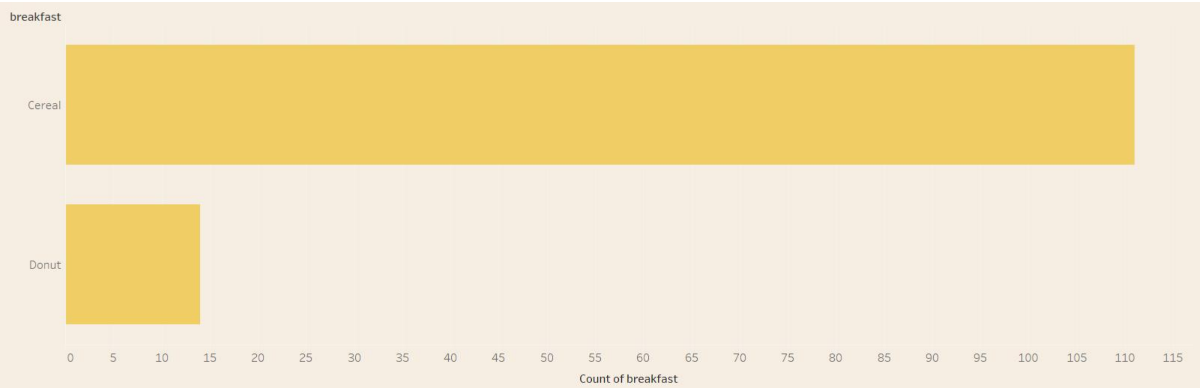
The treemap visualization depicts the distribution of participants' preferred comfort food sources, categorized as *HomeCooked*, *StoreBought*, and *Both*. Each block's area is proportional to the frequency of responses within each category, enabling an efficient comparison of categorical magnitudes. *HomeCooked* foods emerge as the most preferred source, indicating a dominant inclination toward homemade meals, followed by a significant portion favoring *Both*, and a smaller share opting for *StoreBought*. This preference distribution offers valuable insight into food consumption behavior and can inform targeted interventions in nutritional planning, emotional eating studies, or market segmentation analysis within the food industry.



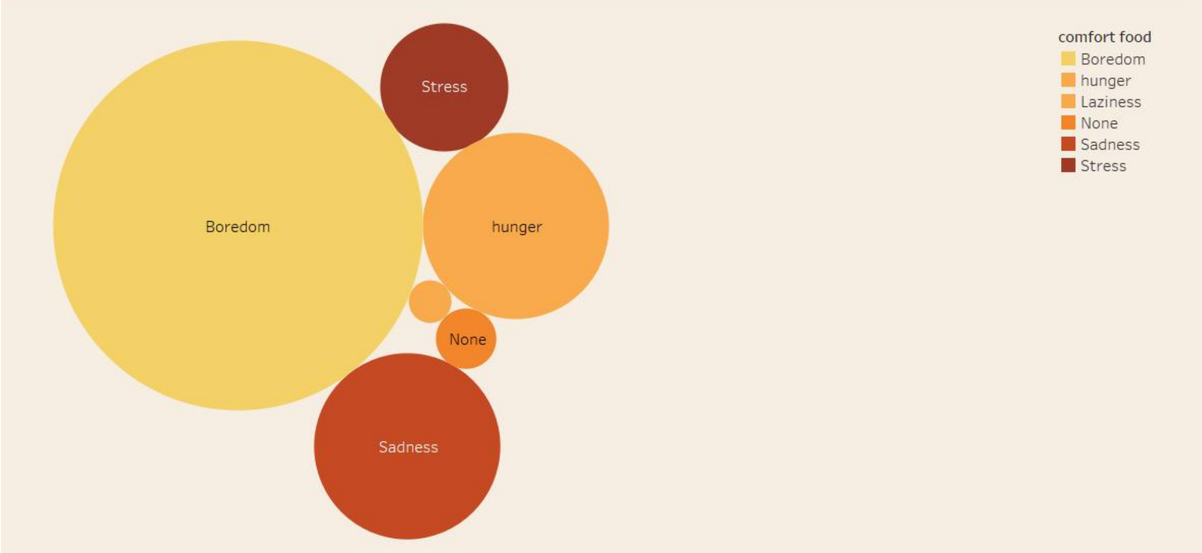
This stacked bar chart visualizes the frequency distribution of respondents' self-reported *DietStatus*, categorized as *Healthy*, *SomethingOver*, and *Unhealthy*. The chart reveals a near-uniform distribution across the categories, with a slightly higher count observed in the *Unhealthy* group, followed by *Healthy*, and a comparatively lower frequency for *SomethingOver*. This visualization provides insights into the overall dietary quality among participants and highlights the need for targeted nutritional interventions. From a data science perspective, this stratification is valuable for clustering analyses, behavioral segmentation, or predictive modeling tasks involving dietary or health-related variables.



