



Visualizations for Smartwatches and Fitness Trackers

Mohammad Alaul Islam

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Mohammad Alaul Islam. Visualizations for Smartwatches and Fitness Trackers. Computer science. Université Paris-Saclay, 2023. English. NNT: 2023UPASG018 . tel-04047471

HAL Id: tel-04047471

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Visualizations for Smartwatches and Fitness Trackers

*Visualisations pour les Montres Intelligentes et les Trackers de
Fitness*

Thèse de doctorat de l'université Paris-Saclay

École doctorale n° 580 : Sciences et Technologies de l'Information et de la
Communication (STIC)

Spécialité de doctorat : Informatique

Graduate School : Informatique et Sciences du Numérique

Référent : Faculté des sciences d'Orsay

Thèse préparée au **Laboratoire interdisciplinaire des sciences
du numérique** (Université Paris-Saclay, CNRS, Inria),
sous la direction de **Petra ISENBERG**, Directrice de recherche

Thèse soutenue à Paris-Saclay, le 16 mars 2023, par

Mohammad Alaul ISLAM

Composition du jury

Caroline APPERT Directrice de Recherche, Université Paris-Saclay, CNRS, Inria, LISN, France	Présidente
Wolfgang AIGNER Professeur, St. Pölten University of Applied Sci- ences, Austria	Rapporteur & Examineur
Pourang IRANI Professeur, University of British Columbia, Canada	Rapporteur & Examineur
David AUBER Professeur, Université Bordeaux, France	Examineur
Rúben GOUVEIA Professeur assistant, University of Twente, Nether- lands	Examineur

Titre: Visualisations pour les Montres Intelligentes et les Trackers de Fitness

Mots clés: Visualisation de la smartwatch, conception du visage de la smartwatch, espace de conception, visualisation des données mobiles.

Résumé: Cette thèse porte sur la recherche sur la conception et l'utilisation de micro-visualisations pour l'exploration de données mobiles et pervasives sur des smartwatches et des trackers de fitness. Les gens portent de plus en plus de smartwatches qui peuvent suivre et afficher une grande variété de données. Mon travail est motivé par les avantages potentiels des visualisations de données sur les petits appareils mobiles tels que les brassards de suivi de la condition physique et les smartwatches. Je me concentre sur les situations dans lesquelles les visualisations soutiennent des tâches spécifiques liées aux données sur des smartwatches interactives. Mon principal objectif de recherche dans ce domaine est de comprendre plus largement comment concevoir des visualisations à petite échelle pour les trackers de fitness. Ici, j'explore : (i) les contraintes de conception dans le petit espace par le biais d'un atelier d'idéation ; (ii) le type de visualisations que les gens voient actuellement sur le visage de leur montre ; (iii) une revue de conception et l'espace de conception des visualisations à petite échelle ; (iv) et la lisibilité des micro-visualisations en considérant l'impact de la taille et du rapport d'aspect dans le contexte du suivi du sommeil. Les principaux résultats de la thèse sont, premièrement, un ensemble de besoins de données concernant un contexte d'utilisation touristique dans lequel ces besoins de données ont été satisfaits avec une richesse

de conceptions de visualisation dédiées qui vont au-delà de celles couramment vues sur les affichages des montres. Deuxièmement, un affichage prédominant des données de santé et de forme physique, les icônes accompagnant le texte étant le type de représentation le plus fréquent sur les faces actuelles des smartwatches. Troisièmement, un espace de conception pour les visualisations sur les faces de smartwatch qui met en évidence les considérations les plus importantes pour les nouveaux affichages de données sur les faces de smartwatch et autres petits écrans. Enfin, dans le contexte du suivi du sommeil, nous avons constaté que les gens effectuaient des tâches simples de manière efficace, même avec une visualisation complexe, à la fois sur les écrans de la smartwatch et du bracelet de fitness, mais que les tâches plus complexes bénéficiaient de la taille plus grande de la smartwatch. Dans la thèse, je souligne les opportunités ouvertes importantes pour les futures recherches sur la visualisation des smartwatches, telles que l'évolutivité (par exemple, plus de données, une taille plus petite et plus de visualisations), le rôle du contexte et du mouvement du porteur, les types d'affichage des smartwatches et l'interactivité. En résumé, cette thèse contribue à la compréhension des visualisations sur les smartwatches et met en évidence les opportunités ouvertes pour la recherche en visualisation sur les smartwatches.

Title: Visualizations for Smartwatches and Fitness Trackers

Keywords: Smartwatch visualization, Smartwatch face design, Design space, Mobile data visualization.

Abstract: This thesis covers research on how to design and use micro-visualizations for pervasive and mobile data exploration on smartwatches and fitness trackers. People increasingly wear smartwatches that can track and show a wide variety of data. My work is motivated by the potential benefits of data visualizations on small mobile devices such as fitness monitoring armbands and smartwatches. I focus on situations in which visualizations support dedicated data-related tasks on interactive smartwatches. My main research goal in this space is to understand more broadly how to design small-scale visualizations for fitness trackers. Here, I explore: (i) design constraints in the small space through an ideation workshop; (ii) what kind of visualizations people currently see on their watch faces; (iii) a design review and design space of small-scale visualizations; (iv) and readability of micro-visualizations considering the impact of size and aspect ratio in the context of sleep tracking. The main findings of the thesis are, first, a set of data needs concerning a sightseeing usage context in which these data needs were

met with a wealth of dedicated visualization designs that go beyond those commonly seen on watch displays. Second, a predominant display of health & fitness data, with icons accompanying the text being the most frequent representation type on current smartwatch faces. Third, a design space for smartwatch face visualizations which highlights the most important considerations for new data displays for smartwatch faces and other small displays. Last, in the context of sleep tracking, we saw that people performed simple tasks effectively, even with complex visualization, on both smartwatch and fitness band displays; but more complex tasks benefited from the larger smartwatch size. Finally, I point out important open opportunities for future smartwatch visualization research, such as scalability (e.g., more data, smaller size, and more visualizations), the role of context and wearer's movement, smartwatch display types, and interactivity. In summary, this thesis contributes to the understanding of visualizations on smartwatches and highlights open opportunities for smartwatch visualization research.

Publications

The work presented in this thesis is based on the following publications and a publication in progress.

- [1] Sheelagh Carpendale, Petra Isenberg, Charles Perin, Tanja Blascheck, Foroozan Daneshzand, **Alaul Islam**, Katherine Currier, Peter Buk, Victor Cheung, Lien Quach, and Laton Vermette, *Mobile Visualization Design: An Ideation Method to Try*, Chapman and Hall/CRC, Nov. 2021, pp. 241–261, DOI: 10.1201/9781003090823-8.
- [2] Alaul Islam, Ranjini Aravind, Tanja Blascheck, Anastasia Bezerianos, and Petra Isenberg, “Preferences and Effectiveness of Sleep Data Visualizations for Smartwatches and Fitness Bands”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2022, DOI: 10.1145/3491102.3501921.
- [3] Alaul Islam, Anastasia Bezerianos, Bongshin Lee, Tanja Blascheck, and Petra Isenberg, “Visualizing Information on Watch Faces: A Survey with Smartwatch Users”, in: *Proceedings of the Visualization Conference – Short Papers*, IEEE, 2020, pp. 156–160, DOI: 10.1109/VIS47514.2020.00038.
- [4] Alaul Islam, Tanja Blascheck, and Petra Isenberg, “Context Specific Visualizations on Smartwatches”, in: *Posters of the European Conference on Visualization (EuroVis)*, The Eurographics Association, 2022, DOI: 10.2312/evp.20221122.
- [5] Alaul Islam, Lijie Yao, Anastasia Bezerianos, Tanja Blascheck, Tingying He, Bongshin Lee, Romain Vuillemot, and Petra Isenberg, “Reflections on Visualization in Motion for Fitness Trackers”, in: *Proceedings of the New Trends in HCI and Sports Workshop at MobileHCI*, 2022.

Publications in Progress

- [1] Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, **Alaul Islam**, Tingying He, and Petra Isenberg, “Studies of Part-to-Whole Glanceable Visualizations on Smartwatch Faces”, in: *PacificVis 2023 - The 16th IEEE Pacific Visualization Symposium*.
- [2] Alaul Islam, Tingying He, Anastasia Bezerianos, Tanja Blascheck, Bongshin Lee, and Petra Isenberg, “Visualizing Information on Smartwatch Faces: A Review and Design Space”, in: Under TVCG Submission.

Acknowledgement

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Petra Isenberg, for her exceptional guidance, encouragement, and support throughout my Ph.D. journey. I am incredibly grateful to her for mentoring me, introducing me to the fascinating field of Information Visualization, and providing me with the freedom to pursue the research that I was passionate about. Her invaluable insights and constructive feedback have been instrumental in shaping my research and personal growth.

I extend my special gratitude to the members of my thesis jury for their valuable time and effort in evaluating my work. I am deeply grateful to my reviewers for their insights, suggestions, and constructive criticism, which helped me improve my thesis writing.

I owe my collaborators a special debt of gratitude for their valuable discussions and feedback on my work. In particular, I would like to thank Anastasia Bezerianos, Tanja Blascheck, Bongshin Lee, Ranjini Aravind, Tingying He, and Lijie Yao for their generous support and insightful feedback.

My colleagues in the AVIZ lab have been a constant source of inspiration, guidance, and support throughout my Ph.D. journey. I am grateful to them for their continuous encouragement, friendship, and guidance. Special thanks to Natkamon Tovanich & Pierre Dragicevic for their help with the data analysis and Alexis Pister & Katia Evrat for assisting me with the French administration paperwork.

I would also like to thank my dear friends in Paris, Shoshi, Abida, Sheida, Fairouz, Anam, Salek, Roni, and their families, for their unconditional support and encouragement. I am grateful to my parents and brother, Ashraful Islam, for their love and support throughout my journey. Finally, I want to express my heartfelt gratitude to my beloved wife, Shaela Quader, for her constant encouragement and love.

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Introduction

I started my thesis work with the goal to understand how to design and use micro-visualizations [93] for pervasive and mobile data exploration. The increasing demand for data visualizations on small mobile devices such as fitness tracking armbands, smartwatches, or mobile phones drives my research interest. In these usage context, my goal is to understand how we can use very small data visualizations, micro visualizations, in display contexts that can only dedicate minimal rendering space for data representations. I focus on situations in which visualizations support dedicated data-related tasks on interactive smartwatches.

