Data Representations for In-Situ Exploration of Health and Fitness Data

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ABSTRACT
Wearable devices that collect and generate masses of health related data, such as number of steps taken in a day and heart-rate have seen widespread adoption among general consumers. The wearers of such devices need to interpret the data being generated to ensure they meet their physical activity goals. Little is currently known about how users of such devices explore such data and the corresponding visual representations, ***in-situ***, i.e. during the course of their physical activity. Through a series of interview sessions with users of health and fitness data, i.e., quantified-selfers, we gained an understanding of how they benefit from in-situ data exploration. Our findings reveal the wide number of in-situ tasks, data types, and requirements for designing data representations that support immediate reflection on data being collected. We further solicited the aid of professional designers to sketch visual representations for carrying out the necessary in-situ tasks identified by our users. From these exploratory studies, we derive broader implications for the design of data representations supporting in-situ exploration.

Author Keywords
Wearable devices; health and fitness data; data visualization; in-situ exploration; quantified selfers.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): User-centered design; J.3. Life and medical sciences: Health.

INTRODUCTION
The growing number of consumers carrying wearable health and fitness trackers collect significant amounts of data about their activities. A survey of over 3,000 adults (in the US) revealed that 69% of this population track health and fitness related information such as exercise routine, or food consumption [23]. People often explore such data to gain insights on their daily activities and to reflect on ways to improve their health [2, 3, 4, 6, 14]. While users commonly inspect their tracked information once the activity is over (i.e., delayed exploration), we are witnessing a shift in health and fitness data exploration where users consume their data during the course of activity, i.e., ***in-situ***, to make decisions on-the-fly for immediate behavioral changes (Figure 1).

Figure 1. A runner checking heart rate information on her smartwatch to adjust her activity.

Prior studies have demonstrated the use of different visualization techniques designed for representing health and fitness information [4, 13, 20, 25]. However, very little is known as to how well such visualizations can be adapted for small screen wearable devices, such as smartwatches and smart bands and whether they can support quick glances and minimal exploration of the data, in-situ. We also lack knowledge on the level of reflection users undertake during activity. We consider this work as a first step toward understanding the requirements and considerations for designing data representations targeting in-situ data exploration of health and fitness data.

We start our exploration by conducting a series of interview sessions with quantified-selfers. Our findings from the interview sessions revealed different categories of questions people have and the types of tasks they consider in both delayed and in-situ exploration of data. We also categorized the types of data visualizations, interactions, and feedback used. We discovered that people's queries about the data change drastically during the physical activity. Furthermore, as an important requirement, the data visualizations designed for in-situ exploration, need to convey insights with minimal disruption of the physical activity.

Based on the requirements we gathered from the interview sessions, we administered design workshops to elicit opinions from designers on how to represent insights extracted from health and fitness data to support in-situ data exploration. Designers sketched a diverse set of alternative designs to effectively represent information on small devices and quickly communicate insights. We report on our findings from both exploratory studies highlighting considerations for designing data representations consumed in-situ.

Our contributions include: (i) a first exploration of users' needs and queries on tracked health and fitness data; (ii) evidence that users access health and fitness data in-situ, with patterns different from that of delayed exploration; (iii) and finally a set of data representation techniques and design considerations to facilitate information exploration in-situ.

RELATED WORK

In this section, we provide an overview of prior research around tracking health and fitness data as well as current techniques to visualize self-tracking data.

Tracking Health and Fitness Data

The rapid growth of wearable technology in recent years has enabled users to monitor their health and fitness related data. Researchers have explored users' intentions and motivations for collecting such data, which includes maximizing their work performance [4, 26], reflecting on lifestyle and health status [3, 4, 6, 14, 15], having positive reinforcement [5, 8], recording and exploring activity trends, competing with others [8]¸ and sometimes just out-of-curiosity [4, 26]. Researchers also revealed that people explore health and fitness information immediately after activities to gain a better understanding of their activities [8, 14], for short term comparative analysis [21], to get a complete picture of the day [5], to compare with their historical data and correlate with their activities [4] or to make decisions based on historical data [7]. Many also record such data for sharing their health and fitness information with peers, friends, family, and colleagues [19] or even to track the checked-in places for their later reflection [16]. Much of the findings above, however, relate to explorations post-activity. There lacks knowledge on how users may explore data in-situ, when the activity takes place.

Exploring data in-situ also fits within the five-stage model for personal informatics, proposed by Li et al [14]. In this model, the five interlinked stages for data usage include preparation (automated or manual), collection, integration, reflection, and action. Action and reflection can be more tightly coupled when the reflection takes place temporally close to the action. We explore this facet of personal informatics systems, in particular for health and fitness data, to understand current limitations and user needs for in-situ exploration, reflection and action.

