Heart Rate Visualizations on a Virtual Smartwatch to Monitor Physical Activity Intensity

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Abstract: We investigate three visualizations showing heart rate (HR) and HR zones (HRZ) data collected over time and displayed on a virtual smartwatch, to monitor physical activity intensity. To understand exercise behavior, we first conducted a survey with 57 participants and found that most of them track their activities (66%) using wrist wearable devices (i. e., smartwatches or fitness bands) and that during the course of the exercise data is primarily represented as text or a combination of text and icon. To support reaching a specific fitness goal, we designed a bar chart visualization combining both current and historical HR and HRZ data. Among the three visualizations, two present an additional chart (i. e., a horizontal and radial bar chart summary), showing the amount of time spent per HRZ (i. e., low, moderate, and high intensity). In a controlled study performed in virtual reality, we compared participants' performance with each visualization asking participants to make a quick and accurate decision while exercising (i. e., playing a tennis-like game). Results from the study show evidence of a difference in task performance between visualizations with and without a summary chart—visualizations showing a summary chart performed better than the version without. Finally, based on our study results we present lessons learned.

1 INTRODUCTION

Wrist wearable devices (e. g., smartwatches and fitness bands) are now more affordable and people increasingly use them to track their fitness data. According to a survey conducted with 4,272 American adults (Pew Research Center, 2022), 21% of them wore a fitness tracker on a regular basis. By supporting automated personal data collection and providing their wearers with instantaneous feedback on their progress, these modern fitness trackers foster data exploration on the go; giving the opportunity to real-time physical performance regulation to meet a pre-set fitness goal.

When people look at the data during the course of an activity, usually they consume the information in short time-lapses—through individual glances of 5 seconds or less (Blascheck et al., 2021). Due to this consumption of the data as a secondary task, the presented information has to be informative and allow reflection in a short time frame. Visualizing the data can help to convey this information; however, one of the challenges of designing visualizations for such a usage scenario is that the provided data should be concise to reduce interruption from the primary activity (Amini et al., 2017).

People using wrist wearable devices when exercising are interested in learning more about their performance and pushing their limits to reach a fitness goal (Amini et al., 2017). Therefore, we conducted a survey to understand which types of data facilitate people to monitor their fitness data while and after exercising, how their device represents the data, and what motivates them to track and analyze their data.

Our survey, but also previous work (Amini et al., 2017; Islam et al., 2020; Neshati et al., 2019a), shows that heart rate (HR) is one of the most common types of data people collect with wrist wearable devices. In the context of fitness data tracking, monitoring HR data is an efficient indicator to control physical performance (Ketcheson et al., 2015; Navarro et al., 2013) (i. e., to foster exertion or vice versa) and gauge physical activity intensity (She et al., 2020) (e. g., HIIT training). This monitoring of HR while performing an exercise lends itself to designing appropriate HR visualizations.

To support in-situ health and fitness data exploration on small wearable devices used on the go, we need to consider different design recommendations

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when creating visualizations (Amini et al., 2017; Islam et al., 2020; Neshati et al., 2019a). Therefore, we leverage the following two considerations in our visualizations design. First, because the provided representations on these small devices often consist of raw textual information—without contextual historical data—issues related to misinterpretation of the data and delayed reactions are susceptible to happen. For this reason, the use of standard and familiar visualization techniques (e. g., bar, donut, and line charts) is encouraged to support activities that require reflection (Amini et al., 2017; Neshati et al., 2019a; Choe et al., 2017). Second, research recommends to combine multiple inter-correlated types of data to easily estimate the distance to the goal (Amini et al., 2017). Hence, minimizing the mental load or the necessity to recourse to external tools. Accordingly, we designed three HR visualizations using a vertical bar chart (Figure 6) to show current and historical HR and HR zone (HRZ) data, as well as a summary of the amount of time a person spent in each HRZ (i. e., low, moderate, and high intensity). The latter was 1) encoded using colors of the vertical bar chart for one of the visualizations, and represented as 2) a separate horizontal or radial bar chart summary for the two other designs.

During the Covid-19 pandemic, it has become more common to exercise in a virtual environment at home (Siani and Marley, 2021). In addition, a virtual environment has ample opportunities to conduct a controlled lab study and to simulate performing a primary (i. e., exercising) and secondary task (i. e., monitoring the physical activity intensity), to test the effectiveness of the three HR visualizations.

Through this research project, we aim to answer the following research questions:

- **RQ1:** Can micro-visualizations on smartwatches support decision making and reflection tasks on the go?
- **RQ2:** How fast and accurately can people explore complex visualizations (i.e., combining multiple data types) on small screens as a secondary task?
- **RQ3:** How do different representations and data aggregation techniques influence data reading and interpretation?
- **RQ4:** To which extent can virtual reality support simulating real world exercising and a smartwatch visualization task?

To summarize, our contributions are threefold. First, we describe our survey's findings on fitness data tracking using wrist wearable devices. Second, we present three HR visualizations, that we implemented based on design recommendations from the literature and existing examples, then empirically assessed their effectiveness in a self-monitoring task in a VR study. Finally, we reflect on the findings and our study results and discuss their implications.

2 RELATED WORK

In the following, we discuss the work related to our research including micro-visualizations, data exploration in motion, fitness data tracking on wearables and fitness trackers and health data monitoring in VR.

2.1 Micro-Visualization in Research

Wrist wearable devices are attracting more attention from different research communities due to their ubiquity in different aspects of our daily activities (e. g., monitoring health, fitness or sleep data). While some research in human-computer interaction explored novel interaction techniques (e. g., to overcome the fat finger problem (Neshati et al., 2021b)), our own work and a number of previous studies in the domain of visualization are interested in investigating data representations adapted to the configuration of these devices (e. g., small screens (Chen, 2017; Neshati et al., 2019b, 2021a; Suciu and Larsen, 2018)) and to their usage context (e. g., visualization in motion (Yao et al., 2020), glanceable visualization (Blascheck et al., 2019; Islam et al., 2022)).

