# EmovDiary: Designing Visualization for Mindful Eating


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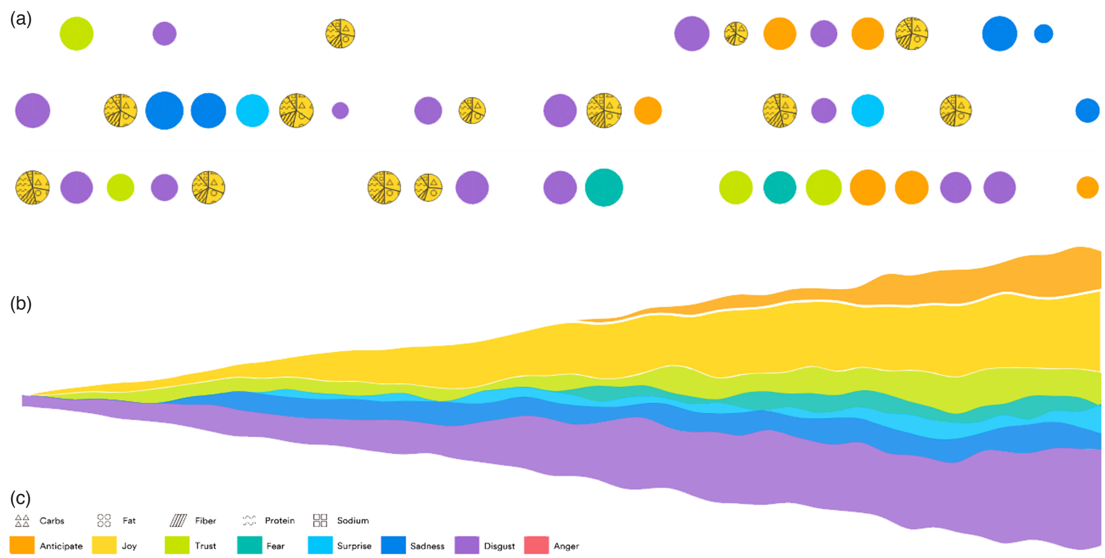


**Figure 1: The visualization interface illustrates the food-and-mood journey of Participant#1 over 25 days by EmovDiary, where all joyful meals are highlighted. There are three visual components displayed in the interface: (a) The *Timeline Layout of Molecules* shows the sequential trend of emotional variations accompanied food records. The Molecules highlighted with textures provide an overview of nutritional distribution among joyful meals. Breathing dynamics are applied on the Molecules to engage the users; (b) The accumulative *Streamgraph* reveals the evolution of calories intake per emotional category. It shares the same x-axis (i.e. the index of the day) with view (a). We also implemented waving animations on this view to enhance user engagement. At last, we present the legend (c) which consists of the intuitive design of glyphs and color encoding schemes.**

## ABSTRACT


Research indicates a strong coupling between food intake and emotional well-being. However, existing applications seldom provide visual interfaces that integrate this coupling to inspire mindful eating. To fill this gap, we propose to build digital profiles on users' food logging data associated with nutrition details and emotion status. In this paper, we present EmovDiary, a two-level representation featuring intuitive glyphs and novel aesthetics. EmovDiary presents a timeline-based interactive visualization that enables users to visually explore their food journeys and spot patterns between personal emotion variations and nutrition intake. The entire solution is implemented as a web-based interface enriched with animation effects to resonate the audience with visual stimulation. Our evaluation shows that EmovDiary achieves effective storytelling of individual's food-and-mood journey, empowered by its intuitive visual design and visual aesthetics. We conclude this paper by discussing our findings on enhancing engagement in mindful eating.




## CCS CONCEPTS


• **Human-centered computing** → **Visualization**; **Visualization application domains**; **Information visualization**; *Interactive systems and tools*;


## KEYWORDS


Food Logging, Visualization, Sentiment Analysis, Interactive System

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# 1 INTRODUCTION

Food and emotions have tight influences on each other. Emotions can act as food stimulus, and vice versa. Apart from providing the nutrients and energy to support our daily activities [25], food also impacts on our emotions [9]. It has been proven that caloric content of diets affects cognitive capacity and particular nutrients influence cognition by acting on molecular systems or cellular processes [15]. On certain occasions, food intake may improve the emotional status because the eating behavior reduces anxiety and discomfort [10]. Hence, people sometimes eat for emotional or habitual reasons [11], which evolves into the technique of mindful eating. Moreover, emerging research indicates that variability exists across individuals [18], which as a result raises the significance of individual-scoped study on the relationship between the nutrition intake and personal emotional effect.

Quite amount of population spent at least one to two hours per day engaged in eating and drinking activities [16]. However, existing applications do not provide equal insights to the amount of attention that we pay to our food intake and its potential emotional effect. Driven by this fact, we want to enable people to understand their food-and-mood patterns by reviewing their daily food consumption with associated emotions, and thus derive personal guidance to assist mindful eating.

How can we make users engage with their daily tracking logs? How can we help regular users understand their emotional food journey? To address these questions, we propose a solution that leverages information visualization to build digital profiles on personal food logging data associated with the emotion records. We aim to enable users to explore, interact with and understand their food journeys. Moreover, we encourage users to actively engage with the interface, to figure out the interesting relationship between their food intake and correspondent emotional effects and as a result eat mindfully.

This paper presents our solution of EmovDiary, a two-level representation featuring intuitive glyphs and novel aesthetics, designed based on the collected time-series logging data. Our timeline-based interactive visualization enables users to visually reflect on their daily nutrition intake and the associated emotional ebb and flow. The entire solution is implemented as a web-based interface enriched with animation effects to resonate the audience. The major contributions of this work are summarized as follows:

(1) Design and implement a two-level visualization on food logging data with emotion records to reveal the relationship between nutrition intake and emotions.
  (a) The first level consists of a *Molecule Representation* and a *RoseViz* textured an intuitive design of glyphs to demonstrate nutritional information.
  (b) The second level contains the *Timeline Layout of Molecules* and the accumulative *Streamgraph*, with animations and interactions applied to facilitate dynamic storytelling.
(2) Leverage metaphorical visual designs, aesthetic animations and dynamic interactions to engage users in long-term food logging and mindful eating.
(3) Evaluate the visualization by conducting a between-subject design study with 21 users and a three-week case study with 20 participants based on their campus life.