Visualizing Self-Tracking Data

Practitioners, designers and researchers all acknowledge the need to adequately represent self-tracking data. Nick Feltron [9], a designer, has tracked personal data since 2005, and represented these using standard data visualization techniques. Similarly, Choe et al. [4] revealed that people commonly use popular data visualization techniques such as line and bar charts, and custom made visualizations for representing self-tracked data. Whooley et al. [26] found that quantified-selfers use binary, structured, and abstract representations to show logged data. Researchers have also developed novel and complex visualization techniques to present self-tracking data. Ng et al. [20] designed a custom visualization, pieTime, to represent aggregated timestamp data with scaled pie slices of varying radii. Vrotsou et al. [25] developed a tool that extracts users' activity patterns from data and represented the patterns in a time geographical manner with activity categories color coded. Begole et al. [2] designed a number of visualizations to represent temporal patterns of users' activities such as when they go for a walk or take breaks. In addition, a number of analogy- or storytelling-based representations have been proposed. For instance, Khovanskaya et al. [13] display information in an unconventional way by emphasizing other relationships with personal data (e.g., "In the time you spent on the web, Apollo 11 would have gone to the moon and back 1.729 times!"). Gemmell et al. [10] developed an authoring tool combining maps, images, video, animations and GPS traces to tell the story about a personal lifetime.

Prior studies demonstrate the use of different data visualizations for representing self-tracked data and don't focus on in-situ consumption of data.

Glanceable Visualizations

Displays that support in-situ data exploration should enable individuals to quickly glance at information with minimal interruption to their primary activity. UbiFit Garden [6] is one of the earliest works to support glanceable display of physical activity information via an ambient representation of activity levels on the background screen of a mobile phone. This non-literal, ambient representation, however, meant that users had to switch to an interactive application to acquire detailed information about their activities. Researchers have also explored different design properties of a *glanceable visualization*. Matthews et al. [18] present a taxonomy of visual variables and a set of design principles for using these variables to accomplish glanceable designs for peripheral displays. They also explored how to enable people monitor a secondary task while multitasking [17]. They revealed that renditions with high-symbolism improved glanceability of visual designs when they are unlearned, but simple renditions (e.g., icons) provide improved performance when learned. These studies are focused on glanceable visualizations for peripheral displays but come short when considering in-situ access to the data, and in particular for small sized displays, such as those of wearable devices. More importantly, for in-situ exploration, glaceability is one requirement, but having access to multiple views, representing the varying tasks, is a more critical need.

HEALTH AND FITNESS TRACKING TOOLS

Current mobile and wearable devices are equipped with powerful sensors, such as accelerometers, gyroscope, global positioning system and heart rate monitor that facilitate tracking health and fitness related activities. In recent years, a number of mobile and wearable applications have become a popular way to keep track of personal information. To get insight into current visualizations for tracked personal information, we surveyed 39 health and fitness applications[1] that are designed for both Android and iOS platforms.

Due to the limited display space, smartwatch applications were found to use fewer data visualization techniques than smartphone applications. The data representations include: *Text* (Figure 2a) – where text or number is used to represent summarized tracked information; *Donut chart* (Figure 2b) – that shows users current stands compared to a target/goal; *Bar chart* (Figure 2c) – where data is represented with horizontal or vertical rectangles; *Pictograph or Icon-based representation* (Figure 2d) – where pictorial symbols are used to represent information; and *Map* (Figure 2e) – where users' tracks are shown in geographic locations. In our informal review, we observed that rather than showing detailed information, these visualizations show summarized information such as total step count or calories burned.

In addition to the visualizations above, smartphone applications use *Line chart* (Figure 2f) –*Pie Chart* (Figure 2g) – similar to donut chart, *Table* (Figure 2h) – where are data are represented in tabular format and *Complex visualizations* (Figure 2i) – such as 2D area charts and multi-series line and bar charts which combine multiple data series. With the insight that mobile and smartwatch applications use popular data visualization techniques, we decided to focus on users' perception of using such visualizations in-situ. Furthermore, we investigate how to design data representations to facilitate in-situ exploration of health and fitness information as this has largely been unexplored.

INTERVEWS

In an attempt to gain insights on current needs for exploration of health and fitness data, we conducted a series of interviews with people who track and explore their health and fitness data on a regular basis. We were interested to investigate (1) whether people explore or wish to explore their data in-situ, (2) what issues and problems they currently face, (3) the types of questions they like to get answers for, and (4) what design requirements a solution targeting in-situ exploration of health and fitness data entails. We opted for having more than one person in each session to stimulate more dynamic and in-depth discussions among participants about the topics.

Figure 2.[2] Common visualization techniques on smartwatch and smartphone applications. a) Text. b) Donut chart. c) Bar chart. d) Pictograph. e) Map. f) Line chart. g) Pie chart. h) Table. i) Complex visualization (e.g., 2D Area chart).