Few empirical studies related to visualization have been conducted to understand representations of micro visualizations—adjusted data representations visualized on small screens of a few square centimeters. Blascheck et al. (2019) evaluated participants' time threshold using three visualizations (i. e., bar, donut, and radial bar chart) in a data comparison task. Bar and donut charts resulted in faster responses. The authors followed up with a replication study (Blascheck and Isenberg, 2021) to compare whether the same results from the smartwatch study could be obtained when displaying the stimuli on a larger screen (i. e., a laptop screen). The authors tested both smartwatch-sized (320×320 px) and larger visualizations (1280×1280 px) on a laptop screen. The overall results showed no difference between stimuli sizes. Neshati et al. (2019b) introduced a novel visualization technique named G-Sparks—inspired by sparklines (Tufte, 2001)—to investigate the effect of compression of a line chart (on the *x*-, *y*-, or *xy*-axis) on task performance. According to the completion time, accuracy and interaction count, results were in favor of the *x*-axis compression technique. Islam et al. (2022) contributed three studies about sleep data visualizations (i. e., floating bar chart and hypnogram) when displayed with three different form factors (i. e., Square, Wide, and Tall) simulating different small devices (i. e., smartwatch and fitness band). Results showed that the suitable form factor depends on the task. In general, both tested visualizations were glanceable (i. e., readable in <5 s). Following these previous works, we contribute a study in the realm of micro visualizations, with focus on fitness data exploration.

2.2 Data Exploration in Motion

Despite their omnipresence in the activities of their wearers (e. g., working, training, cooking), most of the previous studies involving visualizations on small devices (Blascheck et al., 2019; Islam et al., 2022; Neshati et al., 2019b, 2021a) were conducted in a stationary pose. For example, Blascheck et al. (2019) fixed a smartwatch on an adjustable stand simulating the viewing angle and distance at which a smartwatch is usually held while reading information. In contrast, the number of studies that explored visualizations on small wearable devices while in motion is limited. Schiewe et al. (2020) evaluated the performance of two graph-based visualizations showing two foot strike types (i. e., heel and forefoot strikes) in comparison to textual feedback of the current forefoot strike rate on a smartwatch while walking on a treadmill. They found that the real-time graph-based visualizations were preferred over textual data representations. Similarly, Neshati et al. (2021b) explored two interaction techniques with graphs on a smartwatch while walking on a treadmill and when having a standing posture. Yao et al. (2020) defined a first design space of visualizations used while in motion. The dimensions of the design space include the entity in motion, characteristics in motion, as well as the motion relationship between viewer and visualization. In our study, we investigate fitness data exploration—as a secondary task—while playing a tennis-like game in VR. The player is in a high active mode—displacement of the arm to the right and left side to catch balls—before we display the visualization. When the participant is observing the data, they are in a standing posture and a minimum degree of movement is expected. The motion in our case concerns mainly the arm twist and elevation when looking at the (virtual) smartwatch.

2.3 Fitness Data Tracking on Wearables

In their survey, Islam et al. (2020) found that wearers of smartwatches are mostly interested in tracking their fitness and health data. However, due to the lack of knowledge regarding the challenges of data consumption on the small screens of smartwatches, as well as to identify the specific needs of people during and after a physical activity, previous work also performed user-centered research to understand the needs of smartwatch wearers. Amini et al. (2017) conducted interviews with people who tracked their fitness data on a regular basis and found that participants have different needs when the data is explored on the go (i. e., exploring one or multiple values, estimating the progress towards a goal, comparing one or multiple measures with other people's and staying motivated). The authors converted these tasks into data exploration scenarios and invited nine professional designers to prototype visualizations—adapted to the small screen of a smartwatch—that would support in-situ data exploration during a fitness activity. For the goal-based category, most sketches were using visualizations (e. g., donut and pie charts or space filling shapes such as a single bar or icon) instead of text. In addition, in relation to personal data collection, Choe et al. (2017) organized discussion sessions with a group of Quantified Selfers to understand the practices and techniques they employed to collect and explore outcomes from their personal data. Based on the gathered feedback, they generalized the reported problems into three pitfalls (i. e., tracking too many things, not tracking triggers and context,as well as insufficient scientific rigor). In an attempt to summarize limitations related to the exploration and the design of visualizations on smartwatches, Neshati et al. (2019a) report a set of challenges related to the hardware (e. g., lack of memory, limited processing power, limited battery life) and related to the data representation (e. g., lack of guidelines for complex data representation on small screens). They specified that visualization techniques should be applied to represented HR data for an in-situ exploration. These prior studies contributed in building a better understanding of people's behavior when tracking their fitness data. In addition, they informed a set of general design considerations of in-situ visualization that support reflection on the go. We apply two of the aforementioned design considerations (i. e., promote visualizations over textual representations and combine interrelated types of data) to visualize HR data over time. In addition, we test our three HR visualizations to foster data exploration on the go during the course of a fitness activity and to convey meaningful information to reach a predefined goal.

HR data is widely used for health and fitness applications. For example, Albaghli and Anderson (2016) explored data from the embedded smartwatch sensors to keep chronic patients aware of their health state and to facilitate the identification of anomalies by means of visualizations. Also, Muangsrinoon and Boonbrahm (2017) visualized real-time HR and HRZ data on a

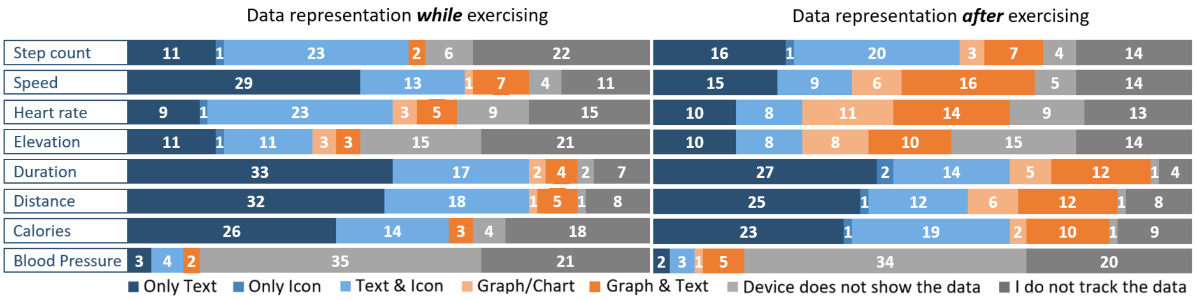


Figure 1: Counts regarding the fitness data (i. e., step count, speed, heart rate, elevation, duration, distance, calories, and blood pressure) that participants reported to check, while exercising (left) and after the exercise (right).

smartwatch, to monitor the physical activity intensity of a cyclist (on a stationary bicycle). The authors found that real-time HR monitoring can help exercising within a desired target HRZ. Likewise, in our study, we explore visualizations of HR and HRZ data to monitor a fitness activity in a goal oriented task.