1.1 Introducing the Smartwatch

” *A smartwatch is a wrist-worn device with computational power, that can connect to other devices via short range wireless connectivity; provides alert notifications; collects personal data through a range of sensors and stores them; and has an integrated clock.*

— Cecchinato et al. [40]

People use smartwatches as personal data collection devices, and with additional wifi or Bluetooth connectivity, smartwatches have access to various types of data. Smartwatches have a long history, dating back to the early days of computer technology. The Hamilton Watch Company introduced the first digital watch in the market in 1971 [158]. Their watch model, Pulsar, used a digital display, and a button was necessary to display the time. In 1983, Seiko, a Japanese company, launched the world’s first TV watch, which allowed users to see different types of data on a watch on two separate screens [54]. One narrow screen showed just time, date, and alarm features, and another screen was used for video output. The Timex Datalink, the first wireless smartwatch, was co-developed with Microsoft in 1994 and could wirelessly download information from a computer [163]. In 1998, Steve Mann invented a wristwatch-based videoconferencing system [135]. All the earliest attempts to build a smartwatch were to make daily life easier by gradually migrating from plugging into PCs to being entirely self.

The early 2000s have seen the beginning of the modern smartwatch evolution. IBM's WatchPad [168], Samsung's SPH-WP10 [103], Fossil's Wrist PDA [68], and Microsoft's SPOT [114] were all notable contributions to the advancement of the modern smartwatch. Pebble's initial Kickstarter [102] campaign to raise funds for the production of a smartwatch collected more than 10 million US dollars in 2012, marking a new era in smartwatch history, indicating an actual demand for such devices. In the next few years, organizations such as Apple, Google, Fossil, Garmin, and Samsung, as well as some new startups, targeted the smartwatch market. Since then, the research and development of smartwatch technology and its adoption by wearers have seen a spectacular increase. According to Statista [183], in 2022, the total number of smartwatch users globally was around 216 million, and it is forecasted that in 2026, the number will be 230 million worldwide. People now increasingly wear smartwatches that can track a wide variety of data.

1.2 Smartwatch Visualization

Despite the fact that smartwatches have grown incredibly popular in recent decades and we see an increase in their use, we still know little about which types of visualizations are most appropriate in the smartwatch usage context. Smartwatches have unique challenges: the display size is small, extended viewing times can be strenuous, viewers are often on the move and have quick information needs [74, 107].

When it comes to smartwatch visualization, “smartwatch face” visualization is perhaps the most fundamental aspect to understand. The screens that wearers of smartwatches look at most often are the “home” screen or “smartwatch face.” These smartwatch faces are the primary screens [74], show time but also a variety of additional data to wearers. They have become mini data dashboards that can give an overview of data such as step counts, heart rates, locations, sleep information or even device-external data such as the current



Fig. 1.1: Photo credit of smartwatch faces from left to right, 1) apple.com, 2) getic.com, and 3) garmin.com

temperature or weather predictions. Watch faces are typically small, have a resolution between 128–480 px per side with a viewable area of around 30–40 mm [23]. Watch faces are often customizable, allowing wearers to choose the data they want to see regularly and at a glance.

One of the difficulties with designing data visualizations for smartwatch faces is that these visualizations typically show many types of independent data (steps, weather, battery levels, etc.) that need to be shown in a coherent watch face design. These non-time/date data functionalities on smartwatches are called *complications* [98]. In this sense, watch faces with several complications can be considered as small personal dashboards with distinctive design challenges. These design challenges include limited display space for a large number of possible complications, device form factors, the wish to express personality through watch face themes and design styles, as well as the mobile usage context that often requires information to be readable at a glance. In addition, watch faces require that time or date is readable and often remains the primary data shown.

If you look at the examples of smartwatch faces, as shown in [Figure 1.1](#), you see the– 1) limited display space for showing data. For smartwatches, it is roughly 30–44mm in diagonal, and for fitness bands, it is half of the smartwatch size; 2) often the targeted usage (such as outside environment, glances, or while in motion); 3) it requires glanceable interactions, that means you need to understand the information as quickly as possible when you see it on your smartwatch. Currently, we have limited to no guidelines for designing visualizations for smartwatches that consider these challenges. To better ground research on smartwatch visualization, it is therefore important to understand how to design for and use visualizations on smartwatches and identify research opportunities.

1.3 Research Context

The research area of my thesis is part of Information Visualization (InfoVis) research. InfoVis is a research area concerned with abstract data-driven graphics or visualizations. It studies and designs computer-supported interactive visual representations to amplify human cognition [36]. My focus in this thesis is micro visualizations or the challenge of creating and reading small-scale visualizations. Isenberg [93] defined *micro visualization* as small-scale visualizations of a few degrees of visual angle in display contexts that can only dedicate minimal rendering space for data representations. Fitness trackers, such as smartwatches and fitness bands, are prime micro visualization usage contexts. For example, a large number of people are interested in analyzing data about their health. To this end, people often wear smartwatches and fitness bands that come with sensors and software that allows capturing data on heart rate, step count, calories burned, or sleep duration. Because of their attached displays, fitness trackers have many opportunities to communicate data to wearers using visualization. I aim to understand how we can use micro visualizations on fitness trackers.

Choosing the data type and showing it to wearers is a fundamental challenge impacting how devices are adopted. In this thesis, I used commercial fitness trackers such as fitness bands and smartwatches because my focus is on data representation and not developing new technologies. However, I acknowledge that many types of wearable displays have been proposed [87] and discuss some challenges related to these in [Chapter 2](#). The work I present in this dissertation is narrowed in scope. Specifically, I focus on understanding the– 1) watch face visualization design space, 2) information visualization on fitness trackers, and 3) static (non-interactive) representations – to establish an empirical foundation for smartwatch visualization research.

1.4 Research Challenges

Because data visualization on small displays has so far been rarely investigated, I focused on tackling the following main research challenges:

- Ch1** *What can help us to imagine future wearable micro-visualizations through a human-centered design approach?*
- Ch2:** *Understanding the broader space of design constraints in the small display context. What is the current practice of smartwatch data visualization to understand untapped opportunities for smartwatch data visualization research?*
- Ch3:** *Understanding the interests and preferences of wearers when it comes to how to visualize data on smartwatches.*
- Ch4:** *What are the constraints of readability of micro-visualizations considering impact of task, size, and aspect ratio in a particular context?*

To address these research challenges, I first started to explore a mobile visualization design ideation methodology through a series of activities as a step towards discovering the potential of smartwatch visualizations. Our motivation was to explore a design methodology that would allow us to design dedicated smartwatch visualizations rather than thinking about how to shrink existing visualizations. I collected and analyzed a large number of extremely varied smartwatch visualization designs that clearly showed the potential of smartwatches to help with in-situ tasks.

After seeing the wide variety of possibilities, my next step was to investigate the current use of visualizations on smartwatch faces. We conducted an online survey with smartwatch wearers, then complemented these results with an online search and analysis of smartwatch face examples, as well as an analysis of the technical capabilities of the watches our participants reported wearing. We found a predominant display of health & fitness data, with icons accompanied by text being the most frequent representation type. Combining these results with a further analysis of online searches of watch faces and the data tracked on smartwatches that are not commonly visualized, we showed opportunities for visualization research.

Next, I conducted a second in-depth study and analysis of visualization designs for popular premium smartwatch faces according to their design styles, amount and types of data, as well as visualization styles and encodings they included. From the analysis we derive a design space meant to provide an overview of the most important considerations for new data displays for smartwatch faces and other small displays. This design space can be used by practitioners as inspiration for different design choices but also by researchers to find open opportunities and ground empirical work on smartwatch visualization design.

After having studied common data types for smartwatches, how data are commonly represented, and a rich set of ideas for future visualizations, next, I wanted to explore, complex charts on fitness trackers. To do so, we tested the readability of micro visualization of sleep data. We ran four studies related to the visualization of sleep data on wearables with two form factors: smartwatches and fitness bands. Our goal was to understand the interests, preferences, and effectiveness of different sleep visualizations by form factor. In one in-person pilot study, and two crowdsourced studies, we then tested the effectiveness of the most preferred representations for different tasks, and found that participants performed simple tasks effectively on both form factors but more complex tasks benefited from the larger smartwatch size.

1.5 Thesis Overview

My thesis work contributes to 1) an ideation exercise for finding the untapped opportunities for smartwatch visualization in the context of sightseeing, 2) findings on current smartwatch use and open opportunities for visualization research and design, 3) a first in-depth description of the design space of smartwatch face visualizations and a research agenda to inform and inspire the visualization community to pursue and improve smartwatch visualizations, and 4) findings regarding the effectiveness of preferred visualizations across three form factors (smartwatch, horizontal, and vertical fitness bands) to make recommendations about visualizations for sleep data.

The thesis is structured into seven chapters. The title and short descriptions of each chapter are listed as follows:

Chapter 2 *Related work on Smartwatch Use and Visualization*

describes my literature review of smartwatch use, smartwatch visualization and a systematic review of smartwatch representations on watch faces and in applications.

Chapter 3 *Smartwatch Visualization Ideation*

provides a simple, generative ideation activity for smartwatch visualization illustrated by our experiences and an analysis of the outcomes of the exercise for smartwatch visualizations.

Chapter 4 *Smartwatch Visualization: A Survey with Smartwatch Users*

presents the findings of a survey with 237 smartwatch wearers, and assesses the types of data and representations commonly displayed on watch faces.

Chapter 5 *Smartwatch Visualization: A Review and Design Space*

demonstrates a systematic review and design space of visualizations on smartwatch faces, which can expose a variety of data to the wearers and often include visualizations. This chapter builds on the prior work described in the previous chapter 4 in multiple ways: a second in-depth study and analysis of visualization designs for popular premium smartwatch face according to their design styles, amount, and types of data, as well as visualization styles and encodings they included.

Chapter 6 *Perceptual Study on Sleep Visualization*

presents the findings of four studies related to the visualization of sleep data on wearables with two form factors: smartwatches and fitness bands.

Chapter 7 *Conclusion*

summarizes my thesis and provides discussion and reflection on possible future work on smartwatch visualization.

Related Work

The practice of using technology like wrist-worn wearables (e.g., smartwatches, fitness bands) is becoming more widespread. Wearers of fitness tracking devices often use visualizations to increase self-awareness, and self-knowledge that may lead to behavioral change. However, research on visualizations for fitness trackers is still sparse. Prior work with wrist-worn devices has focused mostly on presenting new form factors for smartwatches (for example Augmented Forearm [153], Snaplet [188], Doppio [175], Facet [132], Display Skin [34], or Watch accompanied by Strap [112]), improving the technical capabilities of smartwatches (e.g., battery life [141], screen resolution [164], sensors [105, 126, 187, 196], interaction techniques [147, 150]), recommendations to improve engagement with wearers [38, 59, 179], or the role of these wearable devices in people's life [159]). Here, I focus on the use, interactivity, and perception of wearable data visualizations. I discuss related research on wrist-worn fitness trackers' current use and their visualizations after briefly introducing wearable devices.