The rest of this paper is organized as follows. In section 2, we reviewed the related work devoting to present nutrition-emotion relationships, and the existing approaches to emotion and sentiment analysis. Then we describe the visual designs in section 3, where we also elaborates the design concerns and tasks of the visual representations proposed by this work. In section 4, we discuss the implementation methodologies, including data processing workflow and dataset preparation, as well as the interactions and animations applied. We debrief the user evaluation and case studies in section 5. Section 6 is devoted to the discussion on our findings on enhancing engagement in mindful eating. Finally, we conclude this work and future directions in Section 7.

# 2 RELATED WORK

This section reviews the literature most relevant to our work in terms of: (1) existing tools and visualizations designed to present nutrition-emotion relationships, and (2) approaches to emotion and sentiment analysis.

## 2.1 Personal Nutrition-Emotion Analysis

While "Dietary Control" is gaining increasing attention in the field of healthcare in recent decades, a number of food-logging tools have sprouted up catering to both commercial and research purposes. They serve mostly as a meal diary which generates analytical feedback based on users' manually logged food contents and nutrition information [22] or uploaded meal photos [27]. FoodLog [1, 2] is one of the few systems that enable automatic food logging and nutrition analysis leveraging image processing. It is a multimedia food-recording tool that achieves easy logging by food-image detection and food-balance estimation to categorize each meal into one pre-defined category based on the component recognition. Although FoodLog offers a timeline visualization of logged data to enable basic review on both component statistic and original food images, a more informative visualization going beyond timeline diary is needed to enable users to explore, interact, and understand their food journey with their psychological experience. Besides, there is still a gap in rewarding the logging efforts with interesting analytical reviews associated with emotion information.

Some other applications provide emotion reflection based on users' logging activities. EmoTree [11] adopts a tree-form metaphorical design to encode the users' overall feelings about their food intake decisions based on self-report records. The tree will grow in a healthy shape with positive decisions. However, the interface does not provide any details about each food intake decision, so it is impossible for users to track down with any nutrition information. Differing from them, EmovDiary combines both the details of nutrition intake and the information of emotion regarding the eating behavior into the visual representation to help users obtain self-knowledge.

## 2.2 Emotion and Sentiment Analysis

Sentiment analysis is to determine the sentiment of an individual with respect to some topics [12]. It has not been well studied yet but gaining popularity in recent research. Cambria et al. [7] promoted a knowledge-based framework called SenticNet for opinion mining. This work introduced the sentiment dimensions modeled on the Hourglass of Emotions [8], a derivative of Plutchik's Wheel of Emotions [20]. Mohammad [19] created a classifier to detect emotions using tweets with emotion word hashtags as labeled data. It inspired the usage of user-provided indications of emotional content, e.g. emoticons, Emoji, and hashtags. Dystemo [26] is a distant supervision method automatically producing emotion classifiers from tweets labeled using existing or easy-to-produce emotion lexicons. It applies Balanced Weighted Voting (BWV) classifier to overcome imbalance in emotion distribution and on heuristics for detecting neutral tweets. Besides, this work adopts the Geneva Emotion Wheel (GEW, version 2.0) [23] as the sentiment model that covers 20 discrete emotion categories frequently stated in self-assessments. The latter two approaches are especially relevant to our context of sentiment analysis on the unstructured data such as logs, microblogs and social media posts.

## 3 VISUALIZATION DESIGN

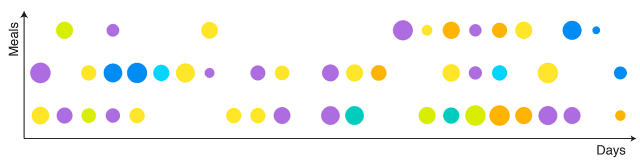


**Figure 2: The Timeline Layout of Molecule representation. Each circle represents a certain type of meal encoded with a dominant emotion. The x-axis represents the date of the tracking records, while the y-axis represents the types of meal that the user had per day. The blank position happens in the following two situations: (1) the user did not take the meal actively (e.g., the user did not have the mood to eat) or passively (e.g., the user did not have the time to eat); (2) the user missed recording the corresponding meal.**

In this section, we presents a series of critical design requirements (**DR1**-**DR4**) that were discussed during the development and the corresponding visual design regarding each requirement.

### 3.1 Design Requirements

Since the purpose of EmovDiary is to enable users to gain self-knowledge of their emotion variations based on food logs, the visualization design should satisfy the following requirements:

**DR1** Present the information of nutrition intake and emotion state for each meal;
**DR2** Illustrate the evolving patterns of personal food choices and emotion variations;
**DR3** Establish the relationship between the food and emotion;
**DR4** Create experience-oriented user interface.

Based on these design requirements, we design the two-level diary visualization to represent the time-series logging data into a meaningful form. The **Level I** is designed to accomplish the **DR1**, It combines the Molecule representation (as in Figure 2) and the RoseViz (as in Figure 3) with an embedded tag cloud (as in Figure 3(b)) to highlight the crucial information of the log in both emotional and nutritional dimensions. A set of novel glyphs (as in Figure 4 (b)) is utilized to enhance the visual intuition. Regarding the **DR2**, we introduce the **Level II**. It combines the Timeline Layout of Molecules (Figure 2) to present trend storytelling, and an accumulative Streamgraph (Figure 5) to dynamically reveal the evolving patterns of personal food intake and emotions. Being consistent among all visual representations, emotion is measured categorically and represented by the same color-coding scheme (Figure 1 (d)). Nutrition information is measured quantitatively and represented by numerical attributes such as radius and size. We set the Timeline Layout of Molecules and the Streamgraph along the same x-axis scale to achieve the **DR3**. Furthermore, explorative interactions and animation effects are implemented in the visualization (**DR4**). The drill-down interaction is added to **Level I**, which enables users to explore the details of each meal. While on **Level II**, some interactions are designed to assist analysis from an aggregation perspective. For example, by hovering on an emotional segment in the Streamgraph, one can trigger the highlighted textures on all relevant Molecules to observe the nutritional distribution of the meals. We also apply the animated dynamics, the waving effect of the Streamgraph and the blinking effect of the Molecules, to enhance user engagement by providing a pleasant and aesthetic analytical experience.

