Increasing User Engagement with a Tracking App Through Data Visualizations

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Abstract: According to the United Nations, 17 percent of global food production is wasted, causing economic losses and significant environmental impact. Digital solutions like food storage management apps can raise awareness and combat this issue. However, their effectiveness relies on consistent user engagement. Therefore, this paper proposes and evaluates data visualization designs to enhance user engagement in mobile applications for tracking food waste. The study involves three steps: discussing the domain situation supported by relevant literature, outlining the process of creating two sets of four data visualization designs and conducting quantitative user surveys to validate the designs. The first experiment assesses user experience, while the second determines user engagement. Results indicate a preference for design approach two (Chart Set B), which also provides more accuracy and higher user engagement when the design aligns with users' sustainability interests. These findings emphasize the potential of engaging data visualizations to curb food waste and contribute to a more sustainable future.

1 INTRODUCTION

Self-tracking tools empower individuals or groups to monitor biological, physical, behavioral, or environmental metrics. The data obtained through self-tracking efforts can be summarized as the quantified self (QS) (Swan, 2013). When designing effective and accessible user interfaces for tracking applications, the use of data visualization techniques is essential. They enable users to see and understand trends, outliers, and patterns in data (Shneiderman et al., 2016). Furthermore, users can quickly gain insights into their behavior, as well as identify and influence their behavioral trends and patterns (Peters et al., 2018).

Bridging the domains of QS, data visualization, and user-centered design, we outline the development of data visualization designs for an application that intends to help users identify and improve their households' food waste trends. The objective is to create data visualizations that are not only informative but also engaging. Peters et al. define engagement in a human-computer interaction (HCI) context as attentional and emotional involvement (Peters et al., 2009). The model of engagement proposed by O'Brien et al. highlights that emotions are closely tied to engagement (O'Brien and Toms, 2008). Finding appropriate characteristics to measure and quantify the level of engagement poses different challenges. Concepts such as PENS (Peters et al., 2018) and contributions by Hung and Parsons (Hung and Parsons, 2017), Edwards (Edwards, 2016) and Kennedy et al. (Kennedy et al., 2016) emphasize that understanding user engagement requires looking beyond technical metrics to capture the complexity of the user experience.

Increased engagement can help motivate users to maintain their attention and interest in the application and update it more consistently. This provides users with more data to explore, a more detailed representation of their QS, and subsequently more insights into their behavior, which could potentially lead to positive behavioral changes. The two conducted experiments aim to firstly assess user experience by using the Single Ease Question (SEQ) (Rotolo, 2023) and the User Experience Questionnaire (UEQ) (Laugwitz et al., 2008) and secondly measure engagement by using the VisEngage questionnaire by Hung and Parsons (Hung and Parsons, 2017) with the different visualization designs.

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2 DATA VISUALIZATION

Munzner introduces the nested model for visualization design and evaluation. The domain situation level aims to define the target users, while the abstraction level helps identify what data is shown and why it is relevant for the user. The goal on the idiom level is to define how the data is shown, and the algorithm level is concerned with effective computation of visual encoding and interaction design (Munzner, 2009). This model inspired the design process of the visualizations for the tracking application. The following subsections represent levels 1 through 3 of the nested model, focusing on the visual encoding.

2.1 Domain Situation

A study conducted in 2012 by Stenmarck et al. shows that 20% of the total food produced in the EU in 2011 was wasted (Stenmarck et al., 2016). It also defines five different sections in which food waste occurs: primary production, processing, wholesale and retail, food service, and households. With about 46.5%, the households sector contributes the most to food waste. This behavior not only results in economic losses but has a significant impact on the environment and causes loss of resources such as land, water, and energy (Institute of Technology Assessment (ITA), 2015).

These issues inspired a group of participants in an interdisciplinary project semester program to find a solution to help people with their food management (St. Pölten University of Applied Sciences, 2023). After going through an iterative design thinking process, the project team proposed an app that guides the user through creating a shopping list, the grocery shopping process, and the use (or waste) of the purchased products: the *What a Waste* app. The target group of the application was defined as people between the ages of 25 and 50 living in Austrian households with at least one other person. The application was tested and adapted by conducting user interviews and field studies using low-fidelity mockups and, in later stages, a high-fidelity prototype.