Participants

We advertised the study in an online classified website[3] as well as on bulletin boards including the general campus billboards at a local university. People interested in the study were asked to complete a short pre-questionnaire about the type of data they collect, duration and activity for which they track and explore their data, and devices used. Based on the answers to the pre-questionnaire, we invited participants who already had extensive experience (i.e., at least six months) with tracking tools and applications and had enough time to possibly reflect on issues surrounding in-situ exploration of their health and activity data. We recruited 10 participants (2 females and 8 males) for the interview sessions. They received a $30 compensation for participating in the study.

Study Material

To ground the discussions, we asked our participants to bring any devices, software apps they are currently using or have used in the past to track their physical activities. Additionally, we encouraged them to bring logged data as well as sample screenshots that they have collected while exploring their activities. We opted to conduct structured interviews. The interview script contained a list of various questions targeted at understanding current practices among health and fitness loggers for collecting and reflecting on data related to their physical activities. Furthermore, we included questions to investigate the potential requirements for designing suitable representations to be used in-situ during the activity. We ended up with 15 questions under six major categories: goals and motivation, activity and data types, tasks and insights, presentation and feedback, and reflection and action. All study material including the interview script and question guide we used for the interviews can be found at out accompanying website[4].

[1] 7 Minute Workout, ASUS ZenWatch Wellness, Blood Glucose Tracker, Calorie counter, CARROT Fit, Diabetes:M, digifit, Exercise Tracker: Wear Fitness, Fitbit, FitStar Yoga, Google Fit, Health Tracker Pro, Heart Rate - Sport Gear + Wear, Heart Rate Plus, Hello Heart, Human: Activity tracker, Lifesum, LIVESTRONG.COM Calorie Tracker, Map My Run, Map My Run +, MediSafe Meds & Pill Reminder, Mi Fit, Misfit Minute, Running and Cycling, Under Armour Record, UP by Jawbone, Workout for Android Wear, etc.

[2] Screenshot images are obtained from online sources.

[3] http://www.kijiji.ca

[4] http://hci.cs.umanitoba.ca/publications/details/in-situ-vis

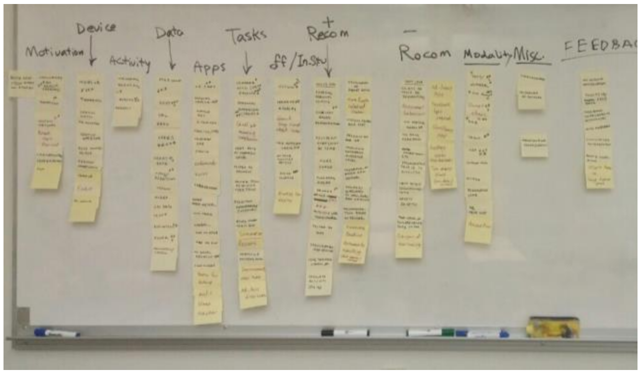

Figure 3. Common themes starting to emerge during the analysis of the interview sessions.

Procedure

We coordinated four separate group interview sessions with two or three people in each session. Each session took roughly between 1.5 to two hours (including a five-minute break time at the one-hour mark). Two researchers were present in each session: a moderator and a note taker. The participants were greeted and asked to read and sign the informed consent form. Each participant also filled out a short demographics questionnaire. After the introduction and general information about the session, the moderator posed each question specified in the question guide and led the discussion by encouraging all participants to respond to the open-ended questions when ready. All sessions were video and audio recorded upon participant consent.

Analysis and Findings

We analyzed notes and transcripts of the session videos using affinity diagraming. Two researchers separately recorded each idea and point made by the participants on post-it notes. The two researchers then came together and looked for related ideas, sorting the notes into groups until all cards were used. Figure 3 shows a snapshot this process. We summarize our findings under the following categories:

Goals and Motivations

Not all our participants had preset goals for tracking and exploring their health and fitness data. In some cases, wearers of health and fitness trackers are interested in learning about their performance to further investigate whether they are dealing with any problems (e.g., not getting enough exercise; P4, P9). On the other hand, people may already have realized a problem motivating them to start collecting data as a way for finding clues to a possible solution. For instance, P6 was not losing any weight despite exercising four times a week so he started tracking his heart rate data to investigate if he can maximize fat burning.

It was also interesting to observe that the common goals and motivating reasons for people to start tracking their physical activities are different from why they continue to do so. Align with prior research claims [3, 4, 5, 6, 8], participants mentioned achieving health and fitness goals (e.g., losing weight and building muscle), becoming active and improving their health, curiosity to try new technology, and influence of family and friends, as the main reasons for starting to track their health and fitness data. However, we identified other reasons as to why one would continue using tools to track their data. Among all, the desire to make new records and push limits was the most occurring answer. Other reasons include social media (P3, P6), fun (P1, P4), and contributing to other causes through donations by the app used (P7). What motivated our participants to explore their health and fitness data in-situ was mainly to **maximize the benefits obtained from the physical activity** to more quickly achieve the above goals, e.g., P6 checking his heart rate to stay in the *fat burning zone* and P4 checking pace information to adjust intensity for the remainder of activity.