2.4 Fitness Trackers and Health Data Monitoring in VR

HR data was investigated in VR and by means of exergames to monitor physical activity intensity and to raise player's awareness about their exertion rate (e. g., to foster exertion (Ketcheson et al., 2015) or to avoid over exercising (She et al., 2020; Yoo et al., 2018)). Moreover, wearables are emerging in VR in different ways. A new concept to explore fitness and game data in VR is a virtual smartwatch (YUR.Watch, 2020). The design mimics a real smartwatch with an extension sleeve. Only information about burned calories is displayed as text on the watch face. The rest of the tracked data (e. g., number of squats and current heart rate) is represented with text and icons and displayed on the watch sleeve. More recently Queck et al. (2022) introduced SpiderClip, a system that enables the exploration of simulated wearables in VR. SpiderClip consists of hardware and software components, allowing the real-time collection and monitoring of spatial and physiological data in VR. The authors validated their design with a proof-of-concept study in which they tested HR data measurements and visualizations during a fitness exercise. The authors visualized the HR data in two different ways: (1) by showing the current HR value on the smartwatch display and on an HR gauge on a separate sleeve, as well as (2) showing the same data on a heads-up display-like representation.

We also leverage the VR environment to implement a tennis-like game, in which we can control and assess participants actions while playing the game (e. g., count the scored balls) and behavior after visualizing the data (i. e., measure response time, record answers). To simulate a real-world experience, we display the HR visualizations on a virtual smartwatch.

3 SURVEY

We decided to approach people who track their fitness data through a survey to learn about their tracking techniques and behaviors while and after exercising to understand 1) the device they rely on and that support their activity tracking, 2) the data they frequently collect and how their device presents it, 3) their motives for self-tracking their exercise behavior, and 4) potential use of fitness data tracking in VR. We summarize insights from the gathered data to design a visualization based on the needs of people.

3.1 Survey Design

We conducted an anonymous online survey with SoSci Survey (SosciSurvey, 2022) and advertised it on different social media and professional platforms (e. g., Facebook groups, Twitter, LinkedIn, and mailing lists). We structured the survey into five sections, which consists primarily of close-ended questions. Our supplemental material (OSF, 2022) contains a detailed list of these questions together with the results of the survey.

The first section was concerned with getting consent and ensuring participants were old enough to participate. Because we are interested to learn how people exercise and track their fitness data, an initial question asked about regular exercise and tracking of data.

Next, we collected general information about the physical activity and the frequency of data tracking. We asked participants if they track all their sport activities using a fitness tracker, how often they exercise per week, where they usually practice this activity and how often they track their individual sport activities.

With the main part of the survey, we intended to learn about participant's primary sport activity. Here we asked what the primary sport activity is, how they

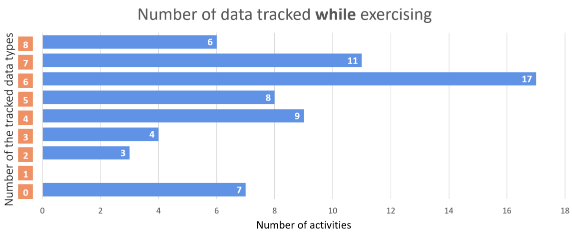


Figure 2: Number of data collect during an activity.

track their fitness data and when they check their fitness data. We were also interested to learn if there is a difference in when participants check their fitness data—while exercising and after the exercise. Therefore, we asked how the used fitness device represents this data during and after the exercise. To learn about reasons why participants track their fitness data, we also asked them what their primary motivation is to check their fitness data during and after the exercise.

In case participants tracked more than one physical activity, we gave them the opportunity to report about their secondary activity using the same questions as for the primary activity.

Last, we asked participants if they also exercise in a VR environment. Those participants who answered the question with yes were asked when they check their fitness data when exercising in VR and how their fitness data is represented. Those participants who do not track their fitness data in VR, were asked if they would be interested to do so and how they would like to represent their fitness data in VR.

3.2 Participants

We recruited in total 57 participants; 16 of them were excluded at the beginning of the survey: 4 participants do not practice any sport activity, 11 do not track their fitness data and one participant was younger than 18 years. The remaining 41 participants confirmed that they exercise on a regular basis: 24 practice their primary sport activity up to 2 or 3 times a week, 7 of them 4 or 5 times a week, 6 once a week, 2 exercise every day, 1 once every two weeks, and 1 participant 2 or 3 times a week. The majority of the participants track their fitness data frequently: 27 always track their physical activity, 13 do it sometimes, and 1 rarely.

3.3 Results

Participants reported a total of 65 sport activities: 41 primary activities and 24 secondary activities. Participants mostly perform their tracked activities outdoors (40 of 65), and the most common types of activities participants perform are running (23) and cycling (17).

3.3.1 Fitness Data Tracking Devices

Participants reported that they track their fitness data on wearable devices for 43 sport activities: for 31 activities they use a smartwatch and for 12 they use a fitness band for tracking. In addition, participants use their smartphone to track 22 activities, 6 activities were not tracked (e. g., swimming) and one participant mentioned using a golf-tracking system (i. e., Trackman Range). This question was designed as a multiple choice question and 5 participants selected more than one device for a single activity: 2 used smartwatch and smartphone, 2 used smartwatch and fitness band and 1 reported to use all three devices.

3.3.2 Data Type and Representation

By comparing the fitness data participants track during and after their sport activity, we found that duration (i. e., 56 answers during the activity and 60 after the activity) and distance (i. e., 56 answers during the activity and 56 after the activity) are the top two tracked types of data (Figure 1). Then come in order: speed, calories, and heart rate as the data types tracked during the activity. After the activity, participants reported that they track calories, step count, and their speed.

Participants tend to track multiple types of fitness data (i. e., 2 to 8 data types) during the activity (Figure 2).