2.1 Wearable Devices

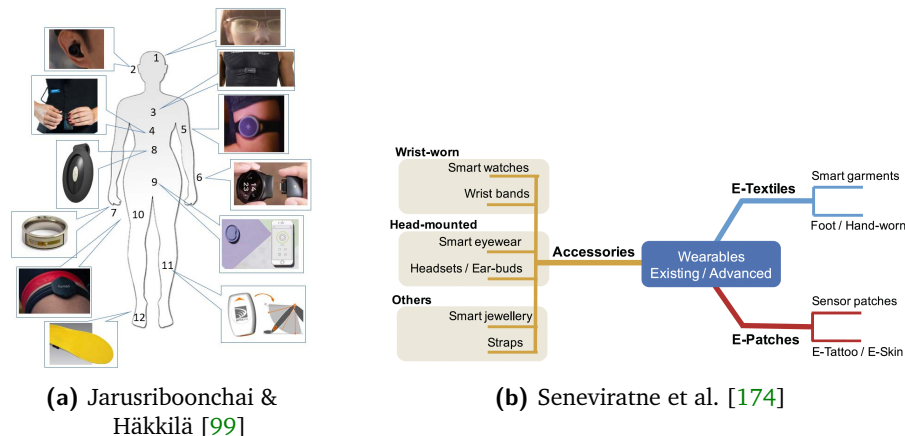


Fig. 2.1: (a) Examples of wearable devices according to the body part the devices are worn on. The numbers indicate the body parts– 1) Head, 2) Ear, 3) Chest, 4) Torso, 5) Arm, 6) Wrist, 7) Finger, 8) Waist, 9) Pelvis, 10) Thigh, 11) Leg, and 12) Foot. (reprinted with permission from the ACM)

(b) The classification of Seneviratne et al. [174] wearable devices is based on three main categories, where each category is divided into sub-categories. (reprinted with permission from authors)

Thad Starner [182] defined *wearable computers* as “any body-worn computer that is designed to provide useful services while the user is performing other tasks.” Although wearable technology can be dated back to the mechanical watches of the 1900s, the emergence of “wearable computing” started only a few decades ago [79]. The first wearable computer in the modern programmable sense was invented in 1981 by Steve Mann, who built a backpack-mounted computer with text, graphics, and multimedia capability to control photographic equipment [79]. From a wearer’s point of view, Mann [134] also described the six attributes of wearable computing, where a wearable device is – 1) *Unrestrictive* to the wearer (e.g., the wearer can do other things while using it); 2) *Unmonopolizing* of the wearer’s attention (e.g., a wearable device is built with the assumption that computing will be a secondary activity rather than a primary focus of attention); 3) *Observable* by the wearer (e.g., the output medium is constantly perceptible by the wearer); 4) *Controllable* by the user (e.g., the wearer can grab control of wearable devices at any time you wish); 5) *Attentive* to the environment (e.g., a wearable device gives the wearer situational awareness); 6) *Communicative* to others (e.g., a wearable device can be used as a communications medium when wearers want it to). Wearable computing is now a much more important part of our lives, with a variety of wearable technologies supporting us in living better lives and working smarter. Wearable technologies, also known as “wearables,” are typically worn on the bare skin, such as worn on the wrist (e.g., smartwatches, fitness bands), on the arms (e.g., belts, straps), on the chest (e.g., electrocardiogram patch), hung from the neck (e.g., chains, necklaces), on the head (e.g., glasses, a helmet), as a piece of jewelry (e.g., on a finger, ear, or in a shoe), or worn on top of clothes (e.g., e-textiles, smart clothes). Based on existing literature, Heller et al. [87] proposed a design space for wearable displays, where they categorized wearables based on their placement on the human body and display content (e.g., intended audience, temporal features, and display technology). They categorized nine places on the body, such as head, torso, waist, legs, foot, arm, hand, wrist, and entire body, commonly used for wearables as accessories, clothing, and body skin. Jarusriboonchai and Häkkinen also grouped 129 wearable devices according to 12 body parts the devices are worn (see Figure 2.1a). Their main focus was customization-enabled wearable devices which allow wearers to modify the technology to meet their own needs and preferences. Similarly, in a survey of existing commercial wearable products and advanced research prototypes, Seneviratne et al. [174] put wearable devices under three categories: 1) Accessories, 2) E-Textiles, and 3) E-Patches (see Figure 2.1b). Wrist-worn devices (e.g., smartwatches, fitness bands) are the most widespread wearables because the wrist is the prevalent placement for wearable displays and is easy to read and reach for interaction [87]. In this dissertation, I narrow my focus to wrist-worn devices because of their increasing use by wearers.

2.2 Fitness Trackers Use in the Wild

Fitness trackers have become an essential tool for quantified-self enthusiasts, self-trackers, sports enthusiasts, and healthcare professionals seeking to track daily activities, achieve personal goals, enhance athletic performance, and monitor patients' health. Quantified Self, also known as self-tracking, self-monitoring, lifelogging, personal informatics, and personal analytics [130], has become a craze for fitness conscious people in their daily lives. In the following, we discuss related research on fitness trackers' current use and visualizations.

Reasons for Wearing Fitness Trackers. Fitness tracking devices such as smartwatches and fitness bands boost the “quantified self” movement, and research has continued to try and understand the wearer's motivation to use these devices. Carrion et al. [38] conducted a study with 30 teenagers using the Withings Pulse smartwatch [193], and the Misfit Shine [177] fitness tracker for a week. The main data participants used were calories burned, steps made, and sleep duration because these were related to sports, and activity contexts participants were familiar with, and related to specific goals they had set. In another similar online diary study with 34 wearers of Fitbit [65] and Jawbone [101] trackers, Asimakopoulos et al. [13] found that multiple factors motivated participants to wear a device: (i) seeing if they met their goal (movement, sleep, calories count); (ii) looking, and feeling good, improving their mood, and to avoid sitting; as well as (iii) getting tips, and recommendations about their health. Choe et al. [43] analyzed 30 videos during which quantified selfers presented the insights gained from their data to understand what people wanted to learn from their personal data. The researchers found that quantified selfers engaged in many insight-generating data analysis tasks (such as looking at trends, correlations, or distributions) to self-reflect. Later studies focused on commonly used features of smartwatches, finding that people mainly used smartwatches to monitor [176], and track activities [137] or respond to notifications [159] in addition to timekeeping. Schirra and Bentley [171] conducted interviews with early adopters of smartwatches with a focus on reasons for adoption and what tasks wearers used the smartwatches for. They found that viewing notifications from the connected device was the most used feature, and notifications about the daily goal from the smartwatch health-fitness sensor motivated them to continue wearing the smartwatch. Similarly, Cecchinato et al. [39] emphasized the benefits of receiving notifications on smartwatches and saw that participants wanted notifications to be (i) glanceable, (ii) priority-filtered, and (iii) contextual.

Setting Self-tracking Goals. People's tracking goals and practices evolve as their needs and understanding change [58, 60]. Individual goals of fitness tracker wearers can be personal depending on their mindset and context. Niess and Woźniak [152] conducted interviews and a survey with fitness tracker wearers and created a goal evolution model to describe how qualitative goals (e.g., I need to lose weight) emerge from internalized hedonic and eudaimonic needs (e.g., I want to feel well in my body) and are translated to the tracker's quantitative goals (e.g., 10k steps a day) through reflection and trust. Therefore, trackers

need to refer to qualitative goals and show wearers how their daily quantitative goals contribute to more significant qualitative goals. However, the challenge with current-day fitness trackers is the normative nature of goals, highlighted in a study by Spiel et al. [179]. An example of such a goal is the tracker's daily step count, which is a marker of fitness, regardless of other factors, such as the wearer's current state of fitness or whether the step is a joyful step or a miserable step. The authors offer design strategies to approach fitness tracker designs through a more diverse lens by allowing more customization to individual needs (e.g., age, sickness) and context (e.g., mood, religious observation, pregnancy). The authors also emphasized implications for designers and recommended displaying fitness tracker data more clearly, by displaying visual representations of a range of bodily movements (e.g., rapid walking, climbing up stairs), including the precise number (e.g., 2k steps). In a recent study, Feron et al. [62] focus on pregnancy as a lens to understand how self-tracking devices are used as people experience a life change. They surveyed 41 pregnant women to understand the use and engagement with self-tracking tools (specifically Fitbit users) as they transitioned into their pregnancies. They found that many women were challenged with reading their tracker-provided raw data (e.g., step count, heart rate), increasingly turning to other people to help them in this process and highlighting the lack of support offered by trackers.

Using Fitness Trackers during Sports Activities. Despite activity tracking, in sports, smartwatches are used for skill improvement support systems, training, or feedback for improvement. Lopez et al. [128] studied the effectiveness of smartwatches as an individual skill improvement support system in sports in baseball pitching action and tennis' serve action, where arm movement is significantly related to skills. They found that on-site feedback (e.g., baseball pitching speed 86km/h) and skill improvement advice (e.g., let's throw with your wrist more flexibly!) after the activity on smartwatches improved the participants' pitching speed. Langer et al. [116] showed a concept for a crash risk indication application for sports smartwatches in mountain biking.

Using Fitness Trackers in Healthcare. Research on smartwatches, used as assistive devices for medical care or illness prevention has also shown promising potential in healthcare, specifically, for elderly population, when remote health monitoring is crucial. Smartwatches can assist with patient health monitoring by keeping track of a patient's medication [104] and reminding them when it is time to take their medication each day [133]. Research has shown the advantages of using smartwatches by deaf and hard-of-hearing people, for example, assisting low-vision people during daily activities [160] or providing environmental sound awareness [72]. Mielke and Brück [140], from their interviews with six deaf people, found that participants were confident about using the smartwatch and described the advantage of the smartwatch use as it is an everyday device used by most people, thus would not stand out and is not recognizable as an assistive device in a social context. Similarly, smartwatches were determined to be the most favored portable device for non-speech sound awareness in a recent study of 201 deaf and hard of hearing people [64]. Others looked at specific smartwatch uses in healthcare field such as stress detection [44, 178], understanding

a wearer's emotional state [162], respiration monitoring during meditation [82], sleep monitoring [41], diet monitoring [108, 173, 181].

Healthcare via smartwatch technology is still in its early stages. Getting both technology and data displays right is critical since gathering erroneous health data or misinterpreting such data might result in harmful side effects [148]. Meyer et al. [139] have shown how visualizing health data in the context of mobile data visualization is difficult and complex. Research has yet to focus on healthcare data representation difficulties on the smartwatch. In contrast to this stream of research, I focus on data representation directly on fitness trackers, specifically on smartwatches, and how dedicated representations should be designed for smartwatches.