Activity and Data Types

In the pre-questionnaire, we asked participants to list the activities for which they collect health and fitness data. The aggregated list includes walking, judging, running, sleeping, cycling (indoors & outdoors), workouts (weightlifting, aerobics), and playing sports (basketball, soccer, skiing). In the interview session, we further asked participants to distinguish between the activities based on whether or not they explore the collected data in-situ or not. In addition to sleeping (eliminated for obvious reasons), the sub-list of **activities deemed suitable for in-situ exploration** of data does not include fast paced activities such as skiing. Two participants (P9, P10) mentioned that, it is even difficult for them to take a glance at their devices during jogging or running. Activities requiring a person's attention were also not deemed suitable for in-situ exploration. This includes group sports as well as activities taking place on roads (e.g., outdoors cycling) due to the fact that people engaged in the activity needed to attend to their surroundings.

Our analysis also revealed five major data types being collected and processed in-situ: step count, distance, calories, pace & speed, and heart rate. Other data types were also collected but mostly processed at a later time after the activity was over (e.g., weight, power and sleep patterns). Despite being interested in tracking a primary data type, most participants (8 out of 10) track more than one type of health and fitness data. With the exception of step count, which in two cases (P3, P9) was the only data collected, participants emphasized the importance of having a **combination of data types** to be able to fully reflect on the performance. For example, P4 and P5 (both professional cyclists) track their heart rate, speed, distance travelled, and position together with time duration and power. To do so, they require the use of **multiple devices** (i.e., Mounted device on their bikes and wearable heart rate strap, as well as a smartwatch[5]). The insight extracted from the combination of the different data types helps them adjust the intensity of their activity.

[5] https://explore.garmin.com/en-US/edge/

Although, current devices, apps, and solutions allow collection and tracking of several health and fitness related data types, participants mentioned the need to **collect more data types** without having to "*input the info manually*" (P6). For example, P6's goal is to build more muscle and he is able to track his weightlifting steps accurately using the built-in accelerometer in his smartwatch; however, he would like to also know how much he is lifting and for how long, to be able to achieve maximum benefits toward his goal. P6 has to input this information manually using a separate app installed on his phone, which has proven to be difficult mostly because he has to pause his workouts frequently.

Tasks and Insights

The types of in-situ tasks people perform to reflect upon their health and fitness data is directly dependent on the kinds of insights they like to extract from the data. Our analysis of the sessions revealed several insights people are interested in when they consider in-situ data exploration. Perhaps the most common form of insight extracted from such data is the **level of performance** related to the physical activities based on both simple and compound values generated by the trackers. For instance, our interviewees collecting step count or heart rate are able to gather information about the number of steps at any point in time during their activities. Sometimes, multiple values may be needed to provide insights regarding the level of performance (e.g., activity duration, distance travelled, and the compound pace value make up performance level insight for a runner). It is worth noting that without prior knowledge about what the performance values mean, they may not be considered insightful. Therefore, continuous tracking of the physical activity over a period of time may be necessary to determine a baseline and understand the possible fluctuations of the data in comparison with the normal/expected values. We observed that despite its simplicity, this type of insight is interesting to all our participants and they all extract such insights in-situ or in their delayed explorations of the data.

As opposed to the insights extracted directly from performance values, a slightly more complex form of insight is constructed based on comparing the level of performance with goals previously set by people tracking their physical activities. Through the interview sessions, it was revealed that this type of insight is common for in-situ exploration and serves as way of keeping people aware of the **distance to the goal**. As an example P8 has heard about the health benefits of taking 10 thousand steps a day so at any point during his daily activities, he is interested in knowing how many more steps he needs to take to reach his daily goal. Similarly, participants also highlighted the need to find out about **distance from limitation or best performance**. Both P5 and P9 emphasized on the fact that they would like to avoid getting over exhausted. This can be provided by calculating the Rate of Perceived Exertion (RPE) to indicate the intensity of the activity and comparing it to the historical data from the tracker. By accessing the performance history, we can also get more insights about current performance by comparing it with previous records and best performances. Although, it is common to extract this kind of insight through delayed exploration, our participants pointed out how in-situ access to such insight can be instrumental in pushing limits and achieving the maximum level of performance.

In addition to comparing data values within one's performance history, it is also insightful to **compare performance between several people** tracking the same data. With the ever growing popularity of social media, health and fitness apps have now incorporated ways for the users to share their data with others in their social network. Five of our participants actively share their performance with friends post-physical activity (e.g., P4 and P5 use the live tracking feature provided by Strava[6]). They also all agreed that insights based on such data provided during the physical activity can help with on-the-fly decisions to take the most advantage of their workout.