Figure 1 reveals that most of the data tracked during the course of the physical activity are represented using either "text" or a combination of "text and icon." In contrast, for the data tracked after the activity, participants use more "graphs/charts" as well as "graph and text" representations.

3.3.3 Motivation to Track Fitness Data

Participants rated Checking a fitness goal highly for both activities (i. e., second reason after "check progress" with 35 answers while exercising and as a primary reason with 47 answers after exercising). Some participants gave examples to explain the fitness goals they target during the exercise, for example: "I usually run with my heart rate being between 140 and 155 bpm. This helps to check if I am overdoing things and if I will be able to finish what I was planning to do—running 1h 45?"

3.3.4 Exercising in Virtual Reality

Only 6 participants exercise in VR. Two participants reported that they do not collect data when exercising in VR, four check their data after exercising (i. e., 2 on a smartwatch or smartphone and 2 in VR). Asked if they would like to see their fitness data in VR, 2 participants chose to visualize the data on a virtual smartwatch, the rest of the answers were distributed based on the different options (i. e., 2 preferred a small panel to the side, 2 chose to visualize the data on a larger panel in front of them, 1 chose a small panel in front of them, and 1 a larger panel to the side).

3.4 Summary

We summarize and categorize the survey's findings:
Data Tracking while Exercising. Results show that for 66.1% of the reported activities, fitness data was tracked on wrist wearable devices. Despite their restricted display area, participants mostly track 6 different types of fitness data during the course of an activity. This is in line with previous research on watch face design (Islam et al., 2020).
Data Representation while Exercising. While exercising (Figure 1, left), participants represent their fitness data primarily as "text" and "text and icon" combinations, not using charts or graphs. The results also show that participants' ultimate motivation for tracking their data is to monitor their fitness progress or goal. This is in accordance to previous research (Amini et al., 2017) and could stem from smartwatch manufacturers not providing such charts and graphs, even though visualization research has shown that participants are able to read charts and graphs quickly (Blascheck et al., 2019; Islam et al., 2022; Neshati et al., 2019a).

As a consequence of this survey, in the following study, we explore visualizations to represent fitness data (i. e., HR data), then assess their efficiency to monitor a fitness goal while exercising.

4 IN-LAB STUDY

In this section we describe our visualization design choice. Then, present the study we ran in VR, followed by an overview on quantitative and qualitative results.

4.1 Visualization Design

We start by explaining the correlation between HR data and fitness activity monitoring. Then, present a sample of existing HR data visualizations and explain how they inspired our visualization design choice.

4.1.1 Heart Rate Zones to Monitor Sport Activity

During the course of a physical activity and depending on the physical effort put into the exercise, the HR can be in a specific zone. For example, during warm-up or cool-down exercises, the HR is relatively low, and

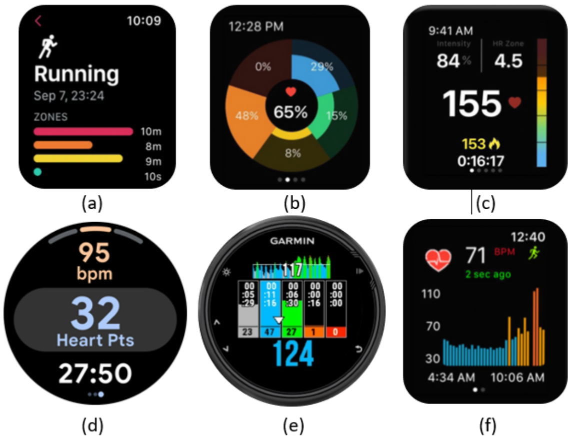


Figure 3: HRZ representations from third-party applications: (a) horizontal progress bar from the *Zones for Training* app (Flask, 2018), (b) radial progress bar chart, and (c) vertical gauge from the *FITIV Pulse Heart Rate Monitor* app (FITIV, 2021), (d) radial gauge from the *Google Fit* app (GoogleFit, 2020), and representations combining HR and HRZ data in the same view from (e) the *HRZMon+* app (MakkasCIQ, 2017): with a vertical and a progress bar chart, and (f) the *Cardiogram* app (Cardiogram, 2017): showing a bar chart encoding both data.

therefore, in the low intensity zone. A person's range of HRZs is based on the percentage of their maximum HR, which is calculated based on the person's age: $max\ HR = 220 - age$ (American Heart Association, 2022) or $= 205.8 - 0.685 * age$ (Friel, 2006) for more accuracy. The number of HRZs can vary from three (e. g., Google Fit and Cardiogram apps (Figure 3, d and f)) up to seven zones (i. e., zone 5 is divided into 3 sub-zones w.r.t. the Lactate threshold, e. g. Heart Rate Zones app (HC Studios, 2022)). For simplification purposes, we chose that our experiment's HR visualizations show only three HRZs. According to the American Heart Association American Heart Association (2022), the three HRZ are defined as low: HR values $\leq$50% of max HR, moderate: HR values are 50-85% of max HR, and high: HR values are $\geq$85% of max HR.

4.1.2 Existing Heart Rate and Heart Rate Zones Visualizations

According to the answers that we gathered from the survey participants on how they display their HR data on their tracking devices during the course of an exercise, only eight reported visualizing "graphs/charts" and "graph and text" representations. Among them, three were using Garmin watches (1 Instinct and 2 Fenix 6X), two used Apple devices (Watch3 and iPhone X), two had a Huawei Band 2 pro, and one an AKWLOVY smartwatch. By investigating the visual-

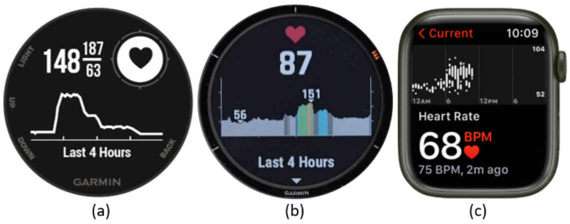


Figure 4: Examples of HR visualizations that participants reported to use during their exercise: (a) line chart visualization on the Garmin Instinct smartwatch (Garmin, 2022), (b) vertical bar chart visualization on the Garmin Fenix 6X (DC RAINMAKER, 2019), and (c) vertical range chart on the Apple Watch 3 (Apple, 2022).