### 3.2 Design for Per-Meal Representation

In order to encompass both the overview and detail information for each meal, we design two states in the visualization to realize proper representation. The first state is the Molecule representation, where the color is used to encode a certain emotion category and the radius (or size) of the circle represents the calories contained by the meal. The second design is a rose-like representation named RoseViz, which is triggered to appear when users hover over the corresponding Molecule. The RoseViz demonstrates both the calories value and the nutritional distribution, and it is color-coded in the consistent way as the Molecule representation to hint the associate emotional status. In addition, the representation utilizes a set of distinguishable glyphs carrying intuitive metaphors of the five major nutrients.The center area of RoseViz is assigned for subsitute details of each meal. By default a descriptive tag cloud is embedded showing the keywords of the log in both food and mood dimension. The photo of the meal, if uploaded, can be triggered to appear by a single-click on the tag cloud area to refresh users' memory during exploration.

*3.2.1 Molecule Representation.* Food is made up of molecules. This idea performs as the rationale following which we design the Molecule visualization. With the design we leverage the artistic approach of visualization to represent the technical facts (e.g., nutritional value) and social aspect (e.g., emotional effect), where the former is encoded quantitatively by the radius and the latter is categorized by the correspondent color. We adopt the calories information to represent the weight of each meal in the logger's food-emotion profile and the overall evolving pattern.

As illustrated in Figure 2, the Molecules are positioned in a two dimensional layout. The x-axis represents the index of the day incrementing from left to right. The y-axis stands for the meal types, representing Breakfast, Lunch, and Dinner respectively from top to bottom. We structure the data in a dual-timestamp layout so as to better reveal the potential underlying trends of the data time series. The visualization is reaonably named as the Timeline Layout of Molecules.

Users can explore in the layout and interact with the Molecules by hovering. A hover event triggers the appearance of RoseViz, which shows the detailed information of each meal, e.g. the nutritional distribution, the log keywords and the image.

*3.2.2 RoseViz.* Rose diagram is a circular histogram plot, originally invented by Florence Nightingale. The original Nightingale Rose Diagram [5] is drawn on a polar coordinate system, where all the categories of data are divided into equal segments on the radial chart by equal distribution of the angle. The proportion of the value that each segment within a category represents is coded by the area size of the associative ring. Thus the radius of each segment extending from the polar center indicates the proportional value. It is less intuitive when absolute value is of users' interest, nor when multiple segments take close proportions.

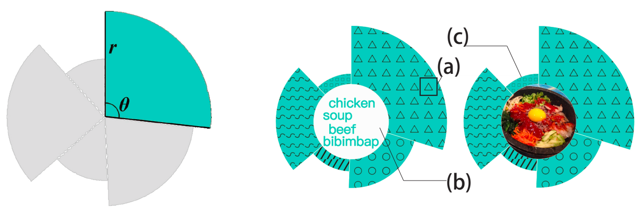


**Figure 3: RoseViz: A derivation of Rose Diagram proposed by this work. (a) Texture representing a nutritional component. (b) Tag cloud of food keywords. (c) Photo of the dishes.**

To address the issues mentioned above, we propose a derivation of Nightingale Rose Diagram (as in Figure 3), named as RoseViz. It is designed to provide more informative demonstration of the nutrition intake per meal, including the emotion annotation, calories values and distribution of nutrients. First, the RoseViz is color-coded holistically using the same color annotating the emotion of this meal. Then similar to the original design, the nutritional value and distribution are reflected quantitatively by the size of the area. But differently, we use both the angle and radius of each petal to indicate the value. To be specific, the angle is coded as a certain portion of PI, linear to the proportion of the demonstrated nutrient in this meal (as in Formula 1). While the radius is calculated as the combination of two ratios multiplied by the unit length, as shown in Formula 2. Thus the radius is not only linear to the relative proportion of specific nutrient but also telling indicating the level of absolute calories value taken through this entire meal.

$$\theta = \pi \times \frac{NutritionValue_{target}}{NutritionValue_{total}} \tag{1}$$

$$r = R_{ref} \times \frac{Calories_{target}}{Calories_{ref}} \times \frac{NutritionValue_{target}}{NutritionValue_{total}} \tag{2}$$

In addition, RoseViz also enables exploratory interactions on the dining details. There is a tag cloud embedded in the center (as in Figure 3 (b)) showing the keywords of food taken of the meal as well as the associated emotions. A photo (as in Figure 3 (c)) of the dishes, if uploaded by the logger, can be triggered by a click on the tag cloud area.

*3.2.3 Glyphs for Nutrition Representation.* We conducted nutrition analysis at the detailed level of nutritional components in this study. Since the the color visual attribute is adopted to encode the emotion information, we need to figure out another approach to distinguish the five major nutrients intuitively.

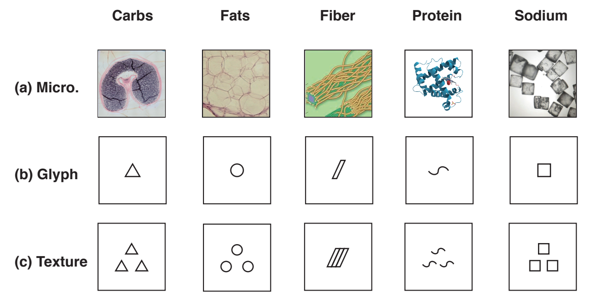


**Figure 4: The glyph design adopted in this study. (a) The representative microscopic structure of Carbohydrate, Fat, Protein, Dietary Fibers and Sodium. (b) The designed glyphs derived from the correspondent microscopic representation. (c) The glyph texture.**

According to the principle of simplicity, visual description should not cause unnecessary perceptual complexity or huge additional learning efforts. Therefore, we design a set of semantic glyphs that are simple enough to impose direct visual intuition on the users. The glyph of each nutrient is derived from the correspondent microscopic representation so that we establish a link between the visual design and its semantic metaphors. The goal is to base our designs on common knowledge so as to enhance the understandability of the visualizations meanwhile reduce the learning efforts for our users.

## 3.3 Design for Accumulative Representation

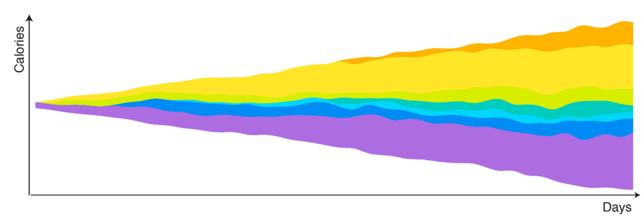


**Figure 5: The Streamgraph illustrates the accumulative emotion-nutrition information. The x-axis represents the date of the tracking records, while the y-axis represents the accumulated calories value of the meal. We present this visualization to give an overview of the calories consumption associated with the emotion, and did not show the exact number for the calories value to avoid the analytical tasks.**

*3.3.1 Streamgraph Representation.* Streamgraph is a type of stacked area graph. It gets famous since 2008 when Byron [6] introduced it to visualize the box office revenues for 7500 movies over 21 year.