The What a Waste application's interface consists of three main tabs. The shopping list view lets the user create a shopping list and is intended to help the user before and during their purchasing process. The storage tab provides the user an overview of their storage's current inventory with additional information about the product such as expiry date and status (full, half, empty) along with the option to add it to the shopping list. Tracking whether an item was used or wasted is done by a popup asking the user how they used each item they remove from the storage list. Lastly, the household view shows an overview of the household's statistics and enables the user to view and edit a household member's profile, which contains information about the user's diet, allergies, and preferences. The heightened awareness about the user's behavior concerning food ideally results in more conscious shopping habits, planning meals, and ultimately less food waste. The overall goal is that the user becomes more aware of their habits and reduces their use of resources, which positively impacts the environment.

2.2 Visualization Requirements

Gaining a deeper understanding of the user's possible goals and tasks when using the application was crucial for defining the visualizations' requirements. Finding out more about people's motivations to reduce their food waste (Giordano et al., 2019), understanding more about the action-cognition-perception-loop (Peters et al., 2009), and matching the different kinds of engagement (Doherty and Doherty, 2019) to it provided a good base understanding for defining the following requirements:

1. The visualization interface should be *easy to use*, so the everyday user can focus on the data rather than the interaction itself.
2. The visualization being *mobile friendly* is crucial since the application is designed for mobile devices. A seamless interaction without scaling or readability issues enhances overall usability, reduces possible user frustration, and supports the previous requirement.
3. *Hierarchy*: Showing how data or objects are ranked and ordered together in a system can help the user identify certain counterproductive behaviors and patterns.
4. *Comparison*: Showing the differences and similarities between values can provide the opportunity to gain insights into patterns and trends.
5. *Data over time*: Showing data over a time period as a way to find trends or changes over time can help identify trends (Ribecca, 2023).

2.3 Visual Encoding

To select appropriate visualization methods for the application, gaining an overview of the different visualization methods and their features, advantages, and disadvantages was important. 42 visualization methods from different sources (Ribecca, 2023; Zoss,

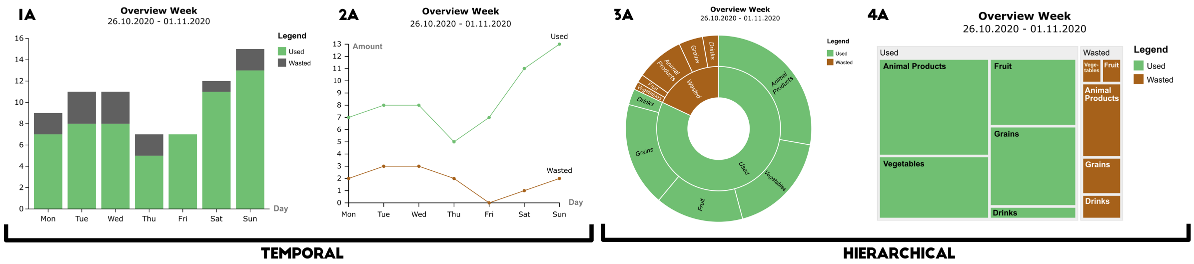

Figure 1: Visualization Group A. The charts in A include two temporal representations encoded as (1A) a bar chart and (2A) a line chart, as well as two hierarchical representations encoded as (3A) a sunburst diagram and (4A) a treemap.