izations provided by the in-house HR applications on the aforementioned smartwatch models and other popular brands on the smartwatch market (statista, 2021) (e. g., Samsung, Fitbit), we could identify three distinct types of HR visualizations, namely, line chart, vertical bar chart, and vertical range chart (Figure 4). These visualizations are often accompanied by textual information on the minimum, maximum, average, or resting HR values. Whereas information on the HRZs is not by default available in all HR tracking applications. Therefore, to track the exercise time distribution over HRZs in real time, smartwatch wearers use third-party applications. We explored some of these applications and grouped the most commonly provided visualizations into five types (i. e., linear and radial progress bar, linear and radial gauge, and combined visualizations (Figure 3)). Progress bar visualizations (Figure 3, a and b) give details about the degree of progress achieved per individual HRZ (i. e., in percentage, or seconds/minutes/hours). In contrast, Gauge visualizations only indicate the current HR value and highlight the current HRZ by fading out the unreached or the rest of the HRZs (Figure 3, c and d). We noticed that only two applications show visualizations of both data simultaneously—allowing direct access to the information (i. e., the wearer does not have to navigate between views or apps).

The HRZMon+ app (Figure 3, e) provides HR and HRZ data using a bar chart and vertical progress bar, respectively. Also, similar to the visualization given by the Garmin Fenix 6X (Figure 4, middle), the Cardiogram app by Apple watch (Figure 3, f), combines the HR measurements over time—shown as a vertical bar chart—to the HRZ information—represented by the color of the bars.

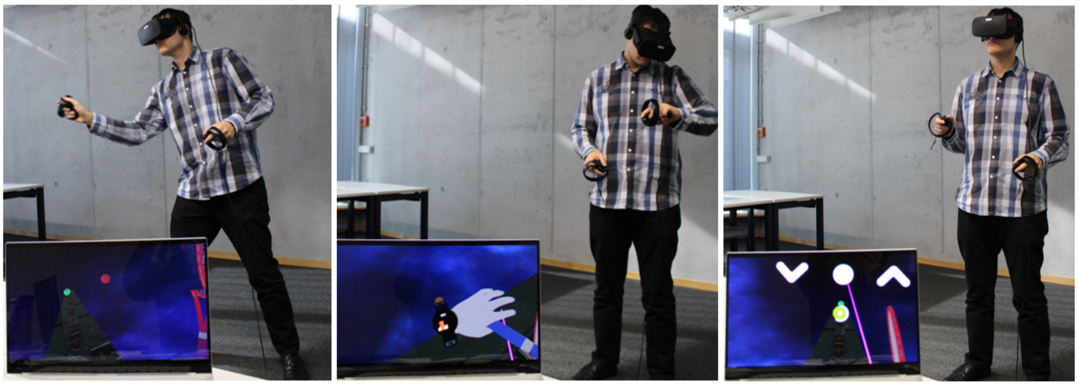
Existing examples and recommendations from the literature inspired the design choice of our HR visualizations. First, our goal was to test how well complex visualizations (i. e., visualizations showing interrelated data) can fit the small screen of a smartwatch. Then, to empirically assess them, by the means of an analytic task: how fast these visualizations can convey precise information to help a person meet a preset goal by adjusting their performance in real-time.

4.1.3 Visualizations Design Choice

We created three visualizations showing the same information, (i. e., current and historical—since the beginning of the exercise—HR, and HRZ data), yet with distinct representations. The visualization choice was mainly guided by the two design considerations from the literature. First, all HR representations must be charts. Then, convey information about interrelated data (i. e., HR measures over time and time spent per HRZ) to help prompt reflection and decision making on the go. Therefore, the first criterion that we want to explore is whether combining the data into a single visualization (1) or showing them separately in the same view (2) influences participants' performance. Hence, we opted for a bar chart visualization—rather than a line or range chart—to depict HR data for two main reasons. First, bar charts have the privilege of visually encoding both the HR measures and zones simultaneously. For each HR measure the bar length depicts the average HR value per minute and the color-coding refers to the HRZ, to which the HR value belongs: yellow for low HRZ, orange for moderate HRZ, and red for high HRZ (Figure 6). Second, with an overview of the historical data, one can quantify and proportionally estimate the time (in minutes) spent per HRZ, by counting or visually grouping bars of the same color. This makes the bar chart visualization an adequate candidate for visualization category (1).

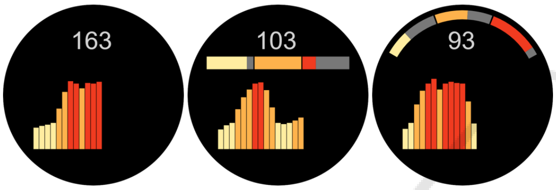
Accordingly, all three visualizations show as the main chart a vertical bar chart of HR measures over time. The current HR value is shown both as the most right bar of the bar chart and as a text value displayed at the top-center of the screen (Figure 6). Micro visualizations are characterized by an absence or a limited set of reference structures (i. e., labels, data axes). Therefore, our HR visualizations show no *x*- or *y*-axis. However, the *x*-axis shows the duration of the activity—a maximum of 21 minutes—and the *y*-axis represents the HR values in a range of 50–190 BPM.

For the visualization category (2), we display the amount of time—in percentage—spent in each of the three HRZ with a separate summary chart. We propose two distinct representations for the summary chart (i. e., horizontal and radial bar chart summaries, respectively; Figure 6 (b) and Figure 6 (c)). The summary chart is divided into three equal parts for low, moderate, and high-intensity HRZ, filled with yellow, orange, and red colors respectively, to indicate the percentage of progress on each HRZ toward a pre-set goal. The gray area depicts the remaining percentage to achieve



(a) (b) (c)

Figure 5: A participant performing the study task: (a) the participant catches the virtual balls, (b) the participant looks at the visualized HR data on the virtual smartwatch, (c) the participant validates his decision regarding the exercise pace (i. e., decrease: down-arrow, continue: circle, increase: up-arrow).



(a) (b) (c)

Figure 6: Examples of the HR visualizations from our study: HR visualization—represented by a vertical bar chart showing current and previous HR values—(a) without summary chart, (b) HR visualization with horizontal bar chart summary, and (c) HR visualization with radial bar chart summary. The horizontal and radial bar chart summary describes the amount of time spent in each HRZ: low intensity: yellow, moderate intensity: orange, high intensity: red.

during the exercise. When designing the summary charts, we ensured that both the horizontal bar and radial bar occupy the same amount of pixels on the watch face. The horizontal summary chart mimics a stacked bar chart, whereas the radial chart summary better fits the screen of the round (virtual) smartwatch.