The Streamgraph layout emphasizes the legibility of individual layers, arranging them distinctly around a central axis. It results in a flowing and organic shape that brings a natural indication of river and waves. To exploit the intuitive visual hints, we decide to use Streamgraph to represent the wave of emotions. Twin goals aim to be achieved: to show the data time series while to convey the evolving sum that indicates the overall pattern. The Streamgraph makes it possible to satisfy both goals at once because the heights of the individual layers are quantitatively comparable, meanwhile the height of the overall graph as an addition of all layers is changing in a distinguishable way overtime.

Figure 5 illustrates the Streamgraph design. The graph consists of a set of layers, corresponding to the time series of nutritional values, specifically value of calories intake distributed into different emotion categories. The thickness of each layer reflects the accumulative value of calories intake by the meals annotated with specific emotion category. The overall stack reflects the evolving sum of calories intake, via the overall height evolving along the logger's timeline.

To be specific, there are four ingredients to be paid important attention in order to generalize the Streamgraph visualization. The first one is the geometry, which is critical because it determines the overall slopes and curvature of the individual layers. The relevant shape parameter is set silhouette in our context. It sets the baseline of the whole graph to be in the middle and adjust the algorithms for slope and curvature computations accordingly. The second is the ordering of the layers. We adopt the ordering of emotion categories based on the Plutchik's Wheel, starting from Anticipate towards Anger in a clockwise way. It is on the one hand conforming to the aesthetic criteria considering the associative color distribution. On the other hand it forms a partition between relatively positive emotions and negative ones. The third ingredient is labeling. As with any visualization, labels are important. The organic forms of a Streamgraph result to more complex mechanism in terms of labeling visual display. Due to simple nature of our dataset and to avoid additional complexity, we decide not to always present the labels, and instead we use external legends and interactions as an alternative solution. Last but not least, color choice is critical. Good choices enable viewers to distinguish different layers while enhance the illustration of multiple data dimensions without adding complexity. The same color-coding scheme with per-meal visualizations is used here for consistency.

Streamgraph can intuitively reveal the patterns underlying the personal logs. For example, the pattern of dominance in emotional food intake is hinted by the relative area size of each layer in the stream. Additional interactions are added to enable further explorations. For example, by hovering on a layer one can ignite all the relevant meals belonging to the selected emotion category with a proportional overview of each meal and the nutritional distributions displayed on the Molecules.

## 3.4 Color Coding of Emotions

Studies in the field of color psychology have proven that color influences perceptions, though in an unobvious way. It adds to the complexity of picking a color for each emotion. Thus, it makes the color-coding of visualizations more challenging. To reduce the complexity of this task and the risk of misleading in color hints, we adopt the color scheme in consistent with Plutchik's Wheel. The model has long been used and widely accepted in terms of emotional perception.

As shown in Figure 1(c), there are eight colors defined. Each color maps to a specific emotion category, e.g. orange for anticipate, yellow for joy, green for trust, blue-green for fear, light blue for surprise, dark blue for sadness, purple for disgust and pink for anger. The colors have been shifted for a certain offset from the original colors in Plutchik's Wheel for aesthetic purpose.

Color-coding is implemented using color hex code of RGB model values. We adopt the RGB model due to its merits of being more compatible across browsers.

## 3.5 Animation Design Rationale

Animation has been used in visual representation to assist storytelling, especially for describing the time series variations [17]. Different from those transition methods implemented for facilitating visualization on large scale data, we use animation to amplify the users' feelings as they watch the final representation.

We try to leverage animation to make the trend visualization more persuasive and memorable. The animation design rational are described in the following two aspects:

**AR1** Reveal the emotion as a reaction to external events;
**AR2** Bridge the linguistic expressions of emotion and the visual forms through the design;
**AR3** Engage the audience through animation.

Based on these rationales, we design two different types of animation effects for the two-level visualizations. The first type of animation is implemented as an opening for the Timeline Layout of Molecules and the Streamgraph. The second type of animation is used to enhance the visual effects, and is implemented on the visual element level, i.e, each molecule in Molecules representation and each stream in Streamgraph are designed with animation to make the visualization more engaging.

# 4 IMPLEMENTATION

In this section, we describe the implementation details for the visualization design discussed in previous section. We first show the details about the datasets we collected from 20 participants and the analysis tasks. Then we describe the processing and analysis procedures based on the raw data. Third, we discuss the implementation details regarding the visual representation.

## 4.1 Data and Task Description

Nutrition intake is vital to our physical health. Because of that, it is tightly linked to our emotional well being. We believe that it is worthwhile to investigate the inherent pattern of personal food-emotion relationships to find out what we eat and how we feel. Thus, we propose to construct a digital diary of our food consumption and the emotions that accompanied them. On one hand, we aim to leverage information visualization to present our food journey as pleasant as the food itself. On the other hand, we would like to gain analytical capability to reflect how food and emotions are correlated for a specific individual.

We approach this problem in the following process. First, we recruit 20 participants to log food details and their emotional feelings at the dining moment. We collect the logged data, process it and transform the relevant information into metrics. Then we come up with the visual designs of storytelling representations. We iterate the designs according to users' feedback in order to better convey the relevant information, such as how fun the food journey looks like, how nutrition and emotions are influencing each other, etc. Ultimately, we implement an interactive web-based visualization interface for users to explore, interact, and comprehend their food-emotion journey.

We collect the data from 20 individuals who have been manually logging their detailed food-emotion information over 3.5 weeks. The food-emotion log dataset contains 609 entries in total. Each entry consists of up to 4 dimensions (as shown in Figure 6), including the logger's device token, submission date and time, a photo of the meal, and original log text (ideally) containing both emotion and food descriptions. Null value is allowed for each dimension.