2.3 Data Representations on Fitness Tracker

For visualization research, smartwatches pose unique usage challenges. Studies have shown that people take a look at a smartwatch on average for only 5–7 sec [73, 74, 137, 159, 190]. Such brief peeks or glances allow for the reading of time (avg. 1.9 sec [159]), but it is uncertain how much more information may be gleaned from a watch face at a quick look. To answer this question, researchers studied low-level perceptual tasks to understand glanceability of smartwatch visualizations [23], the impact of visual parameters (e.g., size, frequency, and color) on reaction times [131], or representation preferences in an air traffic control use case [145]. Recently researchers started to conduct dedicated research on visualization techniques for smartwatches. Some of this research targets novel types of representations such as Chen's [42] temporal data, Suciu and Larsen's [185] time spiral, or Neshati et al.'s [146, 149] compressed line charts.

Smartwatches are becoming increasingly intelligent because they capture and communicate a wide range of information to wearers. However, wearers may abandon smartwatches and miss out on this technology's benefits due to a lack of context-specific data representation or if visualizations are not adequately designed. Niess et al. [151] studied the impact of various approaches to represent unmet fitness tracker goals through visualization on rumination, highlighting that multicolored charts on fitness trackers may lead to demotivation and negative thought cycles. Amini et al. [5] conducted interviews with ten participants to uncover demands for exploring health and fitness data, particularly while people are moving. The most common insights were related to reading single or multiple values, estimating the progress towards a goal, comparing one or multiple measures with other people's, and being motivated. Based on their findings, Amini et al. also asked nine graphics designers to sketch representations for each insight type. Especially for the goal-based insight category, most sketches used visualizations instead of text. Havlucu et al. [84] interviewed 20 professional tennis players and found that the players' abandonment of their trackers was due to the

type of information displayed on the fitness trackers. Participants wished to see tennis-specific data, recovery rate, and nutrition, as well as precise technical data regarding their tennis performance, such as where the ball hit the racket, the speed of a stroke, how the ball bounced off the floor, general mobility on the court, as well as weak points and errors regarding their own game. Schiewe et al. [170] studied real-time feedback during running activities for the 40 participants. They noticed that the participants preferred visualization for self-serviced concurrent visual feedback on the smartwatch over textual data representations.

Outside of the professional sports context, smartwatches also have a lot of potential to be an essential part of the personal health movement. Yet, even with a potentially large target audience, visualization guidelines for fitness trackers are still sparse. Most of the past studies discussed health and physical activity data representations on smartwatches and mentioned the challenges of representing these data types [148]. Neshati et al. [146], for example, explored how to effectively use a smartwatch display for presenting interlinked time series data (e.g., heart rate, breathing rate) with a space-filling line chart technique. Van Rossum [166] suggested smartwatch visualizations aiming for easy-to-understand, clear visuals, using a black background for contrast, and less disturbance in dim environments. Albers et al. [4] showed that the tasks that wearers do when exploring a visualization are influenced by the visualization's design and choices of visual factors (e.g., position, color), mapping variables (e.g., raw data, averages), and computational variables (how aggregated data are computed). Pektaş et al. [156] showed how visualizations using icons and emojis on warnings and alerts could motivate wearers to monitor health related information.

My own research focused primarily on smartwatch faces. As the home screen of a watch, watch faces are the most frequently seen screens of a smartwatch. It is important to understand more broadly how these small-screen displays are designed. Next, I discuss prior studies that discussed watch face data representation or application design.

2.3.1 Smartwatch Representations on Watch Faces and in Applications

To systematically analyze papers on smartwatch face designs or applications designs for data representation, I conducted a small systematic review: [Figure 2.2](#) shows the review results. I collected papers using a snowball sampling technique that started from a first set of articles I had read for prior work. I complemented this approach with a google scholar search with the terms, “smartwatch visualization” and “smartwatch application,” and looked at the first 550 results before results became largely irrelevant. I also looked into the ACM and IEEE digital libraries, searching with the term, “smartwatch,” and looked at the first 100 results. I added papers if they included discussions about data displays on the smartwatch screen,

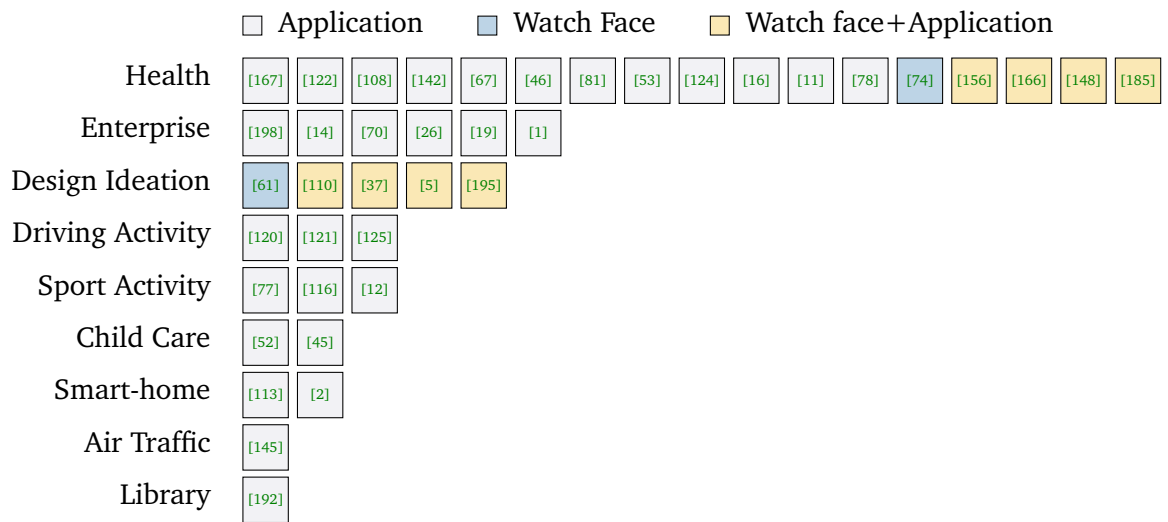


Fig. 2.2: Publications that discuss smartwatch applications and data representation by research areas. The color represents whether the publications discuss the specific application design (application), watch face design (watch face), or both (watch face + application).

and excluded papers purely on technical considerations or interaction-focused content that did not discuss data displays.

I found 40 publications that discussed smartwatch data displays for applications, watch faces, or both. Among them, only 10 papers included smartwatch face design ideas or presented watch face prototypes. The other 30 publications focused entirely on the design and development of smartwatch applications. I categorized the articles also according to their main research focus. Five papers focused on broad design ideations either on watch faces or both watch faces and watch applications. The others focused on specific application contexts such as health (12×), sport activity (3×), child care/health (2×), enterprise application (6×), smart-home (2×), library management (1×), air traffic control (1×), or driving activity (3×). Only two papers [61, 74] focused entirely on smartwatch face design, and eight others reported on both watch faces and applications. Esakia and Kotut [61] describe five guidelines for designing smartwatch applications and evaluated them in a mobile computing class, in which the authors asked undergraduate students to consider the applications as part of a design and development cycle. The design guidelines helped students develop watch faces in the context of a project promoting community physical activity. Gouveia et al. [74] focused on glanceable physical activity feedback for smartwatches derived through an iterative ideation process. They recommend glanceable feedback on the smartwatch face to prompt further user engagement with the presented information.

The significant amount of personal data created by smartwatches and fitness trackers presents a challenge for researchers and practitioners who must make sense of this information while designing data representation. My thesis is concerned with understanding smartwatch visualization design, specifically smartwatch mini dashboard design and smartwatch chart

readability. In a prior study by Blascheck et al., the authors investigated three charts (bar, donut, and radial) with increasing data points shown full-screen on a smartwatch. The researchers' goal was to find minimal perception time thresholds for a simple data comparison task on the smartwatch. On the one hand, my work is closely related to smartwatch perception studies. Such as this one, this thesis explores general smartwatch face designs used in everyday life without a specific usage context. As such, this work is also closely related to other two papers [5, 74]. Amini et al. [5] showed that minimal designs and simple data-driven visualizations in the form of charts have a great potential to support in-situ data exploration on small smartwatch displays. Gouveia et al. [74] proposed six design qualities for smartwatches: being abstract, integrating with activities, supporting comparisons to targets and norms, being actionable, leading to checking habits, and acting as a proxy to further engagement while designing glanceable feedback for physical activity trackers. They designed and prototyped four smartwatch faces, applying those design qualities to understand better how different glanceable feedback affects wearers' engagement and physical activity.

2.4 Summary

In contrast to the stream of research I summarize above, my work complements prior recommendations by systematically analyzing and reviewing smartwatch faces to guide a smartwatch design space which can be used not only by practitioners as inspiration for different design choices but also by researchers to find open opportunities and ground empirical work on smartwatch visualization design. Furthermore, I focus on data representation directly on fitness trackers and how researchers should design specific data representations (e.g., sleep visualization) for the small-scale display. My work contributes visualizations that wearers prefer for sleep data and the effectiveness of preferred visualizations across three form factors (smartwatch, horizontal, and vertical armband) to make recommendations about visualizations to use for sleep data.

In the following chapters, I will describe a workshop study and outcome, exploratory studies on smartwatch face design, and a series of perception studies to look into the readability of micro-visualizations on smartwatches.

Smartwatch Visualization

Ideation

To uncover ways to create new designs for smartwatch visualizations and answer my first research challenge, “What can help us to imagine future wearable visualizations through a human-centered design approach?”, I took part in an ideation workshop in a sightseeing context. The goal of the exercise was to create a rich set of different ideas in the context of a specific use case. The workshop was conducted with Tanja Blascheck, Pantelis Antoniadis, Cristina Morariu, Anne Reuter, and Petra Isenberg, contributing a book chapter [37] and a poster [96]. Any mention of ‘we/our’ in this chapter refers to my co-authors and colleagues.

This chapter aims to offer a simple, generative process illustrated by our experiences with its use, with which designers can derive a rich set of ideas for smartwatch visualization applications that are meant to communicate data visually in a specific context. Designing visualizations for small wearable mobile devices is a challenging task. Many mobile apps that include graphical data representations adjust and simplify desktop-sized visualizations and make them available with simple interactions. These relatively direct design translations point to possible untapped visualization and interaction design opportunities. Considering both the technological and usage differences in mobile contexts, it seems extremely likely that these untapped opportunities exist. Concerning technological differences, visualizations for mobile devices can take advantage of novel input modalities that do not exist on desktops: accelerometers, gyroscopes, or personal health-related sensors for heart rate, oximetry, skin temperature, etc. Through sensors, mobile devices have direct access to data and can provide quick contextual information to viewers. Most carryable and wearable devices also have smaller screens or screens with completely different form factors than desktop or laptop screens. This opens up opportunities to develop novel dedicated visualizations rather than trying to make existing representation techniques fit. Concerning mobile usage contexts, people’s motivation for using mobile visualizations is often much unlike those of stationary office workers sitting in front of larger desktop or laptop screens. In mobile contexts, for example, people: (1) may want to gain better awareness and understanding of their surroundings, and current situation, (2) integrate this situational information into their current activities, and (3) understand, share, or analyze data in non-office surroundings with motion, uncontrolled lighting, or noise.