For the sake of the study and to have an evenly distributed dataset, we generated 27 unique stimuli and used them for all three visualizations. We generated groups of nine datasets, which all had the same current HRZ (i. e., 9 datasets for which the current HRZ was in the low zone, 9 with a current moderate HRZ, and 9 with a current high HRZ). For each group, we sub-grouped the datasets to have a different HRZ containing the minimum percentage of time spent in it (i. e., an equal number of stimuli, in which the progress of the current HRZ is the lowest or the highest). For these three stimuli, we generated two datasets, which represent a more difficult decision and one dataset that was an easier decision. The difficult decision dataset had a difference in number of bars of 1-2 between the two HRZs with the least progress. Whereas the easier decision dataset had a larger difference gap of 4-5 bars–which makes it easier to detect. For example, Figure 6 (a), and Figure 6 (c) show a difficult decision, Figure 6 (b) shows an easy decision.

4.2 Study Task

Fitness Goal. We defined a fitness goal and informed the participants about it before starting the game. The goal was as follows: during an exercise session of 21 minutes in total, they have to try to be in each HRZ equally—optimally 7 minutes per HRZ. To make a decision, participants had to determine from the displayed visualization the HRZ during which they had spent the least amount of time during the activity so far. This can be concluded in two different ways: in the summary chart finding the HRZ with the smallest colored bar or by counting and comparing the bars of each HRZ of the HR visualization. Then, they had to identify the current HRZ, which can be determined by the most right bar in the bar chart. Knowing their current HRZ and the HRZ with the least global progress, the participant should decide whether to decrease, continue with or increase the activity pace. For example, the stimuli without summary chart (Figure 6 (a)) has the high HRZ as the current HRZ and the least time was spent in the moderate HRZ. Therefore, to balance the distribution of time for each HRZ the decision in this case would be to decrease the exercise intensity. The decision for the stimuli with bar chart summary (Figure 6 (b)) is to increase the intensity and for the stimuli with radial bar chart summary (Figure 6 (c)) the decision is to continue with the intensity.

Primary and Secondary Task. During the study, participants are constantly switching between two tasks. The first task involves action and movement. In this primary task, the participant plays a tennis-like game in VR by catching balls from both the left and right side using virtual rackets (Figure 5 (a)). The secondary task requires more reflection and concentration. The secondary task consist of viewing the HR visualization displayed on the virtual smartwatch (Figure 5 (b)), reflecting on the decision to make to reach the preset goal and finally validating their answer by selecting one of the three buttons (i. e., down-arrow for decrease, circle for continue, and up-arrow for increase; Figure 5 (c)). Participants were given 10 seconds to make a decision. If no answer was selected within this period, the answer was counted as incorrect.

4.3 Study Design and Apparatus

We conducted a within-subject study varying the type of visualization shown to participants. Overall, we had three conditions and one task resulting in a 3 × 1 study design. Each participant performed all three conditions of the study. To prevent an ordering effect, we used a 3 × 3 Latin Square to counterbalance the conditions between participants.

We implemented a tennis-like game in VR using the Unity3D game engine. We ran the VR game on a Razer-Blade-15-Studio computer (i. e., CPU 8-Core Intel Core i7, GPU Quadro RTX™ 5000) and an Oculus Rift VR headset. We cleared a space of approx. 1.5 m × 3 m in the study room, so participants could move freely when playing the game. To minimize the risk of bumping into an object (i. e., walls, tables), we set up the room boundary in VR (i. e., displaying a virtual wired wall when getting too close to a real wall).

4.4 Study Procedure

We provided participants with a printed version of the consent form. After signing the consent form, we introduced them to the task via a short presentation. Then, we showed participants an example of each of the HR visualizations and asked them questions to test their understanding of the task. Once explaining the theoretical part was done, we asked participants to wear the VR headset and to adjust it to their head. Then, to find the corresponding lens distance to their inter-pupillary distance (IPD), they had to move the IPD slider until the visuals looked clear.

Each condition was composed of two sessions: first the training session to get familiar with the VR environment and visualizations, then the actual sessions. Participants were exposed to 3 training stimuli and 27 visualization stimuli during each session. In total, each participant performed 90 trials (i. e., 3 × 30), only 81 trials (i. e., 3 × 27) are considered for data analysis. Between conditions, participants could take breaks.

Each session started when the participant pressed the "start" button. A number of balls are shot toward the player from both the left and right side randomly. We asked participants to catch as many balls as possible using two rackets attached to each virtual hand (Figure 5 (a)). To make the switch between the primary and the secondary tasks unpredictable for the participants (i. e., checking data on the fitness tracker does not have to happen on a regular basis), the ball stream stopped after a random number of balls was shot (i. e., 2-7 balls). Then a question appeared in front of the player asking "What would be your decision?" Participants had to look at the virtual smartwatch (Figure 5 (b)), find the answer from the HR visualization displayed on the watch and validate their answer by selecting one of the buttons shown below the question (i. e., decrease: down-arrow, continue: circle, increase: up-arrow; Figure 5 (c)). From the moment the question appeared until participants pressed the answer button a 10 seconds time loader kept counting down. If no button was selected within the 10 seconds the answer was considered as incorrect.

After participants preformed all 90 trials, we asked them to fill out a questionnaire to evaluate the three HR visualizations. Participants who completed the study received € 10 or chocolate for their participation if they were a university employee.

4.5 Participants

We recruited participants via the university's internal mailing list and student forums. In total, we recruited 24 participants: 20 students and 4 researchers of the university, including 11 females and 13 males. All participants were 18 years old or older. They confirmed that they have good eyesight (i. e., their vision is good without requiring an optical aid or is sufficiently corrected by means of an optical aid) and that they do not have a physical injury that constrains them from moving their arms freely.

4.6 Results

We recorded data logs from participants with measures on their performance for each condition, as well as subjective feedback at the end of the study. In this section, we report quantitative and qualitative results.