## 4.2 Data Processing and Dataset Preparation

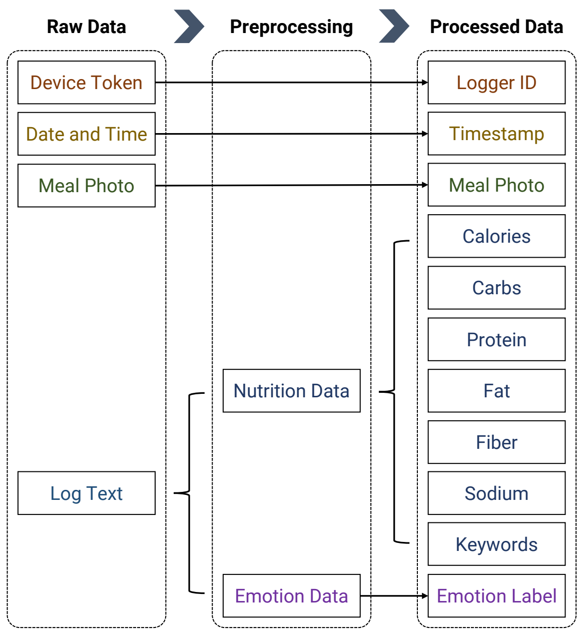


**Figure 6: An overview of data processing workflow.**

As demonstrated by Figure 6, the data processing workflow achieves data transformation and information extraction, and eventually adds new columns to the original dataset. Among all the steps, the data preprocessing tasks are especially crucial. The tasks for data preprocessing includes:

- **T1** Extract the food keywords from original log texts and transform them into nutrition data columns.
- **T2** Extract emotion tags and translate into a categorical sentiment annotation.

*4.2.1 Nutrition Data Extraction and Transformation.* We firstly processed each log entry and extract the food keywords out of text manually. Terms regarding to proportion, for example "one bowl of rice" or "100g beef", are noted down as complementary information to calculate the nutrition. Inspired by [1, 2], we then took the steps of interpreting photos of meals into information following the same logic. The photos were utilized to either (1) validate the food keywords according to image contents, or (2) complement the information of food details including the quantitative estimation of each component. Afterwards, we fed all the food information into MyFitnessPal [1], an open-source tool for calculating nutritions, to transform the food composition and proportional details into nutritional values. The numbers are calculated by MyFitnessPal based on its well-recognized nutrition dataset with the values of each distinct nutrition component taken in the meal [13]. As a result, the following columns are generated and added to the dataset with the value of Calories, Carbohydrates, Protein, Fat, Fiber, Sodium and Food Keywords.

*4.2.2 Emotion Data Extraction and Annotation.* Mining sentiments from natural language is difficult because it involves intense understandings of the explicit and implicit information conveyed by language structures. Inspired by the logic used by [19, 26], we extracted the emotion lexicons and ideograms (i.e., Emoji) as a set of emotion tags and utilize them for emotional categorization. To be specific, on the one hand, we utilized the extracted emotion lexicons such as "happy" or "very sad" as the emotional keywords and map them manually to the most relevant category defined by the Plutchik's Wheel of Emotions. Therefore, the "happy" log got annotated as $Joy \times 1$ while the "very sad" log won $Sadness \times 2$. On the other hand, we made a full use of the Emoji stickers shown in the logs for categorization. As a priori preparation, we carried out the work to classify all the common Emojis into one unit in the Plutchik's Wheel of Emotions or Neutral if it is really far from sentiment. Hence, if a grief face appeared in the log, we will map it into *Sadness* and add a $Sadness \times 1$ to the annotation of this log. After finishing the annotating work of a log, we counted the annotations and define the majority of mappings as its categorization. As a result, a new column containing emotion annotation is added.

To tackle with the task of emotion categorization and annotation, we adopt the model of Plutchik's Wheel Of Emotions [21] due to its simplicity by suggesting only 8 primary emotions: joy and sadness; anger and fear; trust and disgust; and surprise and anticipation. As the model defines, each emotion is culturally independent while each pair is defined as opposite. It makes the problem manageable and visualization potentially simpler. In addition, the model shows connectivity between the ideas of an emotion circle with a color wheel, which eases our work in mapping and validating the color-coding for each emotion annotation. Another advantage of this model is its potential extensibility, due to the derivation possibility of forming eight human feelings by mixing two adjacent basic emotions, and the decomposition possibility by expressing each primary emotion at three different degrees of intensities. For example, serenity is a lesser degree of joy and ecstasy is a more intense one.

*4.2.3 Dataset Preparation.* The result of processed data is stored as a CSV (comma-separated values) file with which it is easy to program. A CSV file stores tabular records in plain text where each line represents a data record and each record consists of identical list of fields separated by commas. It is best used to represent sets or

[1] The link: http://www.myfitnesspal.com/food/calorie-chart-nutrition-facts

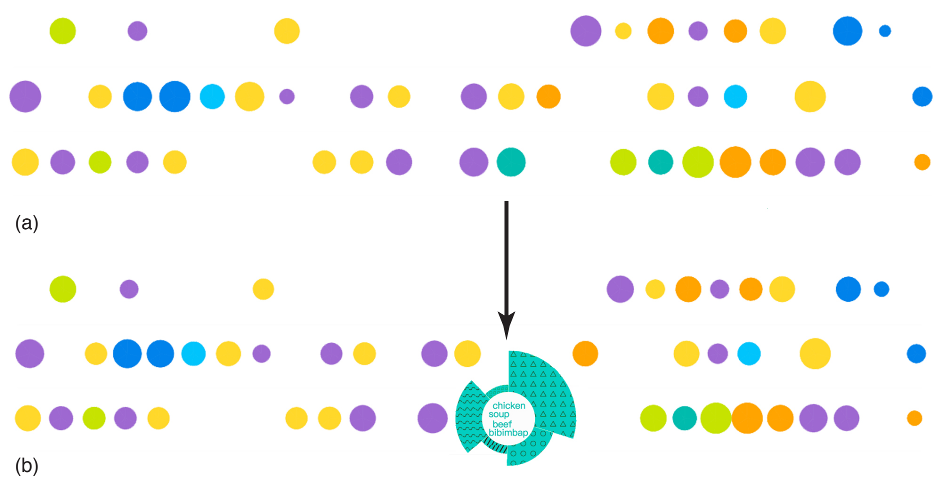


**Figure 7: (a) The Timeline Layout of Molecules in original positioning; (b) Repositioning Molecules when RoseViz is triggered; (c) The bubbles keep repelling to highlight the RoseViz when the meal photo is triggered.**

sequences of records corresponding to a single relation, and features good compatibility across all mainstream computer platforms.