Presentation and Feedback

We asked participants about the types of data representations they have seen and interpreted in the past for exploring health and fitness data. We also asked them to provide reasons as to why they liked or disliked a particular data representation. Participants identified techniques they preferred when it comes to the presentation of the tracking data collected as described below:

- **Simple text and numbers** are often used to represent insights directly derived from single and multiple performance values. Our participants also mentioned using these form of presentations, which contributes to the simplicity and popularity of this representation.
- **Standard charts** such as bar and line charts are common data visualizations used to represent historical data and trends. Maps are another example of standard data visualizations and are used for visualizing GPS data. These types of representations have become common in many statistical tools and apps, and all of our participants were comfortable reading and interpreting them. Standard data visualizations receive high scores for visual literacy [24], but their designs need to be tailored for in-situ use cases in which deep data exploration is not possible. For example, participants suggested adding **indicators and annotations** to the data visualizations in order to draw immediate attention to different parts of the chart and to highlight novel insights.
- **Icons and symbols** are used in representations of health and fitness data to visually convey the type of data. Current solutions mostly use icons as embellishments accompanying value numbers and standard charts. Other possible uses of icons would be to represent units of data

[6] https://www.strava.com/

in pictographs [1, 11]. We received mixed opinions regarding the use of icons: while six participants said they would like to see more icons and symbols incorporated in the data representations, others mentioned they might be "*too distracting*" (P4, P7) especially for in-situ exploration of the data. Therefore, a careful design of data representations for this purpose needs to strike a balance between compelling and distracting uses of icons.

Other types of feedback suitable for in-situ scenarios in which people are engaged with activities requiring their full attention are the use of voice and sound alerts as well as device vibrations (e.g., to notify about milestones reached).

Reflection and Action

Our participants indicated that ultimately, the reason they are interested in exploring their physical activity in-situ is to reflect upon the data being collected on-the-fly and possibly take immediate action to help achieve their health and fitness goals. Examples of behavioral changes mentioned by our participants included, adjusting the pace of their activity (P2, P4, P5, P7, P10) and switching the activity type (P1, P6), and changing the planned route (P4, P5).

Challenges and Limitations

Participants also indicated limitations and issues in regards to current solutions they use for in-situ exploration. The **lack of correlations with other related data types** was a common issue brought up by the participants. As a result, people question whether the insights being communicated have validity. For example, simply showing a cyclist's speed without considering the data about climate or route status does not give the user a clear information on the intensity level of the activity (P6). This is because having a lower speed in poor weather or road conditions, for instance, may very well require equal or higher level of effort compared to a perfect weather and road conditions. Hence, taking into account other related data as well as uncertainty in the target data being tracked becomes an important issue.

Privacy was observed as being a common reason why our participants would disable some of the features on their tracking devices. For instance, when a person starts tracking their run from their home, if shared with others, eventually it is possible to identify the start and finish points of the run as the *home* location of the individual tracking their runs. Several other privacy issues exist in current tools and very few measures are taken to address them. Hilts et al. [12] report on these issues in their comprehensive analysis of fitness tracker privacy and security.

DESIGNING FOR IN-SITU DATA EXPLORATION

Through the interview sessions, we identified a set of requirements for designing data representations supporting the types of tasks and data types explored in-situ. To explore potential data representations satisfying the above requirements, through a series of design workshops, we asked 9 graphic designers (5 males and 4 females) to sketch possible design ideas for in-situ data exploration scenarios. All participants were professionals with experience in information visualization. Participants received $30 cash and a $15 gift card as compensation for their participation.

As listed in Figure 5, we targeted six types of insights people are interested in reflecting upon during their physical activities. For example, for the task of "extracting step count thus far", we framed the insight around the step count value as "You have taken 8,324 steps." We categorize the insights based on the type and number of value(s) included, which gave us six query types: (1) Single Value, (2) Multiple Values, (3) Goal-Based, (4) Comparison (Single), (5) Comparison (Multiple), and (6) Motivational. We explored potential visual representations for each of these categories for a smartwatch with a square display. We targeted self-contained visual designs with no audio or haptic feedback.

Our design sessions lasted two hours with a five-minute break halfway in the session. We explained to the participants, the main limitations for in-situ exploration scenarios as: (1) a short exploration time of less than 5 seconds and (2) a small display size (about 1.5 Inch IPS). We continued by showing several examples of data representations from current smartwatch apps. After the introduction, participants were handed colored pens, pencils, and markers as well as design sheets. On the design sheets we included the text for the target insight to be conveyed and placeholders (Figure 4) representing the display size of a typical smartwatch with the addition of some space to account for the lower pen resolution. For each insight, the experimenter started a 10 minute timer and asked participants to generate as many sketches as possible focusing on: (i) conveying the insight to the user of the smartwatch for in-situ exploration; (ii) selecting data representations that fit the data and insight best. Participants were encouraged to talk out load and had access to extra design sheets. The researcher took notes and at the end, asked participants to describe their designs and rank them based on how well the designs fit the initial requirements.