4.6.1 Quantitative Results

We analyze the mean response time and the mean accuracy per condition (i. e., 648 trials (27 trials × 24 participants) per condition) using confidence interval

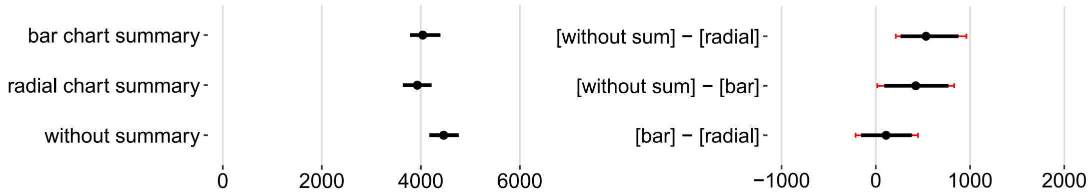


Figure 7: Mean completion time (left) and difference between mean completion times (right) of the three HR visualizations using 95% CIs and Bonferroni corrections.

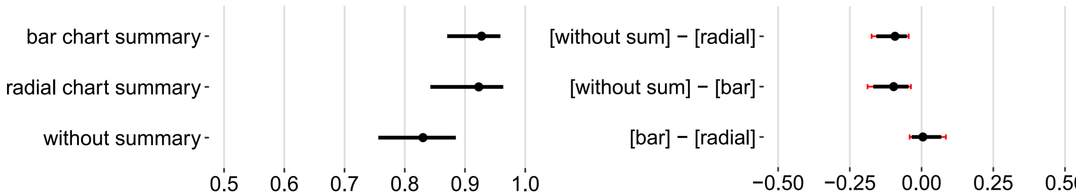


Figure 8: Mean accuracy (left) and difference between mean accuracy (right) of the three HR visualizations using 95% CIs and Bonferroni corrections.

(CI) estimation (Besançon and Dragicevic, 2017, 2019; Cockburn et al., 2020; Cumming, 2013; Dragicevic, 2016). We report the sample means of the completion time and accuracy together with the 95% CI using BCa bootstrapping (10,000 bootstrap iterations). In addition, we report the differences between means to compare the three conditions. We adjusted the CIs of mean differences for multiple comparisons with Bonferroni corrections (Higgins, 2004).

On average, participants were faster with the radial bar chart summary (3929 ms [3637 ms, 4211 ms]) than with the other conditions (horizontal bar chart summary: 4038 ms [3786 ms, 4389 ms], without summary chart: 4462 ms [4173 ms, 4763 ms]) (Figure 7 left). The results show evidence of a difference in terms of completion time (Figure 7 right), for the radial bar chart summary and the without summary chart (CI does not touch zero: 532 ms [263 ms, 874 ms]) and a trend for a difference between the horizontal bar chart summary in comparison to the without summary chart (CI is close to zero: 423 ms [91 ms, 767 ms]). There is no difference in mean completion time between the radial and horizontal bar chart summary (CI crosses over zero: 109 ms [-155 ms, 380 ms]).

Mean accuracy results show that participants' made more accurate decisions with the horizontal bar chart summary (92.7% [87%, 95.8%), than the radial bar chart summary (92.3% [84.2%, 96.2%) and the without summary chart (83.0% [75.6%, 88.4%) (Figure 8 left). There is evidence of a difference for both the radial and horizontal bar chart summary to the without summary chart (-9.2% [-15.7%, -5.2%]) and (-9.7% [-16.8%, -4.6%]); Figure 8 right). There is no evidence of a trend between the radial and the horizontal chart summary (0.4% [-3.3%, 6.7%]); Figure 8 right).

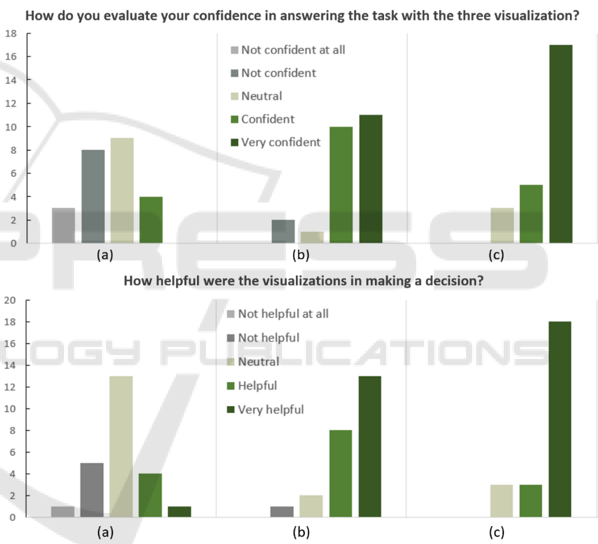


Figure 9: Participants' self-assessment about their confidence (top) and how helpful the three visualizations were (bottom), in answering the task. (a) without summary, (b) with bar chart summary, (c) with radial chart summary.

4.6.2 Qualitative Results

After performing the study with all three visualizations, we asked participants to answer three questions to evaluate their satisfaction with each visualization.

1) How Do You Evaluate Your Confidence in Answering the Task with the Three Visualization? Results in Figure 9 (top) depict participants' self-assessment of the degree of confidence in their answers with each visualization. For the visualization not containing a summary, three participants stated that they were not confident at all about their answers

—which no participant reported for the two other visualizations showing a summary chart. In addition, only four participants found that they were confident in their answers using the visualization without summary chart compared to 21 participants (i. e., 10 confident and 11 very confident) for the visualization with bar chart summary and 22 participants (i. e., 5 confident and 17 very confident) for the visualization with radial chart summary.

Some participants explained this gap in the results by the fact that when the visualization does not show a summary they had to calculate and visually compare the number of bars in each HRZ—which was tedious and time-consuming. For example, one participant stated: “The summary makes me feel more confident about my choice given that I didn’t take a lot of time to think about it.”

2) How Helpful Were the Visualizations in Making a Decision? Only five participants found the visualization without summary helpful for the task (Figure 9, bottom). In contrast, 21 participants agreed that the bar chart summary (i. e., 8 helpful and 13 very helpful) and radial chart summary (i. e., 3 helpful and 18 very helpful) were beneficial to solve the task.

