A Survey on Sleep Visualizations for Fitness Trackers

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Abstract

We contribute the results of an exploratory study and a survey on visualizations for fitness trackers. Fitness trackers are becoming ubiquitous trackers of personal data. They often come with small attached displays that show micro visualizations of data such as heart rate, step counts, sleep duration, or number of floors climbed. Unfortunately, little is known about how wearers of fitness trackers use and perceive these micro visualizations. To collect data on the use of fitness visualizations, we conducted ten personal interviews with regular wearers of fitness trackers. Inspired by frequent responses regarding sleep tracking, we deployed an online questionnaire specifically on sleep visualizations for fitness trackers. Our results show that most participants were interested particularly in seeing previous night's sleep data on their fitness trackers and preferred visualizations that were easy to read like the hypnogram and bar as well as donut charts for sleep phases and duration.

CCS Concepts

• ***Human-centered computing*** → *Empirical studies in visualization; Visualization design and evaluation methods;*

1. Introduction and Related Work

In 2018, 111 million fitness trackers (smartwatches, wristbands and sports watches) were sold worldwide and sales are expected to double by 2022 [Gar18]. Most fitness trackers show micro visualizations representing tracked data such as heart rate, step count, sleep duration, or number of floors climbed. The challenges with fitness tracker visualizations are the small screens and the public nature of the interfaces [GPK*16]. A recent study on smartwatch visualizations [BBB*19] found that bar and donut charts allow quicker data comparisons than radial bar charts. However, there is still a lack of general advice on how to design visualizations for fitness trackers.

Our work takes inspiration from previous research that studied visual data exploration of fitness data on larger form factors, like desktops and smartphones. A study on self reflection [CLZ*17] identified two exploration patterns. First, visual cues, like peaks or extremes, prompt wearers to recall their past behaviors. Second, wearers recall their past behaviors to come up with a question and explore their data. These two patterns include tasks like recalling detail, looking for detail, comparison of time segmented values, identifying trends, making value judgments, finding a distribution, correlation, outlier, or summary, and making a prediction [CLZ*17]. The tasks that wearers perform depend on the design of the visualization and choices in visual variables (e. g. position, color), mapping variables (e. g. extremes, averages) and computational variables (how aggregate data was computed) [ACG14]. A crowd sourcing study [BLIC19] on a mobile phone compared two layouts (linear and radial) representing sleep and temperature data. The authors found that linear layouts allow quicker value reading, value comparison, and range comparison compared to radial charts. Chen [Che17] proposed a smartwatch visualization design for large time series which supports finding specific time-dependent patterns and trends. In contrast to this past work, we contribute the results from two studies specifically about the use of visualizations on fitness trackers.

2. Interviews and Card Sorting

To gain first insights into the space of visualization use on fitness trackers, we conducted an exploratory study consisting of personal interviews and a card sorting exercise, which shed light on the priorities of the wearers when they look at fitness visualizations.

Procedure. We conducted ten interviews with regular wearers of fitness trackers recruited via email in our institution. Each interview, on average, lasted around 30 mins. We asked participants details about their fitness tracker, which visualizations they remembered, and how their use of the associated phone or web app differed from their use of the fitness tracker. For the card sorting exercise [WR88], we gave participants 33 different smartwatch-sized data visualization cards (see OSF). We asked participants to organize these cards into self-defined groups without using visualization type or data type as a criterion. One author transcribed all interviews, categorized the answers to our questions, generated a similarity matrix and a hierarchical clustering dendrogram from the card sorting groups.

Results. The most common data that participants mentioned checking on their fitness tracker included step count (10/10 ×), distance (7/10 ×), and heart rate (4/10 ×). On the associated phone or web