## 4.3 Interactions and Animations

In order to make the visual exploring experience accessible to normal users, we implement the designs using D3.js [4]. D3.js is based on web standards and thus featuring full modern-browser capabilities and good compatibility. In addition, it supports powerful visualization components including efficient visual binding and interactive representations, and a data-driven approach to DOM (Document Object Model) manipulation. Hence, it is an ideal environment in our context to fulfill the design requirement of being interactive and dynamic.

*4.3.1 Handling Visual Clutter.* Due to the limitation of space, visual clutter may happen in the Timeline Layout of Molecules when the second-layer RoseViz is displaying. It hinders the visual exploration process because the neighboring Molecules get blocked.

Inspired by the Fisheye Distortion [3] methodology, we proposed a dynamic repositioning approach (as in Algorithm 1) to handling this problem. By using this approach, whenever RoseViz gets triggered, the x-coordinate values of all other Molecules get recalculated using the day indexes based on their distance and relative position (left or right) to the hovered Molecule. As shown in Figure 7 (b), consequently all other Molecules except the hovered one are repelled. Therefore, the visual clutter between the RoseViz and Molecules is avoided.

*4.3.2 Animation Implimentation.* Animation is an interesting element of information visualization. Well-crafted animated visualizations can further boast their effectiveness in terms of perception, persuasion, storytelling, etc. Therefore, carefully designing meaningful and effective animations is an important task. Two sets of animations have been added to this work. On one hand, catering to the inherent needs of time series data, timeline animations are implemented similarly to a play effect. On the other hand, since some visual elements, e.g. the river-like Streamgraph, have direct links

**Algorithm 1** Repositioning Molecules when RoseViz is triggered

**if** hover event triggered by a Molecule **then**
  $x_{hovered} \leftarrow$ x-coordinate value of the hovered Molecule
  **for** each Molecule other than the hovered one **do**
    $day_{index} \leftarrow$ the day index of this Molecule
    $x \leftarrow$ x-coordinate value of this Molecule
  **if** $x < x_{hovered}$ **then**
    $x_{update} \leftarrow$ move$(x, day_{index})$
**if** hover event released **then**
  **for** each Molecule other than the hovered one **do**
    $x_{update} \leftarrow$ original x-coordinate value of this Molecule
**return** $x_{update}$

to the entities in the real life, we designed and implemented some natural animations to add dynamics and make the visualization more vivid.

**Timeline Animation.** Timeline animation is to play the visualization by gradually drawing a subset of data according to their timestamps. To be specific, we sequentially draw the Molecules based on their day indexes and meal indexes. Meanwhile we fade in the Streamgraph linearly from left to right based on the day indexes. The timeline animation will play every time when users launch or refresh the web-based interface. It contributes to conveying the time-series changes in the way of unfolding narrative and telling the stories overtime to show the evolving process.

**Natural Animation Using Perlin Noise.** Natural animations are effective in making the visualization more vivid and influential, especially when there are natural visual elements such as the river-like Streamgraph. It adds dynamics to the entire representation and builds a direct link between the visualizations and the elements in our real life. As a result it evokes users' emotions.

Inspiration of designing the animations comes from Shiffman's book, i.e., *The Nature of Code* [24], where he introduced various models of applying basic mathematics and physics concepts from the nature to programming. Examples include but are not restricted to forces, flow field, fractals, oscillations, etc. Regarding to the Streamgraph, we designed the animations by simulating natural oscillations and flow field considering the inherent attributes of river that it flows and waves continuously. As for the Molecules, since the layout make them perceived analogical to stars in the sky, we designed animation to imitate stars winkling by way of oscillating their radius.

The animations are implemented via the approaches based on Perlin Noise [24]. Perlin Noise is a type of gradient noise that enables to better represent the complexity of natural phenomena in visual effects. I utilized a multi-pass noise algorithm developed by Gentle [14]. To be specific, the function of *simplex2* is used as an interface to generate 2D perlin noise and simplex noise. To achieve the twinkle effect of the Molecule representation, we continuously change the radius of each circle by adding a sequential *simplex2* noise to the original radius. Similarly, when implementing the animations of Streamgraph, we continuously change the upper-y coordinates of the edge points of each layer by adding a *simplex2* noise based on the original upper-y coordinate. In addition to that, we include a time-dimension offset as the coefficient of the noise in order to simulate the flow field effect of real rivers. The offset is equal to *Math.ceil(timestamp/8)* which proves to produce the most pleasant visual effect according to our configuration tryouts.

## 5 EVALUATION

To evaluate the visual designs proposed in this work, we conducted a between-subject design study including two experiments. The first experiment aims at the effectiveness and efficiency, measured by accuracy of completing the analytical tasks using the proposed visual designs versus tabular presentations. The second experiment is to evaluate the overall usability of the visualization interface, including the rate of aesthetics, intuitiveness and learnability.

### 5.1 Evaluation on Visual Designs

In the first experiment, we compare the accuracy of conducting different analytical tasks using the proposed visual designs versus tabular presentations. The tasks are designed to simulate various application scenarios, including to locate the meal of analytical interest, to distinguish per-meal information and nutritional distribution, to conclude the accumulative food-mood profile. Our goal is to validate if visualizations are effective in presenting specific information correctly, intuitively and efficiently.

21 subjects aged between 18 and 40 participated in the first experiment online. Among them, 12 were male and 9 were female. Since our targeted users are not domain experts but rather regular APP users, we take population diversity into consideration during recruitment. The participants consist of residents from 3 countries (China, US, UK) and professionals from different disciplines (e.g. IT, Biology, Arts, Education, Medicine, Marketing etc.)

After a brief design description of the visual representations and layouts, our participants were asked to finish two rounds of tasks, each containing 5 exercise, regarding both per-meal and accumulative information. During the first round, participants got two static images of the visualization for reference, one per-meal representation (RoseViz) and one accumulative view (Timeline Layout of Molecules and Streamgraph). The second round consisted of the same tasks but participants were asked to refer to two tables containing the data at the same scale. The tasks includes: (1) Locate which day the meal of interest occurs, e.g. the First Joy Meal; (2) Locate the time during the day when the meal of interest occurs, e.g. breakfast, lunch or dinner; (3) Rank the nutrients in the order of calories dominance of one meal; (4) Figure out which mood seems dominant in the first 3 days; (5) Figure out which mood seems dominant during the whole 3 weeks.