To let go of the limitations of designing by translating existing visualizations and adapting them to mobile scenarios, we have devised and explored a flexible design process. This

design process can help us to think of mobile visualizations by considering specific contexts of use, mobile-specific tasks, and personal use cases. Specifically, the design process involves stepping into specific usage contexts and tasks, then taking moments to reflect on the current situation and information needs, ideating design ideas, and reflecting on them with others. The methodology aims to create a rich set of ideas in the context of a specific use case. Assessing the “value” of each idea, refining it, and selecting or discarding it, is a task intrinsic to the motivation of us using the methodology. Therefore, this chapter does not discuss methods to assess an idea’s novelty, effectiveness, or potential success. We also do not claim that the methodology produces “better” ideas than other methodologies if that is even something that can ever be claimed about an ideation methodology. Instead, this chapter offers a methodology we tested and found helpful for generating rich ideas for mobile visualizations that communicate data visually. We detail how the design methodology works in general, how our participants adapted it, and provide examples of the richness of the ideas that emerged in our design workshop.

3.1 Relationship to other Design Methodologies

The basic ideation methodology we used was first explored and then published as a workshop paper by Currier et al. [51] with a focus on in situ journaling by a single person. Here, we give more details on the method, relax the frequency of note-taking and sketching, and give evidence about how the method can be adjusted and appropriated to different scenarios. The method discussed here centers around sketching, a method Buxton [75] describes as a distinct form of drawing that supports the exploration and communication of ideas about designs. Dedicated “data sketches” have been found and studied on whiteboards [191] and supported in data presentation and exploration interfaces [33, 117, 118] giving evidence that people frequently think and brainstorm with data. As a support mechanism for data visualization ideation, sketching has been in particular promoted as part of the Five Design Sheet methodology [165] or the Visualization Worksheets [136]. Yet, these approaches focus on specific details about a given part of the ideation process, such as designing an encoding. Our method is more closely related to approaches for ideation in situated visualization design. Bressa et al. [32] recently discussed a series of seven design workshops that, similar to ours, used a variety of props and sketching sessions to create ideas for situated visualizations. Discussions during ideation centered around several questions that were different from ours, such as where to and how to place the visualizations in the world but surfaced some similar concerns, such as designing simple rather than complex visualizations that can be parsed at-a-glance.

Much of the visualization design ideation advice has tended to focus on specific situations in which factors such as the data and domain experts are known (see, for example, Sedlmair et al. [172]) or to provide specific details about a given part of the ideation process such

as designing an encoding [165]. Our approach takes inspiration from several sources including behavioral sampling [27, 55], repetitive sketching techniques [76], and enactment of scenarios [90]. Within the larger ideation space, our method belongs to the empathic design methodologies [184]. The goal here is for designers to learn how their designs might be experienced in the intended usage surroundings. Many of the techniques that exist to help designers understand these real-world experiences range from simple “what-could-be” observations, role-playing, or taking existing prototypes into target environments. Bodystorming [154] is a technique similar to ours as it focuses on design sessions in the intended context of use coupled with discussions and further brainstorming on-site. It has been promoted for the ideation of ubiquitous computing interfaces but follows a different preparation phase as it gives participants specific design questions to target.

On a higher level, our method follows in the tradition of the IDEO Method Cards [91], which intentionally provide a minimal description as a starting point—typically, one image, a title, and 2–3 sentences. This minimal description helps trigger within each person or group of people an ideation method that best matches their current needs. In this chapter, we provide more detail, intending to focus on smartwatch visualization scenarios while still offering considerable flexibility in the execution of the methodology. Each group adapted the method to their personal, current situation, but within these variations, all groups found it a rich idea generator.

3.2 General Steps of the Ideation Method

In general, the ideation activity takes 1–3 hours. It is intended to be done as a paired activity with another person to share the experience and discuss ideas with. Together both partners *choose an activity* (for example, going to the supermarket, going to the museum) that is agreeable to both partners as well as the mobile context for which they would like to design (e.g., phones, smartwatches, fitness bracelets). Next, both partners choose and *prepare note-taking material* and decide on a note-taking procedure. Note-taking materials can consist of digital devices, mobile device props made out of other materials such as paper or cardboard, or simple notebooks. Once materials and situations are ready, both partners should use a note-taking procedure that works for their scenario. Typically, both partners start with their activity and stop after an agreed-upon time interval (*choose note-taking interval*), with every 30 minutes being a good first estimate. During every activity gap, each partner individually evaluates their information needs in the current situation and sketches a visualization that would address these needs in the current situation for the chosen mobile device (*ideate*). Notes should be added to the sketches, so ideas are clearly communicated for later re-assessment of the sketches. After the sketching time *both partners discuss* their ideas and add comments, adjustments, or variations to their notes and sketches. Then, partners continue with the activity for the next time interval and repeat the previous two

steps. It is ideal to try the activity at least four times or more as needed. After the end of the exercise, partners meet as a group to go over all their sketches, generate affinity diagrams, and choose the most promising ideas to iterate on further.

3.3 Smartwatch Ideation Activity

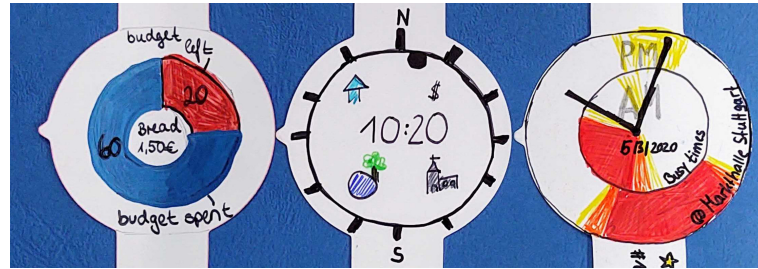
Ideation exercises can help derive new forms of smartwatch applications that have been used successfully. Gouveia et al. [74], for example, focused on glanceable physical activity feedback for smartwatches derived through an iterative ideation process. Through participatory design workshops with children with ADHD, Cibrian et al. [45] identified tensions when receiving notifications on a smartwatch and challenges in designing wearable applications supporting children's self-regulation. Similar to these two examples, we were interested in ideation activities focused on deriving new ideas for smartwatch visualizations. We focused on a specific usage context, sightseeing, rather than attempting to derive broad but unspecific visualization ideas. In contrast to the prior work, our designs were derived during the activity, in situ, and attempted to capture the information needs of participants in specific locations and during the activity itself.



Fig. 3.1: a physical paper prop.

We conducted the workshop during a half-day group sightseeing activity in Stuttgart, Germany. We aimed to see whether the methodology could generate a rich set of smartwatch visualizations dedicated to the activity. We gave every participant a physical paper prop (see [Figure 3.1](#)) in the shape of a smartwatch. The group, consisting of six people, two foreigners (one who had never been to the city), three locals, and one person who grew up in the area but had been living abroad for over 16 years, started to explore the city of Stuttgart by visiting sights and stopped every 30 minutes. Each individual evaluated their information needs in the current situation and sketched a visualization on the prop that would address these needs in the current situation. After the sketching time, the two partners discussed their ideas and added comments, adjustments, or interpretations to their notes and sketches. The ideation exercise took place at different locations, including a market hall, the town hall with a famous pater-noster elevator, twice in a museum with a historic clock collection, and during lunch. We collected 34 sketches from the group. The following idea descriptions are grouped by the locations where the smartwatch visualizations were thought of.

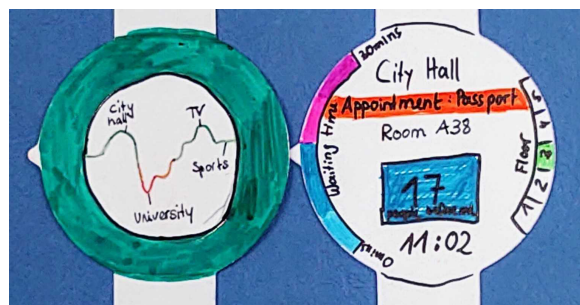
Stuttgart Market Hall



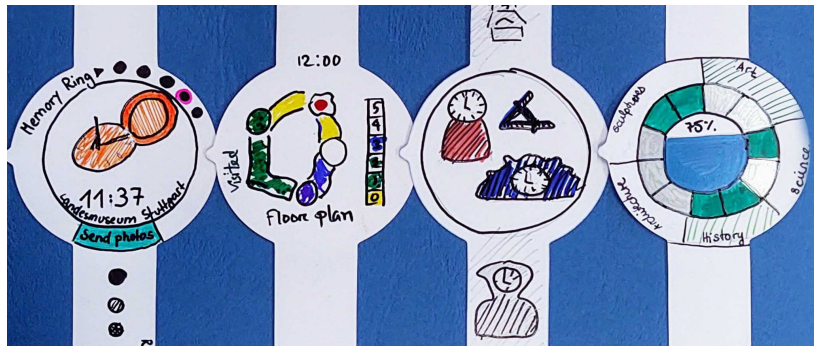
We created eight sketches, which we categorized into three groups. One group of four sketches was about apps that would help with shopping inside the market hall, such as a shopping list, a budget manager, or a product info display. One sketch described a smartwatch application to find sights in proximity to the wearer's current location. Three sketches concerned apps, which give additional information about the current sight, such as opening or busy time periods and facts about the place, ratings by other tourists, or how one can pay for products (cash or credit). The left image shows a budget manager for souvenirs, money already spent, and how much a current item of interest costs. The middle image is a smartwatch face with an abstract map background that shows sights in the vicinity. Each icon can be touched for more information. The right smartwatch face gives detailed information about the current sight being visited. The two inner rings show busy times, while the wristband (not visible) shows additional information and ratings about the place.