The horizontal bar chart illustrates the categorical distribution of breakfast consumption among participants, segmented into *Cereal* and *Donut*. The visual indicates a strong preference for cereal, with a significantly higher frequency compared to donut consumption. This disparity reflects a potential trend toward healthier breakfast choices within the surveyed population. From a data science perspective, such class imbalance is important to recognize for accurate descriptive analytics, and it may inform feature engineering or behavioral clustering in dietary habit modeling. The simplicity of the chart also allows for quick interpretation in exploratory data analysis (EDA) stages.

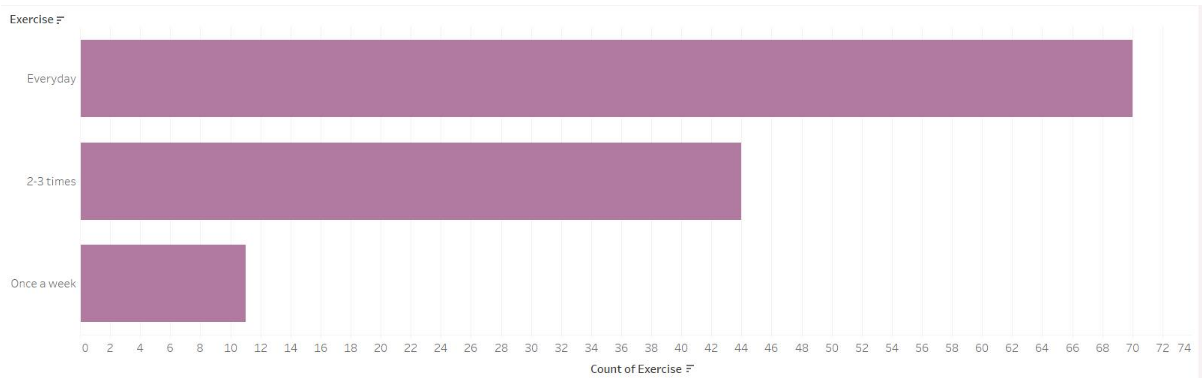


The visualization is a bubble chart that illustrates the distribution of self-reported reasons behind comfort food consumption. Each bubble represents a distinct emotional or behavioral trigger, with the size denoting its relative frequency within the dataset. Notably, *Boredom* emerges as the most dominant factor, followed by *Sadness* and *Stress*, highlighting the emotional drivers of eating behavior. Smaller bubbles like *Laziness* and *None* indicate less common responses. This type of chart is commonly used during exploratory data analysis to uncover patterns in categorical data. The insights derived here can guide behavioral segmentation and inform targeted strategies in wellness, marketing, or product design.