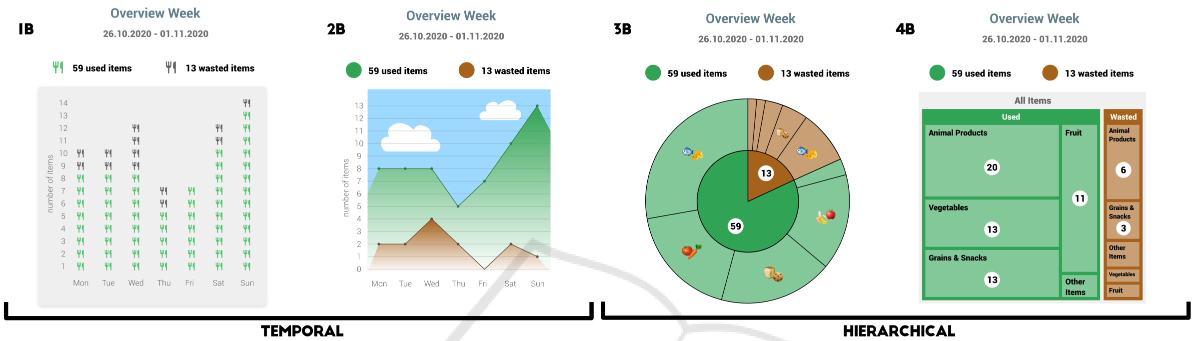

Figure 2: Visualization Group B. The charts in B also include two temporal representations, encoded as (1B) a pictogram chart and (2B) a stylized area chart, as well as two hierarchical representations encoded as (3B) a stylized sunburst diagram and (4B) a stylized treemap.

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2019; Datalabs, 2014; Valcheva, 2020; Munzner and Maguire, 2015) were gathered and analyzed by identifying which visualization method meets which of the previously defined requirements and which techniques were appropriate for the application's data set.

The following four methods met four out of five requirements: histograms, line graphs, stacked/grouped area graphs, and treemaps. The following eight methods met three out of five requirements: area graphs, bar charts, multi-set bar charts, pictogram charts, pie charts, radial bar charts, stacked bar graphs, and sunburst diagrams.

After drafting initial concepts, we decided to create two temporal and two hierarchical visualization designs to convey consumption and waste over time and (sub)categories of consumed and wasted products. For the following experiments, two sets of four visualizations each were designed. The first set (Charts A) includes conventional data representations of each of the chosen types. The second set (Charts B) proposes alternatives to improve the charts from the first set, providing icons and metaphors that could foster engagement. The charts are designed as follows:

1. **Bar and Pictogram Charts.** Both charts visualize data that represents a state in time, which makes them temporal (Esri, 2023). Chart 1A is a bar chart that is used to show discrete numerical comparisons across categories. Chart 1B is an Isotype (Doris, 2020) or pictogram chart. The use of icons gives a more engaging overview of small sets of discrete data, where an icon can represent one or any number of units. This technique makes comparison of different categories easy and also overcomes barriers created by language, culture, or education. The two charts are not directly comparable; however, we agreed that a bar chart would be the best option to compare against the pictogram chart.
2. **Line and Area Charts.** Charts 2A and 2B are also temporal visualizations, and both use the line chart visualization method. Chart 2A is a simple line chart visualization that displays quantitative values over a continuous interval or time period. A line graph is most frequently used to show trends and analyze how the data has changed over time. Chart 2B uses the grouped area graph visualization method. It is a version of the line graph technique, with the area below the line filled in with a certain color or texture and the graphs starting from the same zero axis.
3. **Sunburst Diagram.** Charts 3A and 3B both use the sunburst diagram visualization method, which shows hierarchy through a series of rings that are

sliced for each category node. Each ring corresponds to a level in the hierarchy, with the central circle representing the root node and the hierarchy moving outwards from it.

4. **Treemap.** Charts 4A and 4B are both treemaps, which are used to visualize hierarchical structure while also displaying quantities for each category via area size. Each category is assigned a rectangle area, with the subcategory rectangles nested inside (Ribecca, 2023).

To create the first set of data visualizations (Charts A) the software RAWGraphs (Mauri et al., 2017) was used. To make more detailed changes, such as the placement of labels and colors, an SVG editor software was used.

The second set of visualizations (Charts B) was created using an iterative design process. Keeping Experiment II in mind, interactive/clickable mockups with illustrated gamification elements (Trivedi, 2021) and emoji (Bai et al., 2019) were created using Adobe XD. There were three versions in total and each version was tested with two experts from the fields of HCI, data visualization, and usability. With each version, the feedback from the expert interviews—which concerned color encoding, legends, categorization, readability, and labeling—was implemented.