Town Hall—Riding the Paternoster

Stuttgart's main town hall has one of the few remaining functional and publicly accessible paternoster elevators, which is a hidden tourist attraction in the city. Here, we collected seven sketches in three different categories. Two sketches focused on a smartwatch app related to elevator riding more generally, with information about which floor one was on, which services were available on the floor, or potentially also the position and waiting time for other elevators. One participant enjoyed the ride on the paternoster and drew an app that would capture his excitement throughout the sightseeing trip—showing a spike during the visit at the paternoster. The outside ring color represents an average level of excitement for the day (left image). Three apps were related to an imagined visit to the town hall for administrative purposes (right image). The purpose of the visit, place, and time of the appointment are shown, as well as an average wait time and an indication of how many people (17) are in the front line. All three were focused on way-finding in the rather large administrative building of the Stuttgart town hall.

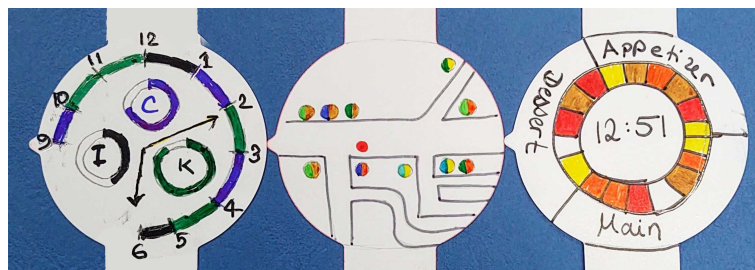


Landesmuseum Stuttgart—Clock Exhibition



Next, we visited a local museum featuring a historic clock and a scientific measurements exhibition. Here, we had two ideation sessions during which we collected 11 different sketches. Three sketches contained an app that would help with the problem of taking photographs of exhibition pieces for memory keeping (left image). Two further sketches included floor plans of the museum with tracking of which rooms one had already visited (second image). Two sketches showed apps that would allow us to have a closer look or get general information about exhibition pieces close by (third image). Two sketches (right image) were concerned with giving an overview, recommendation, and ranking of exhibition pieces in the museum as a guide on what to view next. As we were getting closer to lunch and the end of our sightseeing activities, two sketches showed information about upcoming events and the time left for the museum visit.

Lunch



To conclude our ideation activity, we went for a joint lunch in a local café, and after ordering food and drinks, we did one more sketching session that resulted in eight sketches. Three sketches were concerned with the day as a whole. Two displayed a history of activities throughout the day, and one focused on showing the weather to inform future sightseeing activities. One app showed a daily overview of the sightseeing activities of the day with measures of knowledge or calorie gain and burn (left image). Four sketches were related to the restaurant experience focusing on apps that would help to find a restaurant based on price, type of food, or ratings (middle image). One app was related to choosing a menu item based on customer reviews, for example, which dessert other people spoke positively about on public ratings (right image). One app concentrated on more detailed information inside the restaurant, such as waiting times, the assigned table, restroom information, or other people one could meet based on social media connections.

3.4 Insights from the Sketches

We wanted to analyze the sketches in-depth to find underlying patterns in the designs and draw inspiration for future smart- watch visualizations. To analyze the 34 sketches, we conducted an open card sorting [194] exercise with printed copies of the sketches. The dimension of each image was 12.5 cm × 18 cm. The session lasted for one hour. Here, we report on the most interesting categories observed from the card sorting.

Applications vs. Watch Faces. We found two different types of interfaces people sketched (see [Figure 3.2](#)): Watch faces (18 ×) that showed the time in addition to other information and applications (16 ×) that did not show time. 44% (8/18) of the watch face designs and 50% (8/16) of the applications included visualizations in the form of charts and maps. Perhaps, applications showed visualizations more frequently because no space needed to be dedicated to displaying the current time. On the watch face designs, time was shown in two ways: analog time imitating classic dials or digital time using text. 83% of the designs used a digital time representations (15×) and only 17% used an analog time (3×) display.

Information Needs. We grouped the sketches into eight categories based on the information need categories the designs mainly targeted: entertainment (7×), shopping (6×), activity tracking (5×), tasks (5×), restaurant (4×), navigation (4×), elevator riding (2×), and weather (1×). Interestingly, not all designs targeted sightseeing-related information needs. Specific locations, such as the town hall, also elicited ideas related to administrative tasks. However, entertainment-related information needs were the most common. These included mainly ideas related to memory keeping or showing additional data about interesting sights or exhibit pieces seen. A contrast in targeted information needs was visible when comparing the watch face with the application interface designs. For example, information about an activity (4×) (e.g., calories burned, step counts) or task keeping (5×) (e.g., appointment scheduler, day tasks plan) was more common on watch faces than in application-type (1× activity overview, 0× task keeping-related info) sketches. However, entertainment-related designs (e.g., memory keeping, exhibition recommendation) were more apparent in application-type (5×) interfaces and less in watch face (2×) designs.

Data Representation. We found that most of the data were represented using charts (10×) (see an example in [Figure 3.3a](#)) followed by icons (9×) (see an example in [Figure 3.3b](#)), text (6×), icon+text (4×), icon+chart (1×), and last pictograph (1×). A few sketches also showed a map/navigation (4×) or icon+map (2×) (see [Figure 3.3c](#)) representation. Charts were mainly radial bars (6×), bars (2×), heatmap (1×), and a line chart (1×). The radial bars represent proportion-type data, such as budget spent at the market, goal-based data, such as calories burned based on total goal, or distance traveled in meters. Maps abstracted particular locations, such as the street view showing restaurants in [Figure 3.2d](#) or the building floor plans on the watch strap in [Figure 3.3c](#).

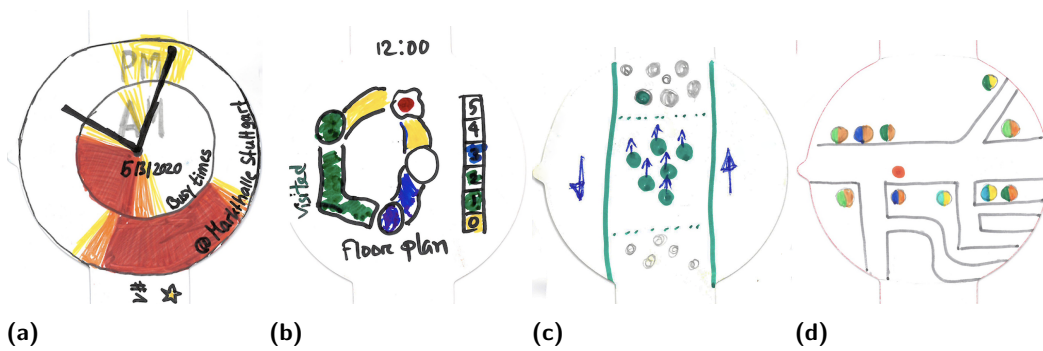


Fig. 3.2: Smartwatch face (a & b) and application (c & d) ideas. The sketch (a) is an analog watch face representing the market crowd in the morning and the evening using a heatmap; (b) is a digital watch face with a museum floor plan tracking which rooms one had already visited; (c) represents the townhall elevator: how many people are riding up or down in a real-time; and (d) shows the restaurants in a specific area: colors represent price, types of food, or rating; the single red dot shows the wearer's current position.

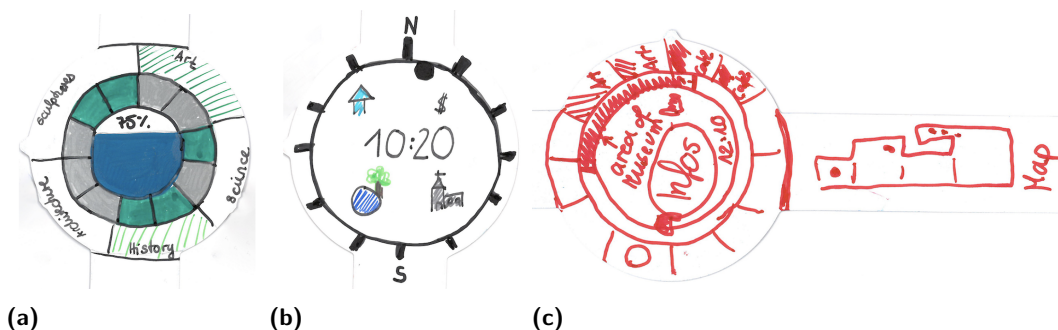


Fig. 3.3: Three representation ideas. (a) shows an overview, recommendation, and ranking of exhibition pieces in the museum as a guide on what to see next; (b) shows an abstract map with icons representing visited places in the vicinity; (c) shows a floor plan on to the watch strap about the wearers' position in the museum and visited exhibition pieces on the watch face.

Going Beyond the Display. Eight sketches included visualizations on watch straps to complement the main display. The watch straps mostly showed static contextual information such as maps (see [Figure 3.3c](#)), and additional information about a visited place (e.g., ratings, established year, the total area). One example included dynamic data showing the current floor on a map while riding an elevator.

3.5 Discussion

In this chapter we contribute an ideation method for designing mobile visualization as well as examples of using the method to generate designs in a specific usage context—sightseeing. Our motivation for this workshop was to start developing methodologies that will encourage us to design mobile visualizations directly by basing the design process on: 1) visualization needs that emerge while we are on-the-go and 2) visualization designs that were thought of

directly for on-the-go technology. We think that a great deal of flexibility in this ideation methodology is not only possible but should be encouraged and explored. We also think that the two most powerful aspects are the in situ work and the repetition. We think that the context had a significant impact on our design processes. When it was possible to sketch on-site, one could transfer thoughts directly to the sketches, minimizing chance of missing ideas. However, some places were not comfortable enough for sketching, and, if possible, people took quick notes, maybe keywords and a vague sketch that made sense in the context. Sometimes these worked but some participants said that quick notes often were too brief and they could not recall the intention when trying to sketch them later. Another influencing factor related to context is the different observation opportunities each context offers. We have explored just one context for smartwatches. In reflecting on our exercise, we suggested that several quite consistent aspects across all the trials led to a successful design experience with rich ideas:

Being in-situ: One important part of this methodology is that we tackled the idea at a location of possible use, with the individuals doing the ideation being actually physically present at the given location.

Being at the moment: This idea is essentially a time-wise ‘in situ.’ It is our impression that this immediacy was useful in triggering ideas.

The repetition: While the idea of trying to think of a new idea every so many minutes did not appear to be necessary to be rigidly applied, notion of repetition seemed to be generative. That is, getting one idea and then getting another and then another and so on, seemed to be freeing in itself. In a way this took the pressure away. A person did not have to get the perfect idea first, they could just keep going.

The props: Our workshop was successful and hinted at the possibilities of designing novel devices by being able to draw on a paper prop. Some participants even presented data needs beyond the watch display and sketched them on the watch strap. One constraint was that our given paper prop (see [Figure 3.1](#)) only had a round watch face. It would be interesting to see if and how designs change if we provide a square-shaped paper prop.