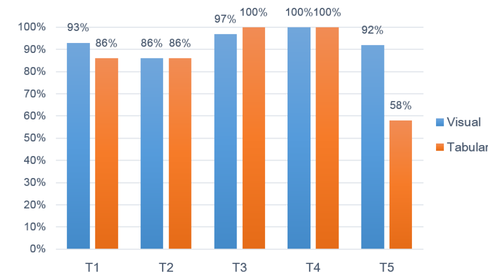


**Figure 8: The average accuracy of all participants in T1 - T5.**

Figure 8 shows the average accuracy of all participants completing T1 - T5 using our visual designs versus tabular presentations. The visual design and tabular presentations do not yield much difference in terms of completion accuracy on per-meal tasks (T1 - T3). But the graphs perform much more effective when it comes to three-week accumulation, generating a 0.82 - 0.58 accuracy gap higher than the tables. It is interesting to see the huge difference between T3 and T5. According to the accuracy results, the data table seems outperform the RoseViz when comparing calories dominance per nutrient within one meal, but turns out to work very weakly in presenting the dominance per mood during 3 weeks. Hence, we interviewed some of the for reasons:

"I feel more assured seeing numbers when doing quantitative comparison tasks, especially when the numbers are close."

"The graphs play a great role when data scale turns huge. I could count one by one for one meal or even three days. But I cannot handle the three-week task by counting. I love the River!"

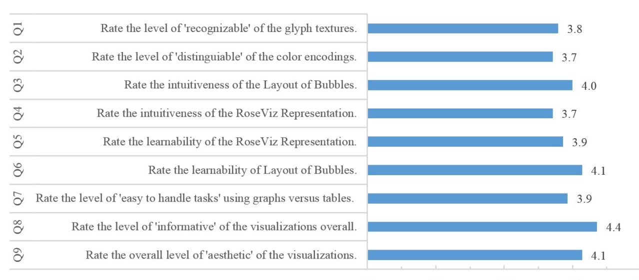


**Figure 9: Likert scale questions and results on the usability evaluation. The results ranges between 1 to 5 (negative to positive)**

### 5.2 Evaluation on Usability

On completing the tasks introduced above, the participants were asked to fill out a questionnaire regarding the usability of our visualizations. It consists of nine questions in a Likert scale raging

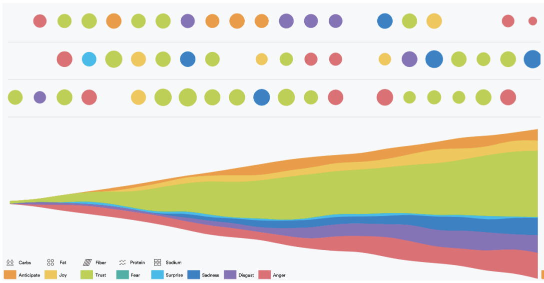

**Figure 10: Participants #5 with 55 records**

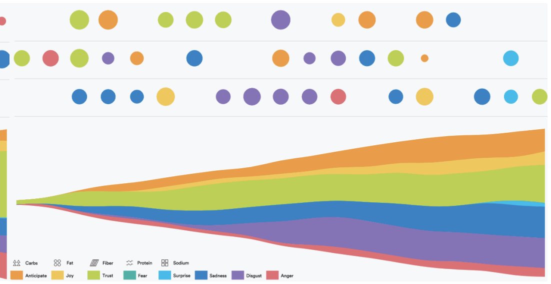

**Figure 11: Participants #7 with 37 records**

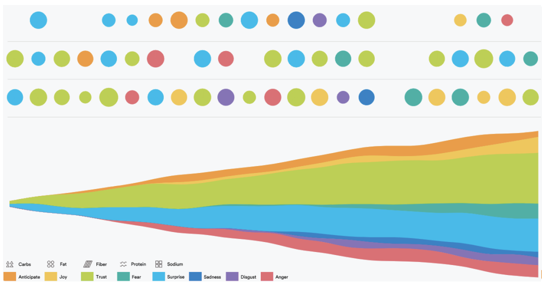

**Figure 12: Participants #11 with 57 records**

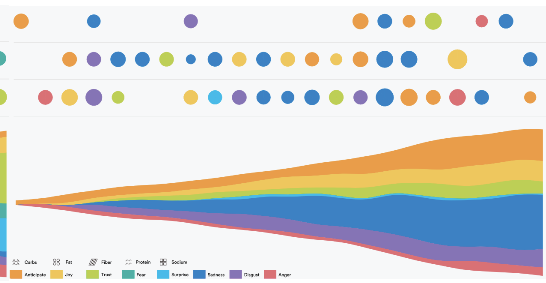

**Figure 13: Participants #13 with 44 records**

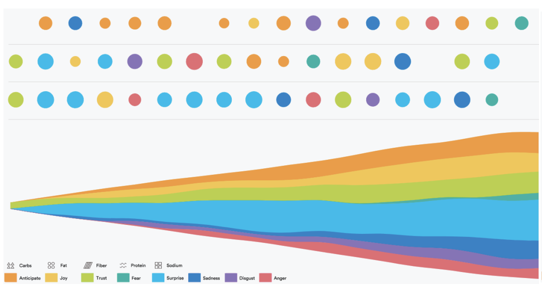

**Figure 14: Participants #19 with 49 records**

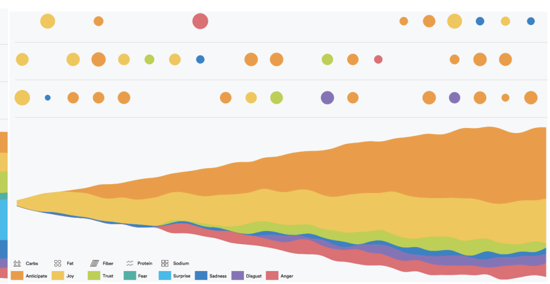

**Figure 15: Participants #20 with 38 records**

between 1 to 5, covering the following facets to be rated: perceived effectiveness, intuitiveness, ease of learning and aesthetics.

Figure 9 shows the results of nine questions regarding usability evaluation. Overall, the participants consider our visual designs informative, intuitive, aesthetic and easy to learn. Most of them validate that the visualizations are more effective in assisting the analytical tasks in the experiment rather than data tables. While according to interview feedback, users expect data to be shown when necessary to supplement the graphs.