Figure 4. Designer sketching ideas for in-situ exploration of different activity related information.

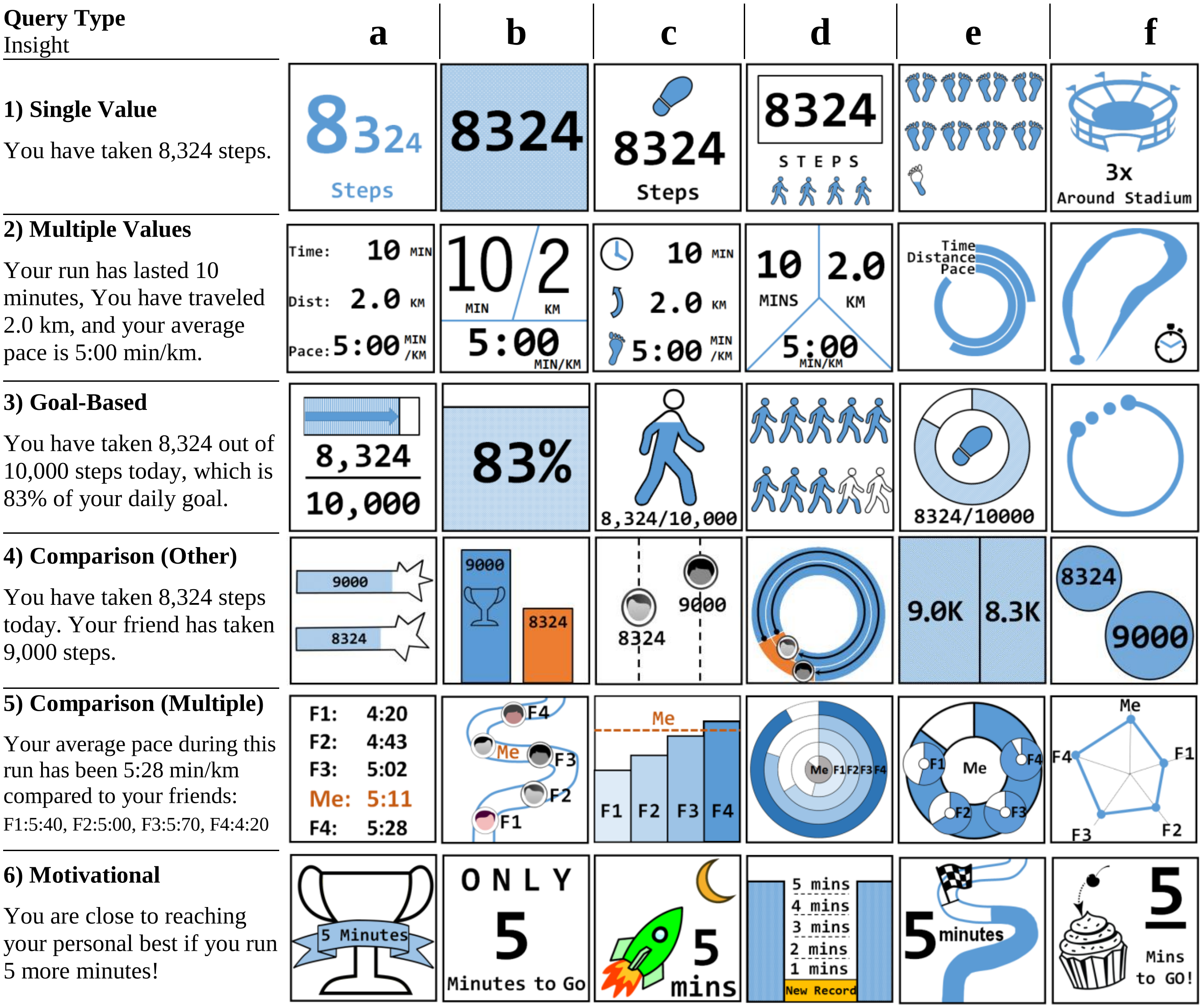

Figure 5. Example design sketches collected from designers for the six types of queries and insights.

Lessons Learned

We collected a total of 170 sketches. Two researchers independently coded 10% of the design sketches and refined the coding scheme until they had reached agreement on their codes (i.e., tags and categories to characterize the designs). Both researchers completed the coding on the remaining sketches. In what follows, we summarize the resulting design themes based on the proposed designs for each insight.