The notes and sketches: We strongly suggested that note-taking and sketching were done immediately so that no information needs were lost. However, participants may sometimes need to choose a comfortable space for drawing and sketching to guarantee safety.

3.6 Summary

We studied smartwatch visualization design ideas in a specific usage context—sightseeing. We suggest trying this ideation approach bearing primarily in mind: being in situ; being at the moment; and having or creating a device mock-up. We have found the exercise to

be delightfully effective. After we started, ideas just seemed to flow forth. In addition, it seems that a great deal of flexibility can be applied to this methodology without losing its generative power. We are now interested in whether we can further adjust, or invent new ideation methodologies that can help us tease out new ways we can generate ideas that also leverage more of the unique features of common mobile devices, such as their input, output, and sensory capabilities. We found several data needs concerning smartwatch usage contexts that clearly differed from common usage (e.g., health-fitness data). These data needs were met with a wealth of dedicated visualization designs that go beyond those commonly seen on watch faces with a focus on visual design rather than interaction. Watch straps were predominantly used to show details related to the main display rather than completely different information. Future research needs to establish the feasibility and usability of watch straps as data displays. Concerning data representations we saw in particular icons used in creative ways. Icons are rare on standard desktop-based representations but may be useful for micro visualizations because they can label as well as represent data.

Smartwatch Visualization: A Survey with Smartwatch Users

In our ideation activity, we found a very large space of possibilities for smartwatch visualizations. As my research is device-oriented, I also wanted to better understand the current space of visualization used on smartwatches. I contributed with my co-authors Anastasia Bezerianos, Bongshin Lee, Tanja Blascheck, and Petra Isenberg the findings of a survey with 237 smartwatch wearers as a short paper at IEEE VIS 2020 [95]. We specifically investigated the types of data and representations commonly shown on survey respondents' watch faces. I describe this work here. Supplementary material is available at— <https://osf.io/nwy2r/> and any mention of 'we/our' in this chapter refers to my set of co-authors.



Fig. 4.1: Smartwatch face examples (from Facer [127]) with increasing amounts of data items and representation types. From left to right: Simple Design (Oscar Balabriga), Material Volcano (BlueIceshard), Pie Charts II (Sunny Liao), Minimal Colors H (AK Watch), and Earthshade (Brad C).

In this work, we investigate the use of visualizations on watch faces, the primary or home screens [74] wearers see when glancing at or turning on their watch [9, 199]. These watch faces are typically small, have a resolution between 128–480 px per side with a viewable area of around 30–40mm [23] and show the current time together with several data types, such as step count, location, and weather information. Watch faces are often customizable, allowing wearers to choose the data they want to see regularly and at a glance. Given the large variety of data available to display on smartwatches, we were particularly interested to answer the following research questions:

- Q1:** Which data types do people show on their watch faces?
- Q2:** In which form is the data currently represented?
- Q3:** What more can we visualize?

To answer these questions, we first conducted an online survey with smartwatch wearers, then complemented these results with an online search and analysis of smartwatch face examples, as well as an analysis of the technical capabilities of the watches our participants reported wearing. We contribute findings of current smartwatch use and open opportunities for visualization research and design.

4.1 Methodology

We conducted an anonymous online survey, for which we recruited regular smartwatch wearers at least 18 years of age.¹

Survey design. Our survey consisted of three sections, primarily containing close-ended questions. The first was designed to elicit general information about a respondent's watch face. Here, we asked questions about the respondent's watch shape and in which form (analog, digital, or both analog & digital) they read the time on the first screen or home screen of their watch. The second section focused on which additional data types—such as step count or temperature—were shown on the respondent's watch face. In addition to offering common kinds of data types as options, we had an *other* text field for participants to fill out in case their watch face showed data not in our list.

Tab. 4.1: Categories of data types shown on watch faces.





Category	Data type
Health & Fitness	Heart rate/ECG waveform, step count, sleep related info (e.g., quality, duration), distance traveled, calories burned, floors/stairs climbed, and blood pressure
Weather & Planetary	Weather info (e.g., sky condition), temperature, wind speed/direction, moon phase, humidity, and sunset/sunrise time
Device & Location	Watch battery level, phone battery level, bluetooth, wifi, and location name
Other	Data and representation type not in our list (open textfield)

To derive the list of data types for our survey (Table 4.1), we consulted prior research [190] and analyzed images of popular watch faces from Facer [127], a watch-face download and generation page/app for Android, Samsung, and iOS watches. Inspired by categories used in the Facer app, we grouped possible kinds of data into three categories: **health & fitness** related data, **weather & planetary** data, and **device- & location-related** data.

For each kind of data we asked participants to tell us *how* the data was shown on their watch face. We provided participants with five possible representation types accompanied by a text description (Table 4.2) and by an explanatory image (Figure 4.2). These categories were

¹IRB approved under ref. no Paris-Saclay-2020-002 CER.

Tab. 4.2: Representation types on watch faces.

Representation	How data is displayed
Only Text	as text, including numbers (e.g., text to display heart rate 68 bpm)
Only Icon	as an icon (e.g., a pulsating heart representing heart rate )
Icon + Text	as text with an icon for context (e.g., a static heart with text to show the current heart rate )
Only Chart/Graph	as a simple statistical chart (e.g., showing recent heart rates )
Text + Chart/Graph	as text with a simple chart (e.g., heart rate linechart )

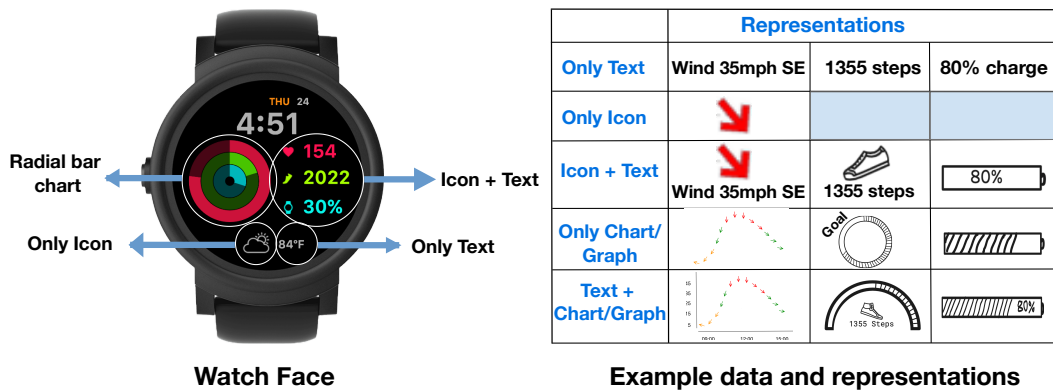


Fig. 4.2: Explanatory image of answer choices shown to participants.

based on how numerical or categorical data are displayed on more than 500 watch faces that we collected from the Facer app and internet searches.

In the final section of the survey we asked participants to provide the brand and model name for their smartwatch so we could verify the plausibility of their responses. We also asked participants to optionally upload a picture or screenshot of their watch face for verification. More details about the questions and format are available in the supplementary material.

Participant recruitment. To reach a wide range of smartwatch wearers we advertised our survey on popular social media (Reddit, Twitter, Facebook, Instagram, and LinkedIn), and asked colleagues to spread the call to their labs. The survey was available online for 30 days during April and May, 2020.

Data quality. We took several steps to ensure the quality of our collected data. From the 463 total responses, 177 were incomplete and another 31 failed our screening procedure. We asked participants to wear a smartwatch or at least have it available around them (e.g., charging, holding) to ensure that they do not answer questions from memory. We prompted them to verify if that was the case. The 30 participants who answered “no” were not allowed to continue to the survey. We also excluded one participant who did not sign the consent form. We had 255 complete responses for data analysis.

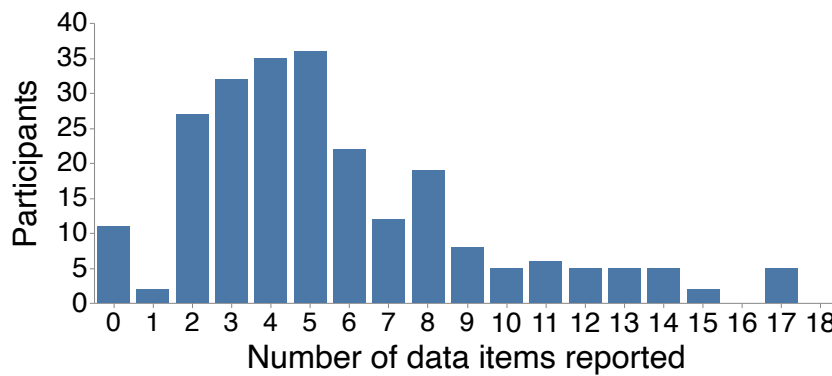


Fig. 4.3: Number of data items present on a respondent's watch face.

We discarded 18 additional participants: Five of them reported to seeing every single kind of data, and their responses did not match the watch face image they provided. Three participants reported the names of several smartwatch models, so we could not determine which one they recorded during the study. Another 10 wore fitness bands rather than smartwatches and were excluded due to their dedicated focus on fitness data and limited display capabilities. We report results from the remaining 237 valid responses.

4.2 Analysis & Results

The majority of participants reported wearing a smartwatch with a round display (150×), followed by a square (68×), and rectangular display (17×). Two participants reported having Squaricle / Rounded watch types. Most participants (149×) reported that the data items on their watch face are static and do not change (automatically or manually, e. g., by tap or swipe). Forty six participants reported their watch face changed automatically while 42 reported that they could manually swap data shown on their watch face. Participants' smartwatches came from 20 different brands with Apple (76×), Fossil (51×), Samsung (36×), Garmin (17×), and Huawei (12×) being the top five brand (80% of our respondents).

4.2.1 Q1: Which data types do people show on their watch faces?

We were first interested to see whether people had configured their watch faces to show a large amount or only a few data items. On average, participants reported showing a median of 5 different data items on their watch faces. [Figure 4.3](#) shows that having 3, 4, or 5 data items were the most common answers.