## 5.3 Case Study

We carry out a case study to evaluate the effectiveness of the visualization design based on the 20 participants data. First, we present those data through the visualization design to observe the diversity among all the participants. Then we try to analysis the emotion variations and identify the food intake pattern through the representation. Here we present another six visualization results which present with more than 35 records. We will show how we analysis results along the aforementioned two aspects.

### 5.3.1 *Emotion Variations.*

Since we use color to encode the emotion information in our design, we trace the emotion variations based on the color distributions. Following this clue, we leverage the time-series emotion pattern to analysis intra-relationship along all the posted days, and use the overview to see the inter-relationship when compared between any two participants.

**Temporal variations.** We first observe the Timeline view of Molecules to dig into details of the emotion variation based on time. At the week-level, we can tell that some participants tend to have a negative emotion in previous two weeks (e.g., Participants #5, #7, and #11). As we mentioned earlier, the data are collected within three weeks which across a final exam week. This means all the participants were going to prepare their final exam during the first week and take the exam on a certain day during the second week. Then some of them get relieved at the third week (e.g., Participants #20), but the others become even worse due to the exam results were released (e.g., Participants #11 and #19). While for each meal, we found that participants who take breakfast tend to have more positive emotion in the morning, except there would be some pressure tasks need to deal with in the daytime. For example, as

Participant #11 reported in the logs, he usually had a cheerful morning breakfast on the campus. But if there would be an exam during the day, he would feel uncomfortable when taking breakfast.

**Accumulated emotion patterns.** From the overview of the Streamgraph, we can see that some participants tend to have more positive emotion (e.g., Participant #20) in daily life, while some others are pessimistic (e.g., Participant #13) and sensitive (e.g., Participant #5). Participants also reported that the waving effect of the emotion wave makes them feel relieved and soothed when they were watching the visualization.

*5.3.2 Food Intake.* As shown by the visualization results, some participants skip the breakfast quite often (e.g., Participant #13), while some participants take their every meal with a similar amount of calorie (e.g., Participant #11). We can tell that Participant #20 is on a diet, and this conclusion is verified by the participant's logging records. We can also tell some participants (e.g., Participant #19) take more food in supper, while others would like to have a big meal at noon (e.g., Participant #13).

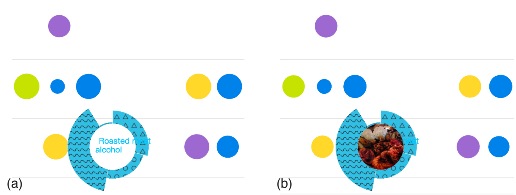


**Figure 16: The "surprise" item identified from the Participant #13.**

We also conduct the drill-down analysis from the timeline view. For example, after identifying there is a "surprise" event in Participant #13's final representation, we are curious about what did the participant take for that meal. After clicking on that event, we see that the participant took a high-protein meal with alcohol, which is quite unusual compared with the other meals (as shown in Figure 16). After checking with the logging records, we know that the participant attended a reunion party at that night.

Moreover, we try to find the relationship between the emotion variations and food intake. Some participants take more food when they get in a negative emotion (e.g., Participant #13), while some others take more when they feel positive (e.g., Participant #15). However, we did not find any evidence to support the correlation between these two factors. As from the collected data, we see participants consume the carbohydrates the most among all the emotion categories.

## 6 DISCUSSION

In this section, we present our findings and discuss future directions regarding enhancing engagement in mindful eating.

**Improving efficiency in quantitative analysis.** Following the evaluation tasks, we interviewed some users on the effectiveness of each visual design in its correspondent task. One interesting fact is that they all find the Streamgraph helpful and mindful, because it aggregates multi-dimensional data overtime and presents an accumulative perspective which is hardly perceived. They also mention that it is almost impossible to process similar information using tabular data, which lacks efficiency and intuitive influence. Another common feedback is on the RoseViz, our users agree that it outperforms the data table in qualitative analysis and it is easy to scale due to efficiency. But when conducting quantitative tasks, such as the ordering task in the evaluation, they felt numbers are more assured. Therefore, some users suggested putting numbers or ranks directly on the visualization so as to assist both qualitative and quantitative analysis. We take it as one potential improvement.

**Presenting accumulation to motivate long-term engagement.** Accumulation is difficult to process manually. For example, though people could easily remind what the food and mood were during a special meal recently, they seldom remind how much fish or how many joyful meals they have gone through in the recent week. According to our interviewed users, seeing one's accumulative profile is informative and inspiring, and it is one of the motivations to use the system. Moreover, people are usually motivated to vision themselves improved. Since the accumulative view presents an evolutional profile over time, it composes guidance for people to behave (e.g., adjust food choices or mood training) better and enhances long-term engagement.

**Making the user experience fun.** Some users praised the work after the evaluation as meaningful and full of fun. One participant commented, "I want to play more tasks!" The pleasant visual effects, lively animation, dynamic interaction, and variable shapes jointly contribute to making the user experience fun. Being fun is crucial in attracting beginner users and helpful in driving engagement among the population.

## 7 CONCLUSION AND FUTURE WORK

Nutrition intake and sentiment analysis have long been at the interest of researchers. As recent studies indicate that the correlation between nutrition and emotion exists, it becomes inspiring to study the topic from individual's perspective and to explore its potential application in personal guidance on mindful eating. Our work intends to leverage information visualization to build digital profiles on personal food logging data associated with the emotion records. We propose our solution of EmovDiary, a two-level representation for nutrition-emotion visualization and novel layouts to enable timeline storytelling that reveals the evolving patterns. The integrate solution is implemented as a web-based interface which enables users to explore, interact with and understand their food journey. We also utilize metaphorical designs, aesthetic animations and dynamic interactions to engage the users, aiming to enhance their long-term engagement so as to develop the habit of mindful eating. We evaluate our solution with experimental user studies and surveys, as well as real-world case studies among 20 participants. It is verified that our visualization is intuitive and effective, and the integrate interface is usable.

As for future work, efforts have been planned majorly in the following two directions. On one hand, we want to achieve automatic data processing, for example to apply machine-learning approaches to extract and transform nutritional information as well as emotion category. On the other hand, since research reveals that the influence of diet on human brain is not a standalone effect but integrated with actions of other lifestyle modalities, there is huge potential to work on combining multiple dimensions based on behavioral data collected from sensors or social network.

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