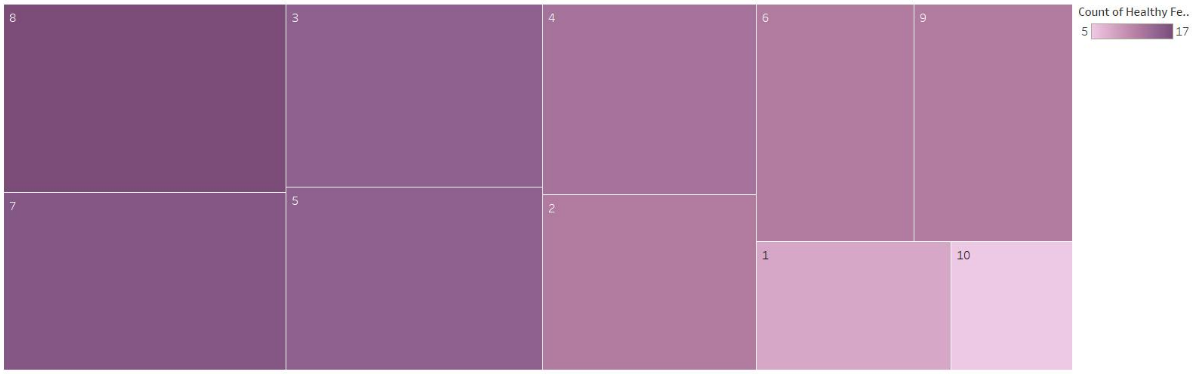


Dashboard 3: Health and Nutrition

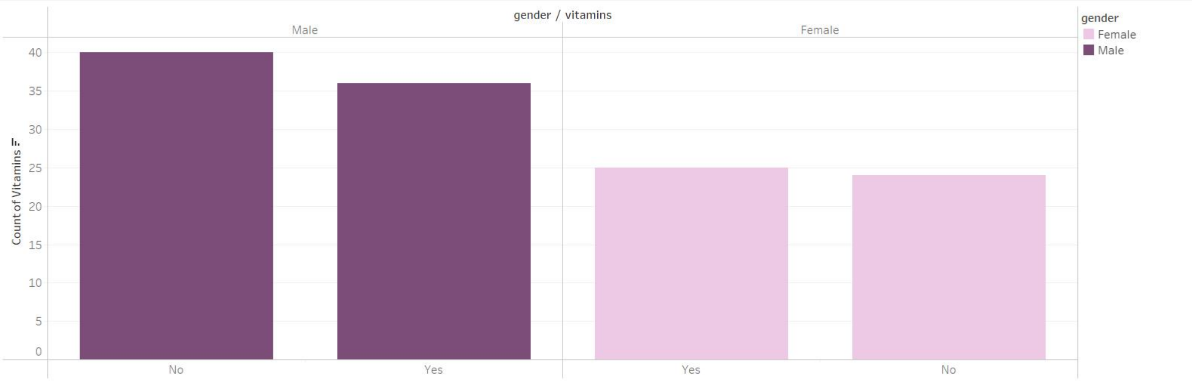
This bar chart presents a categorical distribution of exercise frequency among individuals, serving as an exploratory data analysis (EDA) tool. The x-axis captures the count of respondents, while the y-axis encodes ordinal categorical labels—"Everyday," "2-3 times," and "Once a week." From a statistical standpoint, the "Everyday" category dominates with the highest frequency (n = 70), suggesting a positive skew toward daily activity. The visualization provides insight into behavioral clustering and population-level trends in physical activity. Such descriptive analytics can inform feature engineering in predictive modeling for health-related outcomes. Additionally, the chart aids in hypothesis generation regarding lifestyle patterns and public health interventions.



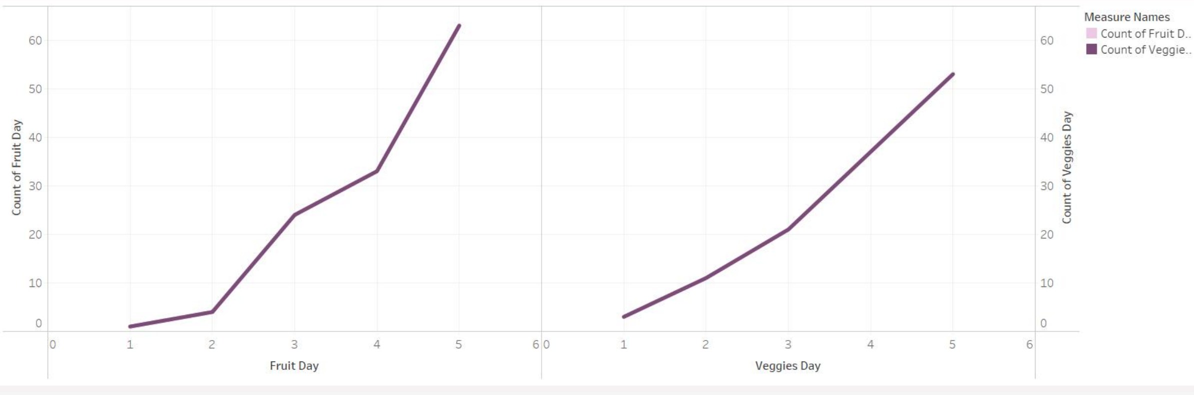
This treemap visualization provides a multivariate perspective on the distribution of "Healthy Feeling" counts across ten ordinal categories. Each tile represents a distinct category, and its area is proportional to the frequency of responses—serving as an effective method for visualizing hierarchical and part-to-whole relationships. The use of a color gradient, from light pink to deep purple, leverages visual encoding to denote varying intensities of counts, with darker hues indicating higher frequencies. This graphical summary aids in pattern recognition and cluster identification by enabling rapid comparison of dominant versus underrepresented categories. As a data scientist, this falls under the realm of descriptive analytics and can serve as a precursor to more advanced techniques such as segmentation or correlation analysis with additional variables. It's particularly useful in dashboards or reports for stakeholders who benefit from visually intuitive summaries.