3 EXPERIMENT I

The study's goal was to test the user experience and performance with two different types of visualization approaches (Charts A and Charts B) and to identify users' preferences for one of the design types. Only static visualizations of the weekly overview of used and wasted items were used for this study.

3.1 User Study Setup

To compare the different visualization approaches, a survey was created. First, the participants' demographics were collected, followed by questions about their households, food waste habits, and digital literacy. The order of the visualization sets was counterbalanced (Lazar et al., 2017). Each visualization was followed by a question about the visualized data and the Single Ease Question (SEQ) (Rotolo, 2023) about the task using a Likert scale from 1 (very difficult) to 7 (very easy). Each set of charts was followed by the User Experience Questionnaire (UEQ) (Laugwitz et al., 2008) to assess the user experience of the data visualizations. At the end, the participants selected their preferred visualization for each type and one overall favorite.

3.2 Results and Analysis

Success rates for each question asked about the data visualized in the charts were calculated, as well as the mean (*M*) and standard deviation (*SD*) for each task's SEQ. To calculate the results of the UEQ, the UEQ data analysis tools were used. A statistical analysis using R was conducted to provide further insights into the obtained data of the experiment. An alpha level of .05 was used for all statistical tests.

3.2.1 Test Subjects

24 people took part in the study. The participants were aged between 25 and 58 years old ($M = 30.29$). 10 of them identified as male, 11 as female, and the remaining preferred not to indicate their gender. 21 lived in Austria and 3 did not. 9 lived alone and 15 lived in a shared household with between 1 and 4 other adults and/or children. On a scale of 1 (no attention) to 7 (a lot of attention) of how much attention the participants pay to their household's amount of food waste, they indicated a mean of 5.41 ($SD = 1.38$).

3.2.2 Success Rates and Easiness

The success rates and the SEQ results for Charts A and Charts B are summarized in Table 1.

Table 1: Success rate (*SR*), mean (*M*) and standard deviation (*SD*) of SEQ.

	Charts A		**Charts B**	
	SR	M (SD)	SR	M (SD)
1	91.67%	3.87 (1.3)	95.83%	6.29 (1.1)
2	79.17%	4.75 (1.5)	87.50%	6.08 (1.3)
3	100.00%	4.96 (1.5)	100.00%	5.79 (1.3)
4	100.00%	6.46 (0.6)	91.67%	6.79 (0.5)
	Overall $SR = 92.70\%$		Overall $SR = 93.75\%$	

The results show that success rates were generally very high, except for Chart 3A. The SEQ results show that answering questions for Charts 1A and 2A was harder compared to questions for Charts 3A and 4A.

Success rates for Charts B were also high, and the SEQ results show that answering questions for Charts B was fairly easy (see Figure 3).

Spearman's rank correlation was computed to assess the relationship between success rates for questions about Charts B and the participant's level of attention paid to food waste. There was a positive correlation between the two variables, $r(22) = .51$, $p = .011$. This suggests that the higher the level of attention paid to food waste, the better the success rates when answering questions about the visualized data in Charts B.

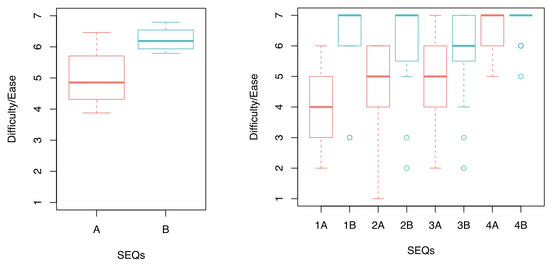

Figure 3: Overall SEQ results and results of each SEQ.

3.2.3 User Experience

Table 2 shows the UEQ results divided into 6 different dimensions, with their corresponding mean (M) and variance (V). Values between -0.8 and 0.8 represent a more or less neutral evaluation of the corresponding scale, values > 0.8 represent a positive evaluation, and values < -0.8 represent a negative evaluation (Laugwitz et al., 2008) (see Figure 4).

Table 2: Mean (M) and variance (V) for each dimension of the UEQ.