Single Value

28 design sketches were obtained for the *single value* query (Figure 5-1) and four major design themes emerged:

Text and numbers: We were not surprised to observe that the majority of the designs (11 sketches), relied on text and numbers following the principles of typography to represent the single value insight. Most of the sketches included short text as labels for the numerical value included in the insight (i.e., number of steps) but designers also sketched cases where they deemed it "*unnecessary*" to include a label. Participants proposed ideas to enable quick extraction of information (e.g., in Figure 5-1-a, the main digit of the number is shown in a bigger font size). Moreover, the idea of adding visual effects to mark different milestones was also proposed (Figure 5-1-b: background is turned blue after 5k).

Data-driven visualizations: We found only 5 sketches using some form of data-driven visualization. Pictographs (Figure 5-1-e) were the most common in which for each 1000 step counts, a set of foot print icons were added to the screen coloring the icon gradually as step count goes up. Overall, designers did not rank the use of data-driven visualizations highly appropriate for the single value query.

Icons and images as embellishments: Several designs (9 sketches) incorporated icons and images as embellishments and a way of quickly conveying the data type being represented. For instance, designers included a walking person silhouette or a foot print icon to show that the data related to walking (Figure 5-1-c, d).

Metaphors: We also collected sketches using some form of metaphor or analogy to make the value in the insight "*relatable*" (P6). Participants argued such analogy could be helpful especially when people first start tracking data to get a sense of what the values mean. Figure 5-1-f shows relating step count value to the number of laps around a stadium.

Multiple Values

The subset of designs generated for the *multiple values* query (Figure 5-2) included 23 sketches. The insight includes three different simple and compound values to communicate insights about *pace* in a physical activity.

Partitioning space based on different layouts: The added pieces of information posed an extra challenge for our designers to find ways to organize the information. More than half of the designs (14 sketches) included strategies for partitioning the space. Different layouts and orderings were proposed to display the three numerical values, their corresponding label, and data unit to satisfy the glanceability requirement. Most designs, listed the values vertically (Figure 5-2-a) but we found variations in size, and angle of the partitions (Figure 5-2-d) to make the design "*cleaner*" (P4), highlight importance, or imply some kind of order. For example, the design in Figure 5-2-b shows the two simple values grouped at the larger partition on the top and the compound value underneath in a smaller partition.

Icons as labels: As an alternative to text, some designers (3 sketches) replaced labels with icons (Figure 5-2-c). One participant (P8) explained: "*icons can tell the same information quicker while taking up less space*".

Scarcity of data-driven visualizations: Participants struggled with designing data-driven visualizations to accurately depict this insight. Only 4 sketches contained data-driven visualizations (e.g., Figure 5-2-e, f), 2 of which were not valid representations and none were ranked high by the designers. Participants attributed the different data types to the scarcity of simple data-driven visualization options.

Goal-Based

Through the interviews, we had identified that Goal-oriented motivations are among the top reasons for tracking health and fitness data. Therefore, we included this query (Figure 5-3) to explore design options for the presentation of smartwatch wearers' performance level relative to their preset goal. We collected 27 sketches for this query.

Inappropriateness of textual representations: From the analysis of sketches in this category, it was evident that designers preferred simple data-driven visualizations such as the one in Figure 5-3-a over representations including only text and numbers (less than 15% of the sketches). However, participants suggested displaying short encouraging messages once the user gets close to reaching the preset goal.

Donut charts: Pie charts and donut charts (i.e., pie chart with an area of the center cut out) have been a popular data visualization choice for communicating insights to a wide audience [22]. This is especially true when encoding single series of data for the estimation of the proportion of part to whole. Our participants used donut charts to visualize the proportion of the level of performance towards the goal (i.e., number of steps to the daily goal of 10k steps). Figure 5-3 shows two examples of data representations using donut chart. The designs are made more appealing by the smart use of the available real state in the middle of the chart to place a related icon (Figure 5-3-e) or dots turning into a solid line as progress is made (Figure 5-3-f). Designs including donut charts also ranked high by the designers for their simplicity.

Alternative designs for proportion estimation: While donut charts are a popular data visualization for proportion estimation, we were positively surprised to see many creative designs (60% of the sketches) following the same concept: partially filling the space on the screen (Figure 5-3-b), partially filling a single bar (e.g., Figure 5-3-a), or partially filling an icon (Figure 5-3-c). *Space filling* designs were ranked high by the designers for their efficient use of the whole screen. Furthermore, participants suggested the use of animation (e.g., gradually filling space) to make the designs more compelling, However, they emphasized that if used, the animations should be kept short (P9) and applied to few instances of the exploration (e.g., upon reaching a threshold).

Comparison

As seen in Figure 5-4 and 5-5, we had two insights focused on the comparison of activity performance between people sharing their data. We decided on separating the insights based on single versus multiple comparison values to see if the proposed designs would diverge. We collected 59 sketches for these queries (31 and 28 sketches respectively).