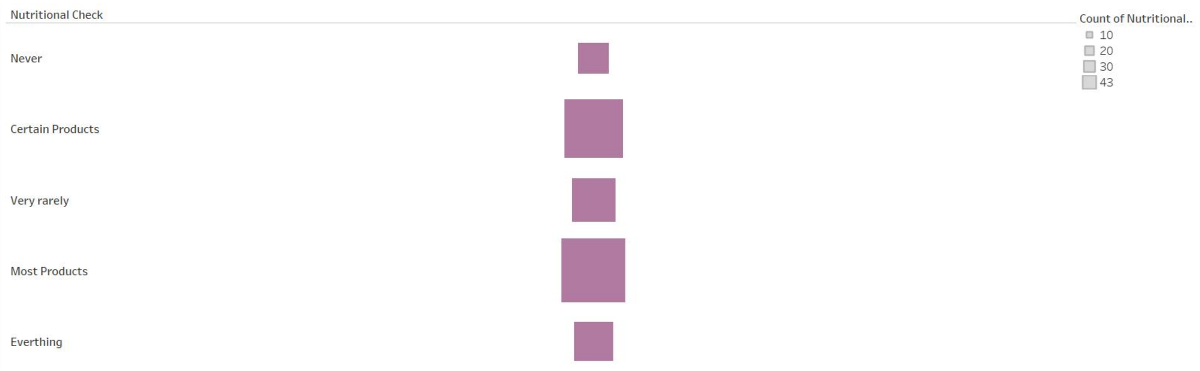
This grouped bar chart visualizes the interaction between two categorical variables: gender and vitamin intake ("Yes" or "No"). Using color encoding—purple for males and pink for females—it communicates frequency distributions along the x-axis (intake status) and y-axis (individual count). The chart reveals a gender-based divergence in health behaviors: a greater number of males report not taking vitamins, while females demonstrate a slight skew toward consumption. This visualization functions as a tool in descriptive analytics, aiding in population stratification and behavioral pattern detection. Such bivariate analysis is instrumental in health informatics for informing interventions, particularly when integrating demographic variables into predictive models. It highlights potential segmentation opportunities for targeted awareness campaigns or further statistical testing like chi-square analysis.



This dual line chart visualizes temporal trends in the consumption frequency of fruits and vegetables across six time intervals. The x-axis represents sequential "Fruit Day" and "Veggies Day" periods, while the y-axis quantifies their respective counts, indicating volume or frequency. The parallel trendlines—light purple for fruit and dark purple for vegetables—demonstrate a positive correlation and upward trajectory over time, suggesting improved dietary adherence or intervention impact. This form of time series visualization supports exploratory data analysis (EDA), making it easier to detect seasonal patterns or behavioral shifts. From a data science lens, it lays the groundwork for modeling longitudinal health behavior or conducting regression analysis. It also offers a comparative framework for measuring variance in categorical nutritional metrics over time.