3) Which Visualization Did You Prefer the Most? Finally, we asked participants to choose the visualization they preferred the most based on aesthetics, efficiency and confidence. The majority of the participants (83%) preferred the visualization with the radial chart summary, 17% opted for the visualization with the bar chart summary, and none voted for the visualization without summary.

5 DISCUSSION

In general, participants could accomplish the task successfully with the three visualizations by providing quick responses (i. e., <5 s) and with most of the answers being correct (83%-92.7% on average). However, when interrelated HR data was depicted using two visualizations (i. e., the vertical bar chart and the summary chart), participants’ performance increased. A particular preference was accorded to the visualization with the radial chart summary (w.r.t. aesthetics, efficiency, and confidence in the provided answers).

In this last section, we discuss our findings and highlight some advantages and limitations that we identified from our results or participants’ feedback.

5.1 Exploring Visualizations on Small Screens While Exercising (RQ1)

Smartwatches are usually underestimated for the amount and quality of information they can provide because of their restricted display area. Previous work (Islam et al., 2020) and our own survey show that most data is shown as text, icon or as a combination of text and icon on the smartwatch. However, representing raw textual information does not allow for deeper reflection when exercising (Amini et al., 2017; Neshati et al., 2019a). Therefore, visualizing the data can overcome this challenge, but requires careful design of these visualizations to fit the small screen. By following design recommendations from previous works (Amini et al., 2017; Neshati et al., 2019a; Choe et al., 2017), we opted for the use of simple and familiar visualizations (e. g., bar and radial charts) as a replacement for raw textual data, to support reflection in a goal-oriented task.

Our final results showed that the small screen of a (virtual) smartwatch can convey informative feedback with minimum interruption from the principal activity in a short amount of time (<5s), which is in line with previous studies (Blascheck et al., 2019; Neshati et al., 2021a, 2019b). This is even true, when people perform a primary task (playing a tennis-like game). The recourse to simple visualizations on smartwatch screens has a positive impact on the reflection time and outcome in general, especially for tasks performed while in motion or that involve task switching.

5.2 Multiple Visualizations to Support Complex Data Interpretation (RQ2 & RQ3)

According to our survey and other previous works (Islam et al., 2020; Choe et al., 2017), people tend to track multiple types of data at the same time during their activities. However, if no clear relation exists between the data, combining multiple data types—especially if using different visualization techniques—simultaneously can make data interpretation a complex process (Neshati et al., 2019a; Choe et al., 2017). In this study, we focused on visualizing interrelated data types to serve answering a common question, namely, HR measures over time and the total amount of time per HRZ. All three of our visualizations showed the same information but differently. In the visualization without a summary, it was possible to estimate the total amount of time per HRZ by summing bars with the same color. However, this was time consuming and led to more errors of interpretation. Furthermore, many participants reported that the task was mentally tiring and they felt uncertain about their answer. For example, one participant mentioned: “In the visualization without summary I always was not sure if I have not missed anything” another stated that “it was difficult to solve the task without the summary.” Accordingly, we assume that the task would be harder to handle for a longer exercise period (i. e., >21 minutes).

Our results show that providing the total amount of time per HRZ using a separate visualization (i. e., by adding a horizontal or radial summary chart) made the data processing and the interpretation of the data easier and more efficient (e. g., “having a summary is a nice extra feature that is definitely helpful”). This opens up new research questions on the impact of data aggregation on different tasks that require reflection and with different data granularity (i. e., more than two data). Also, the maximum number of visualizations a smartwatch can display simultaneously and still convey meaningful and clear information could be inspected.

5.3 Monitoring a Physical Activity in Virtual Reality (RQ4)

This study had the ultimate goal of simulating multiple tasks (i. e., primary and secondary task) with the secondary task requiring a participant to read data on a virtual smartwatch. For this, we designed visualizations and displayed them on the virtual smartwatch simulating the size of a standard real watch. In the following, we discuss how a virtual smartwatch can simulate a real watch to study micro visualizations.

Rendering Quality. In general participants found the visualizations' rendering clear enough (i. e., participants were able to extract the necessary information without problems). Some participants mentioned that “the rendering quality seemed to be equally good” or “was good, easy to read” when we asked them to evaluate the rendering clarity. However, some reported that the text value indicating the current HR measure was blurry, which made it hard to read. For the proposed task, this information was not crucial to answering the question. We suggest that future works involving micro visualizations in VR do not or only sparsely include text-based representation on the watch to avoid alteration of the texts' quality.

Visual Jitter. Although, when retrieving information from the visualization on the smartwatch, participants were not moving, they performed a quick arm-twist to look at the virtual smartwatch. One participant reported that the speed at which his arm moved affected the clarity of the visualizations for a short time (i. e., the faster, the more blurred the representation). We do not consider this effect as a problem. First because it is brief; second, because it simulates the effect of jitter that can also occur when visualizing data on a real smartwatch.

Restricted Displacement. On the one hand, running the study in a controlled VR environment helped us to quantify participants reactions (i. e., response time and accuracy). On the other hand, it was limiting participants in terms of displacement space. We could not risk participants' safety by testing our study setup with exercise activities that involve high motion in a real environment (e. g., walking or running) or continuous displacement (i. e., in the room or on a treadmill). Therefore, the VR environment was a good trade-off between realism and safety of participants.

6 CONCLUSION

In this paper, we report the results and findings from our survey and VR study. We created three HR visualizations guided by our survey's findings and by design considerations from the literature that support visual data processing and reflection on the go. Through a study, we demonstrated the efficiency of the three visualizations displayed on small wearable devices in guiding a person to make decisions about their exercise pace. We also found that data aggregation impacted the performance of the participants. The HR visualizations showing a summary of the total time spent in each HRZ represented with a separate radial and horizontal bar chart summary were more helpful to perform the task. Participants preferred the visualization with radial bar chart summary the most.

Overall, the obtained results are promising and encourage us to further explore in-situ visualizations in situations that require quick reflection in general, and in the context of fitness data tracking more specifically—whether by means of a real or a virtual smartwatch. A combination of both modalities can be considered using Augmented Reality.

A possible extension of this work would be to test the same or similar visualizations with different data granularities. In addition, testing the HR visualizations with real HR data would further show how usable the visualizations are in a real-world context and in situations where the attention is split between a primary and a secondary tasks.

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