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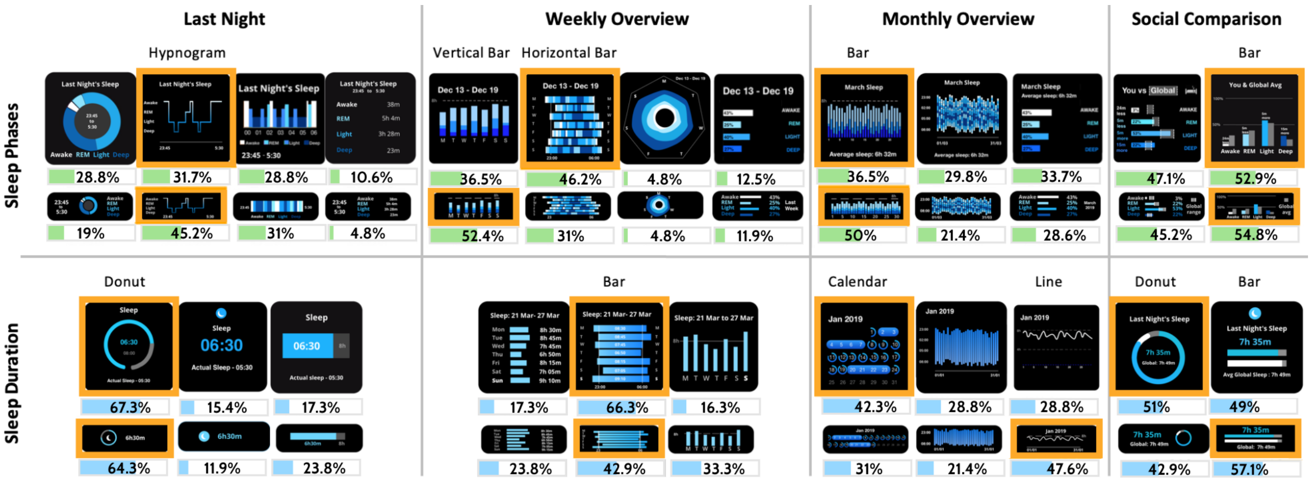

Figure 1: *Sleep visualizations that respondents chose for different time granularities and social comparison — based on the form factor of their fitness tracker (smartwatch vs. wristband). Orange borders highlight the most preferred designs.*

app, they reported to check the previous night's sleep (8/10 ×) and longer-term data (6/10 ×) more generally. A common comment (4/10 ×) was that participants wished to see sleep data directly on the fitness tracker but it was often not available.

The most common criterion (6/10 ×) used during the card sorting was the temporal context, in which participants usually checked these visualizations (e. g. daily morning, daily evening). This was reflected in the clustering, in which four cards with different details of previous night's sleep like duration, sleep phases, sleep quality, and heart rate were frequently clustered together, whereas weekly and monthly sleep cards that people had reported to read from the app were in other clusters. From this first exploratory study, we saw interest in exploring detailed sleep data on fitness trackers which was correctly not possible on people's fitness trackers. Therefore, we decided to concentrate our next questionnaire in this area.

3. Questionnaire on Sleep Tracking Visualizations

To learn more about visualization use and preferences for sleep data, we designed and deployed an online questionnaire.

Questionnaire Design & Procedure. Our questionnaire included questions about fitness tracker details, tracking behavior, and preferences for seeing sleep data. We recruited participants via Facebook, Twitter, Reddit, and personal emails. We deployed the questionnaire using Google Forms (see OSF).

Results. We recorded 146 valid responses. 84% of the respondents wore their fitness tracker while sleeping every night. Most participants checked their sleep data only from the phone app (89.7%), while 1.4% checked only their fitness tracker, and 8.9% checked both devices. The common times to check sleep data were during the day when the wearer is free (42%) and mornings after waking up (33%). The majority (75%) of respondents reported to pay attention to both text and visualizations when checking sleep data.

Table 1 shows responses about which type of sleep data participants would like to see on their fitness tracker. The relative frequency

Table 1: *Sleep data that respondents would like to see on the tracker*

	Last Night	Weekly Overview	Monthly Overview	Social Comparison	Not Interested
Phases	119 (82%)	65 (45%)	46 (32%)	12 (8%)	14 (10%)
Duration	131 (90%)	75 (51%)	53 (36%)	15 (10%)	6 (4%)
Schedule	95 (63%)	69 (47%)	50 (34%)	12 (8%)	28 (19%)
Quality	120 (82%)	72 (49%)	51 (35%)	17 (12%)	12 (8%)
Metadata	124 (85%)	63 (43%)	46 (32%)	16 (11%)	15 (10%)

of responses for all types of sleep data were from highest to lowest: data on previous night > weekly overview > monthly overview > social comparison. Respondents were most interested to see sleep duration and least interested in schedule. In the questionnaire, we also asked participants to choose their preferred visualization for a range of data types based on their fitness tracker's layout. Figure 1 highlights in orange the most preferred designs per sleep data and fitness tracker layout. In general, participants preferred visualizations like the hypnogram [SCBRP08], bar and donut charts that were easy to read and had the right balance of information and graphic density.

4. Discussion

From the interviews, we learned that looking at detailed sleep data on their fitness trackers is of interest to people. Yet, the questionnaire showed that a large percentage wanted to see mostly last night's and weekly sleep data. Interestingly, we found that respondents showed no clear preference for one type of chart but preferred charts based on data type and granularity. Five out of 8 times, the most preferred designs were the same for both the smartwatch and wristband form factors. In the future, we plan to conduct an experiment to compare various sleep visualizations to identify the ones with the best performance and compare these to people's expressed preferences.

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