	Charts A		**Charts B**	
	M	V	M	V
Attractiveness	0.410	1.72	1.243	1.40
Perspicuity	1.073	1.17	1.823	1.26
Efficiency	0.875	1.46	1.167	1.66
Dependability	0.823	0.74	1.177	1.25
Stimulation	0.198	2.12	1.063	1.53
Novelty	-0.698	2.11	0.823	1.92

The results for the UEQ for Charts A show a positive evaluation of the perspicuity, efficiency, and dependability of the charts. Comparing the data to a benchmark data set, however, shows that the results for all scales are either below average (50% of results better, 25% worse) or bad (in the range of 25% worst results). Charts B, on the other hand, yield a positive evaluation for all scales, with novelty being the lowest and perspicuity the highest. Comparing the data to a benchmark data set shows that the results for all scales are either above average (25% of results better, 50% worse) or good (10% of results better, 75% of results worse).

A Shapiro-Wilk normality test for each scale of each visualization type shows that the data for UEQ results for Charts A are normally distributed. The data for Charts B are also normally distributed apart from the data for perspicuity and novelty. A two-way ANOVA was performed to analyze the effect of the scale and the visualization type on the corresponding mean scores. The test revealed that there was a statistically significant effect of scale ($F(5) = 14.20, p < .001$) and visualization type ($F(1) = 62.23, p < .001$) on user experience, though the interaction between these terms was not significant. This suggests that participants had a better user experience with Charts B compared to Charts A.

3.2.4 Preferred Visualizations

Each of the 24 participants was asked to indicate their favorite chart for each category and an overall favorite visualization.

- Of Charts 1, 21 people prefer the pictogram chart (1B) and 3 the bar chart A.
- Of Charts 2, 20 participants prefer line chart B (2B) and 4 line chart A (2A).
- Of Charts 3, 16 people prefer sunburst diagram B (3B) and 8 sunburst diagram A (3A).
- 22 participants prefer treemap B (4B) and 2 treemap A (4A).
- Overall, 8 people indicated bar chart B (1B), 7 line chart B (2B), 4 treemap B (3B), 2 treemap A (3A), 2 sunburst B (4B), and 1 sunburst A (4A) as their favorites.

The results show that participants tend to prefer Charts B over Charts A. The overall favorite is bar chart B (1B), closely followed by line chart B (2B), which both are temporal visualization methods.

4 EXPERIMENT II

The goal of this study was to determine engagement with the interactive versions of Charts B only, and to identify which variables have a (positive) effect on user engagement.

4.1 User Study Setup

Two different surveys were used for evaluation, one for the temporal visualizations and the other for the hierarchical visualizations. Visualizations were counterbalanced for controlling the assignment of treatments and allowing a clean comparison between the experimental conditions (Lazar et al., 2017). Moreover, the users were instructed to test the visualizations on a mobile device, since the application and therefore the visualizations are designed for mobile devices.

Demographic data such as age and gender were collected, as well as details about the participant's household and their awareness of their food waste. Moreover, data about possible motivations for reducing food waste based on Giordano was collected