Highlighting the performance differences: The majority of designs (34 sketches across both queries), took advantage of simple data-driven visualizations such as bar, donut, bubble, and radar charts (Figures 5-5-b, c, d, f) to show differences between performance levels. In fact, several of the designs for the multiple comparison values, were just an extension of the design for the single value query. For example, design concepts in figure 5-4-b and 5-5-b were used for both queries (i.e., a bubble chart with profile image of people positioned on parallel vertical lines or abstract route map). Moreover, it was important for our designers to clearly highlight the performance level of the person exploring the data. To this aim, designers used different strategies such as the use of a popping color (Figure 5-5-a), adding annotations such as reference line in a bar chart (Figure 5-5-c), and using position and size to distinguish the target person's performance value (e.g., Figures 5-5-d, k, I).

Gamification: Several designers considered such comparisons as competition between people sharing their data. For example, there were several sketches based on a typical scoreboard concept (e.g., figure 5-5-g) in which people's performance values are treated as scores. As another example, the design in Figure 5-4-e is inspired by the idea of the *tug-of-war* game where the space partition for person with better performance *pushes* the line to the other side. The idea of gamifying data representations supports our design requirement of maintaining motivation among users.

Motivational

The last insight listed in Figure 5-6 generated the most number of design ideas (33 sketches) is about motivating and encouraging people to maintain high levels of performance or push limits and make new records.

Iconic and animated representations: The pattern of using icons was followed and more apparent for this query: 61% of the designs included icons, or images as seen in Figure 5-6. In addition, while designers mostly avoided and argued against the use of animation for in-situ communication of insights throughout the session, we found several designs (9 sketches) promoting animation and visual effects to "*build suspense*" (P5) and "*make a big deal about the user's accomplishment* (P9)". The main reason given by the designers was the one-off nature of the insight and the fact that the animation is only played once the user passes a threshold. Examples include countdown to breaking record followed by a drastic visual effect to reward the accomplishment: flashing background (Figure 5-6-d), shooting a rocket ship to space (Figure 5-6-c), and putting a cupcake together (Figure 5-6-f).

DISCUSSION & FUTURE WORK

For our interview sessions, we decided to only interview people who used tracking tools extensively to help ensure that participants had enough experience with the tools to reflect on issues surrounding in-situ exploration of data. Even among this experienced set of participants, four indicated that they had not been able to explore their data during the course of their activities, or in-situ. This was not, however, due to the lack of interest but as a result of shortcomings in current tools. Designing solutions targeting in-situ exploration of data requires first understanding the types of questions users are seeking to ask about their physical activities. The insights people are interested in range from simple updates on their performance to comparisons of their performance with their preset goals or peers. Designs focusing on such in-situ scenarios, need to convey the data-driven insights quickly through simple representations while keeping the user motivated to move towards their goals, to discover new goals, to push their limits, and continue improving their health and fitness status.

Based on our exploratory studies (i.e., interview and design workshop sessions), we highlighted design considerations fulfilling the requirements for designing data representations to support in-situ data exploration on small smartwatch displays. Professional designers preferred *'clean' designs with minimal use of text* to allow extracting insights quickly. They achieved this by maximizing the use of the available space (i.e., *space filling* designs), removing or *replacing labels with icons* and taking advantage of *simple data-drive visualizations* familiar to users such as maps and standard charts (e.g., bar, donut, and bubble charts). Furthermore, designers employed strategies to quickly guide user attention to important pieces of information.

It was also interesting to learn about approaches taken by the designers to maintain motivation, reward accomplishments and encourage users to get to the final goal or set new records. This was done by the use of *metaphors* to communicate data insights through concepts more familiar to the users, careful incorporation of *animations*, and *gamification* to promote healthy competition.

We expect the list of design considerations to be expanded when other factors are introduced. For example, one can characterize designs based on the type of triggers, level of interactivity, and color vs. greyscale visualizations.

Future work could explore design options targeting a large number of data points. Examples include, comparing performance with 6 or more friends, and visualizing historical data. We did not include insights showing performance trends since visualization of such data trends is a complex task even for standard size displays and it usually requires interactivity to allow filtering of data.

Other possible extensions of our work would be implementing the top-rated designs proposed by our 'experts' to evaluate their effectiveness in conveying the target insights. Longitudinal studies can explore whether users can successfully explore their data in-situ and if such exploration has any impact on users' performance, overall health and fitness status.

CONCLUSION

In this paper, we offer a first look at how consumers explore health and fitness data, *in-situ*. Through a two-part exploration, we identify the core tasks and queries users adopt during their fitness activities. From the first study, we observe that users demand and expect more from current consumer level devices. In particular, users have varying forms of queries, all of which can generally be handled with little to no extension in the data being generated. Using this information, we asked designers to offer visual representations that can aid in understanding and exploring such data. With emphasis on the glanceability, designers converge to a fix number of key visual representations that support such visual queries. Based on these, we provide general implications that can aid in the design and implementation of visual support for complex tasks used for health and fitness tracking in-situ.

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