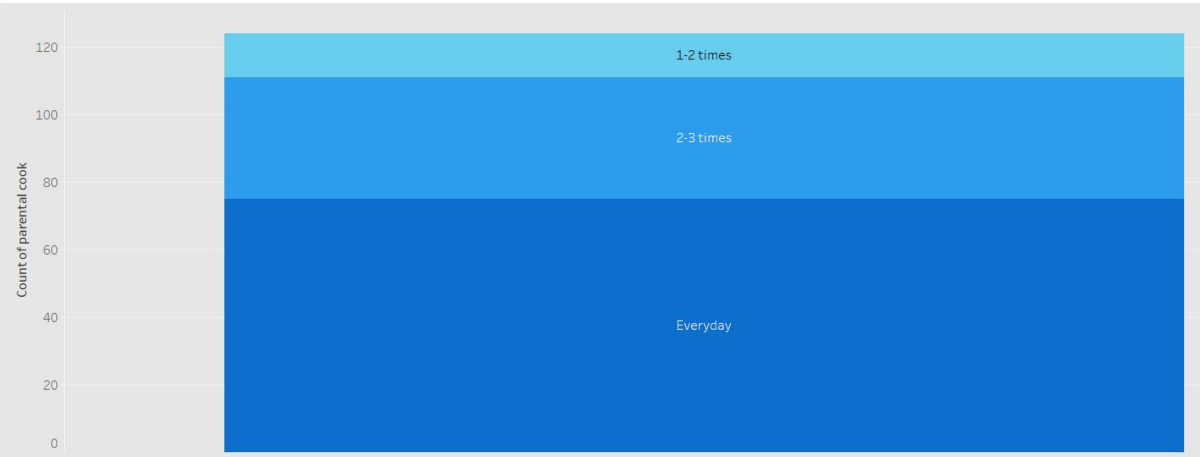


This horizontal bar chart illustrates categorical frequency distribution related to how often individuals check nutritional information on product labels. The y-axis displays five ordinal categories—ranging from "Never" to "Everything"—while the x-axis represents the count of respondents. The most dominant category, "Most Products," indicates a high engagement with nutritional labeling (n ≈ 43), suggesting a general trend toward informed consumption behavior. Color encoding and bar length facilitate comparative analysis across segments, making it a valuable tool for exploratory data analysis (EDA). This descriptive visualization enables data-driven insights into consumer habits, with potential downstream applications in health promotion modeling or behavioral segmentation. It may also serve as a basis for hypothesis testing in nutritional awareness research.

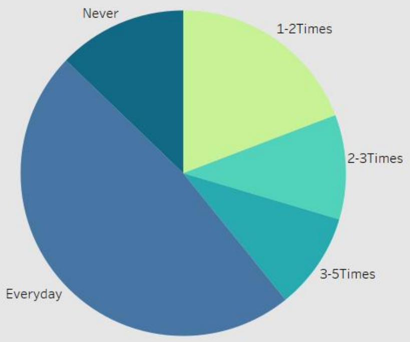


Dashboard 4: Parental Influence and Eating Out

The visualization is a **stacked bar chart** illustrating the frequency distribution of parental cooking habits across three categorical intervals: *1–2 times*, *2–3 times*, and *Everyday*. Each segment within the bars is color-coded to represent these frequency groups, allowing for intuitive **visual segmentation**. The **y-axis encodes absolute frequency**, quantifying the number of parents who fall into each category. This format is particularly useful for comparative analysis, enabling quick assessment of dominant behaviors within the dataset. The visualization supports **descriptive statistical exploration** and is valuable for identifying lifestyle patterns in family environments. Such insights may inform hypotheses in studies relating to nutrition, time-use analysis, or intergenerational household routines.



The visualization is a **pie chart** representing the distribution of individual preferences for dining out, segmented by frequency categories. Each slice of the chart reflects a **proportional share** of responses to the variable *Eating Out Preferences*. The category *1–2 Times* dominates the chart, signifying it as the most commonly reported frequency, while *Never* has the smallest share, suggesting it is the least prevalent behavior. This chart utilizes **area encoding** to illustrate **nominal categorical data** with intuitive visual impact. It is particularly useful during **univariate analysis** for uncovering trends in consumer lifestyle behaviors. Such insights may assist in **market segmentation** or in designing consumer-centric strategies in the hospitality and food service sectors.



The visualization is a **bubble chart** depicting the distribution of meal payment behavior, with each bubble representing a different monetary range. The bubble size encodes the **relative frequency** of individuals falling into each payment bracket, ranging from *$5–$10* up to *Over $40*. The most prominent category is *$10–$20*, indicating it as the mode within the dataset, while smaller bubbles suggest less common payment ranges. This form of **area-based visual encoding** is effective for presenting nominal categorical data during **univariate analysis**. It allows for quick comparative insights into spending habits and supports downstream tasks such as **customer segmentation** or **affordability profiling**. The chart aids in identifying purchasing thresholds that could inform pricing strategy or consumer behavior modeling.