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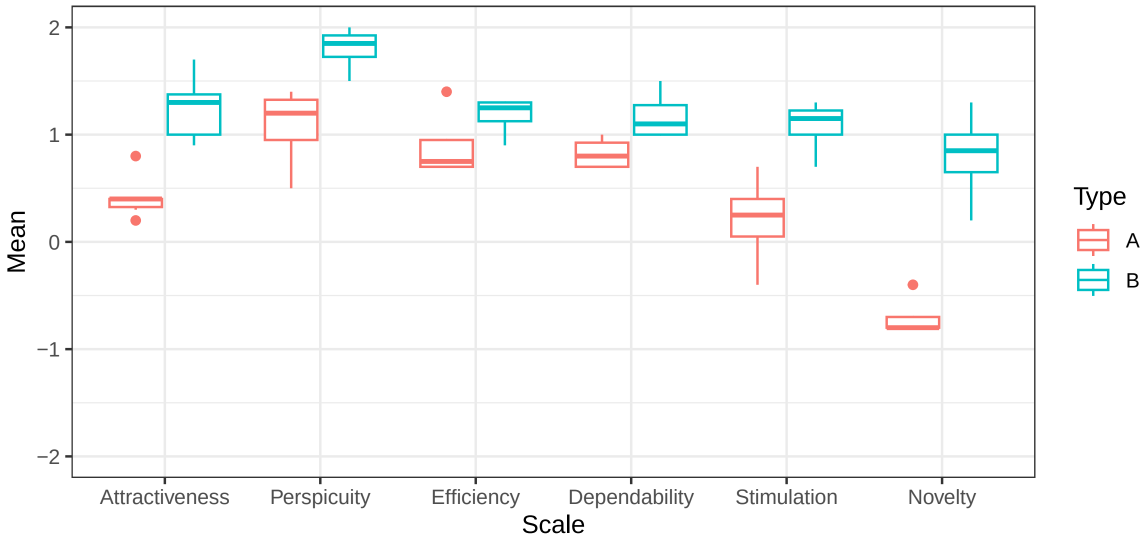

Figure 4: UEQ scores for each user experience dimension and for each visualization set (Charts A and Charts B).

(Giordano et al., 2019). After the exploration of each visualization, the user was asked to answer three questions about the visualized data and to complete the VisEngage questionnaire (Hung and Parsons, 2017), which focuses on engagement with data visualizations and covers eleven different engagement characteristics with two items each, to determine their engagement score. After going through the same process with the second visualization, the participant had to select their preferred visualization design and had the option to leave feedback.

4.2 Results and Analysis

Temporal and hierarchical visualizations were analyzed separately in a between-subjects design. A test of normality was performed on the two main variables of the data set. The overall engagement score was calculated based on the seven-point Likert scale, which ranges from strongly disagree (1) to strongly agree (7). The sum of the values indicates the engagement score, which ranges from 22 to 154 (Hung and Parsons, 2017). The performance was calculated based on the number of correct answers to the questions about the visualization designs. The mean and standard deviation of the participants' ages, the overall engagement score and the engagement scores per visualization method were calculated, as well as overall performance and performance per visualization method.

To determine the correlation of selected parameters, the Pearson method was used. A chi-squared test as well as parametric tests, which included ANOVA and a t-test, were conducted. The Wilcox and Kruskal–Wallis tests were used for the non-parametric tests. An alpha level of .05 was used for all tests.

4.2.1 Temporal Visualizations

14 people, of which 6 identified as female and 8 as male, took part in the survey. The participants of the survey were rather young, with an average age of 26.14 ($SD = 8.33$). The overall average of engagement scores was 95.54 ($SD = 22.14$) with the line graph method showing a slightly higher average ($M = 100.64$, $SD = 24.44$) than the pictogram method ($M = 90.43$, $SD = 19.08$). Overall performance of the participants was relatively high, with an average of 84.52% ($SD = 23.10\%$). Performance when interacting with the line graph visualization was higher ($M = 90.48$, $SD = 15.63$) compared to the pictogram visualization ($M = 78.57$, $SD = 28.06$).

Based on the data set, it was possible to conclude that the users had a higher engagement score on their favorite visualization design since a Pearson correlation coefficient showed a positive correlation, $r(26) = .41$, $p = .031$. A t-test showed that there was a significant effect for the user's favorite visualization, $t(25.52) = -2.29$, $p = .03$, with visualizations which were marked as favorite showing higher engagement scores ($M = 104.43$, $SD = 21.95$) than visualizations which were not marked as favorite ($M = 86.64$, $SD = 19.11$) (see Figure 5).

Lastly, a Pearson correlation coefficient was computed to assess the linear relationship between the engagement score and the attention a user pays to how much food their household wastes. A strong positive correlation was detected, $r(26) = .57$, $p = .001$ (see Figure 5). A one-way ANOVA test showed that the

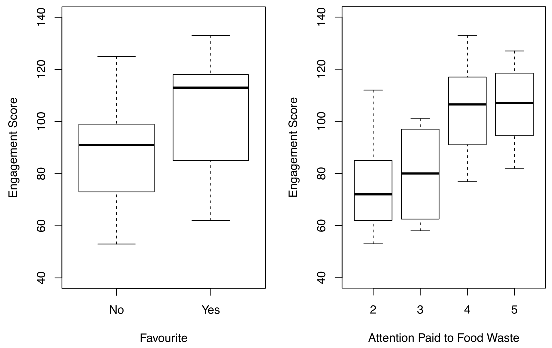

Figure 5: Engagement for (not) preferred temporal visualizations and Engagement scores by attention paid to food waste for temporal visualizations.

effect of the attention paid to food waste in a household was significant, $F(3,24) = 5.02$, $p = .008$. A post hoc analysis using the Tukey method conducted a pairwise comparison and showed that the average engagement score of the 5 participants who selected 4 ($M = 105.10$, $SD = 18.21$) and the 4 participants who selected 5 ($M = 106.13$, $SD = 15.81$) on a five-point Likert scale, upon getting asked how much attention they pay to food waste in their household, was significantly higher than the 3 participants who marked 2 ($M = 76.00$, $SD = 20.67$) on the same scale ($p < .05$).

4.2.2 Hierarchical Visualizations

14 people, of which 8 identified as female and 6 as male, took part in the survey. The participants of the survey were middle aged with an average age of 31.29 ($SD = 14.78$). The overall average of engagement scores was 100.00 ($SD = 22.71$) with the sunburst method showing a slightly higher average ($M = 103.14$, $SD = 21.73$) than the treemap method ($M = 96.86$, $SD = 24.04$). The overall performance of the participants was relatively high, with an average of 83.33% ($SD = 24.84\%$). Performance when interacting with the sunburst visualization was higher ($M = 88.10$, $SD = 16.57$) compared to the treemap visualization design ($M = 78.57$, $SD = 30.96$).

The data set's values for engagement scores and performance showed a strong positive correlation when computing a Pearson correlation coefficient, $r(26) = .60$, $p < .001$. This suggests that a higher engagement score results in better performance based on the survey's data.

A Pearson correlation coefficient showed a marginally significant positive correlation, $r(26) = .38$, $p = .046$, of the engagement score with the attention a user pays to how much food their household wastes. A one-way ANOVA test did not show an effect of the attention paid to food waste in a household, $F(3,24) = 1.53$, $p = .23$.

5 CONCLUSION

The results of Experiment I show that the user performance with the two visualization sets was comparable. However, participants perceived the tasks as easier with the new stylized charts (Charts B) over the basic ones (Charts A). The overall favorite in the set was the pictogram chart (1B), closely followed by the stylized area chart (2B). These findings are supported by the results of the statistical analysis for the UEQ, which suggest that participants preferred the attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty of visualizations in Charts B compared to Charts A.

While it was not possible to identify a single visualization method that unequivocally led to increased user engagement in Experiment II, the results show that the engagement score was higher for the visualization the user marked as their favorite. Moreover, people who pay more attention to food waste in their households had a higher engagement score when interacting with the temporal visualization designs. These findings can be recognized in the engagement model by O'Brien et al. The user's general interest in the topic can be linked to the parameters of interest, motivation, and specific goal for the point of engagement (and reengagement) thread. Heightened engagement scores when interacting with the user's favorite visualization can be traced back to the parameters aesthetic and sensory appeal, interactivity, novelty, interest, and positive affect for the period of engagement thread (O'Brien and Toms, 2008).

Limitations of the study to keep in mind are the use of the treemap visualization method (Group, 2023) and the impact of the chosen colors on the user. Moreover, providing a summary of the data only in Charts B might limit the comparability of the two sets of charts.

The study illustrates that by stylizing conventional data representations, users can perform tasks more easily and enjoy a better user experience with the visualizations. Taking these findings into account when designing data visualizations for mobile tracking apps can potentially lead to users updating the apps more consistently, resulting in more accurate results and potentially influencing changes in behavioral trends and patterns. Further studies, however, including longitudinal ones, must be conducted to comprehensively assess the effect of user engagement with visualizations and mobile tracking apps in bringing about effective behavioral change.

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