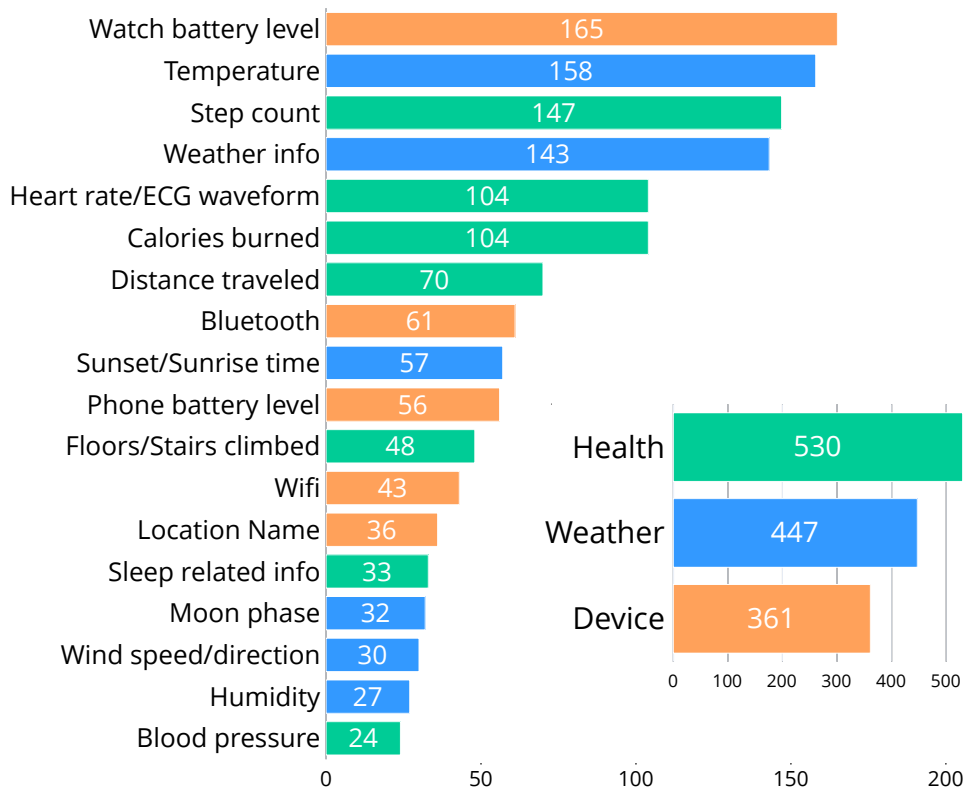


Fig. 4.4: Distribution of data types participants displayed and saw on their watch faces (left); aggregated by categories on the right.

Next, we wanted to learn which data types were the most commonly displayed (Figure 4.4). From the three categories we asked about, **health-fitness** related data were the most commonly reported (530×).

The most common data type in this category was *step count* (the third most common overall, 147×). *Temperature* was the most frequent **weather & planetary** data type (the second most common overall, 158×). For **device-location** related data, *watch battery level* (165×) was the most displayed and also the most common overall. The most commonly mentioned data types from the free-text responses were: *standing up count* (43×) and *exercise/body movement time* (24×).

Next, we wanted to learn about individual watch faces. We analyzed, which categories were most common per watch face and which data types often appeared together. On average, most of the data shown on an individual watch face came from the **health & fitness** category. Participants reported seeing on average: 2.24 **health & fitness** ($Mdn = 2$, 95% CI [1.98, 2.48]), 1.89 **weather & planetary** ($Mdn = 2$, 95% CI [1.69, 2.08]) and 1.52 **device-location** related data ($Mdn = 1$, 95% CI [1.35, 1.7]) on their watch face.

To know more about which types of data are commonly shown together, we performed a co-occurrence analysis of data types participants saw on their watch faces. The graph in Figure 4.5 shows combinations of two kinds of data that can be found on at least 25% of our respondents' watch faces. The thicker the link, the more frequent the data pair appeared

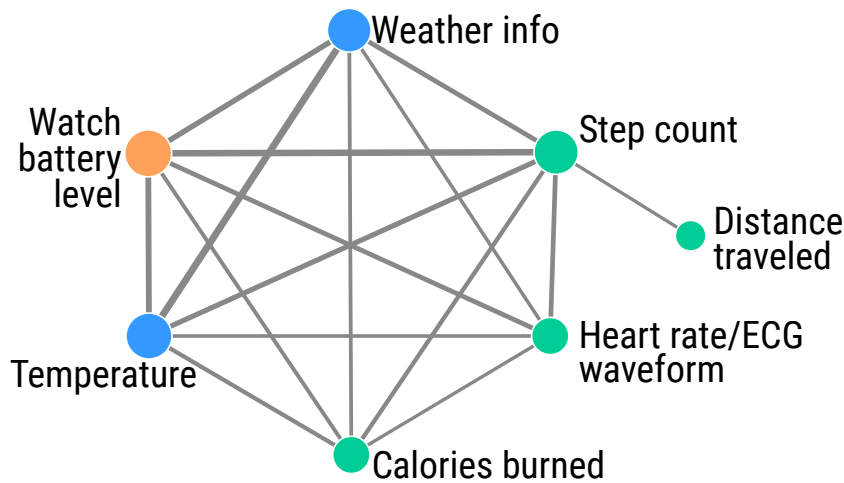


Fig. 4.5: The graph shows common pairs of data types displayed on the watch faces our 237 survey participants used. The thicker the link, the more frequent the data pair appeared on people’s watch faces. Circle colors correspond to three data categories: Health & Fitness, Weather & Planetary, and Device & Location.

on people’s watch faces. Circle size corresponds to how often participants reported seeing this data type. Circle color corresponds to the data type category. Only connections that appeared more than 59 ($\approx 237 / 4$) times are shown.

4.2.2 Q2: In which form is the data currently represented?

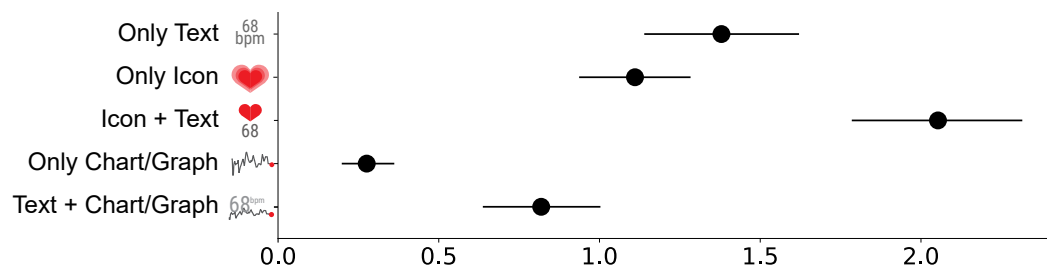


Fig. 4.6: Average number of representation types for each participant.

Figure 4.6 shows the average number of representation types each participant had on their watch face. Icon+Text was the most common representation type, used to display on average two kinds of data types on each watch face ($M = 2.05$, 95% CI: [1.78, 2.32]). The next most common were Text Only ($M = 1.38$, 95% CI: [1.13, 1.66]), and Icon Only ($M = 1.11$, 95% CI: [0.93, 1.3]). Representations using visualizations were less common. Chart+Text ($M = 0.82$, 95% CI: [0.64, 1.03]) and Chart Only ($M = 0.28$, 95% CI: [0.2, 0.37]) appeared less than once per watch face on average.

In Figure 4.7 we can see how many participants showed each data type with each representation type. Data types most commonly displayed with either Chart Only or Chart+Text were *calories burned* ($14 + 30 = 44\times$), *step count* ($10 + 32 = 42\times$), and *watch battery levels* ($14 + 28 = 42\times$).

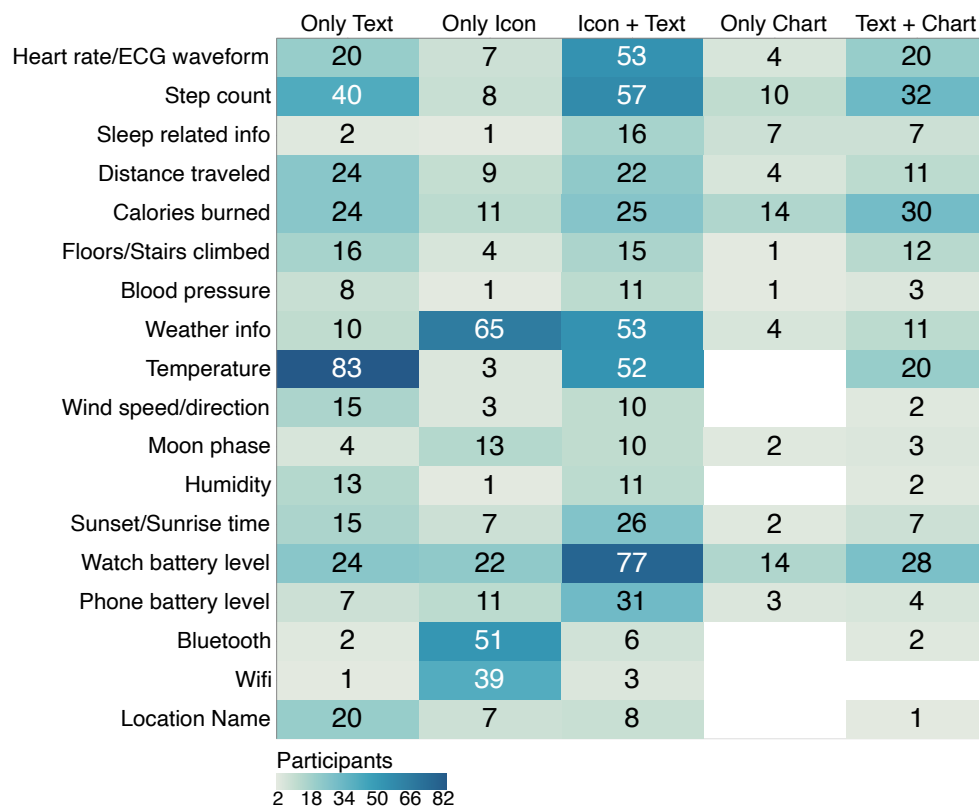


Fig. 4.7: Representation types reported for different data types.




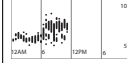













































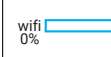



Complementary search of representation types. Surprised by the high number of icons reported, we decided to investigate further how different information can be displayed on watch faces. We conducted an extensive image search, during which we looked for examples of each representation type in current use. We looked at popular watch brands' websites, searched the internet for images (keywords: smartwatch face, popular smartwatch, smartwatch, etc.), and looked at examples from the Facer watch face creation and distribution app. [Table 4.3](#) shows exemplary graphics for each kind of data × representation type combination, redrawn for image clarity.

We found only few examples online of data types represented by an Icon Only ❤️ display. Yet, [Figure 4.7](#) shows that participants reported seeing Icon Only ❤️ representations for almost every data with on average around one Icon Only ❤️ display per smartwatch face. We discuss this discrepancy further in [Section 6.6](#).

4.2.3 Q3: What more can we visualize?

Complementary investigation of device capabilities. To find untapped opportunities for visual representations, we looked at technical details for the 54 smartwatch models (from the 20 brands) our participants wore. We found that all smartwatches had fitness or activity tracking as a core feature, including measuring and display of body movement, steps, sleep patterns, or dedicated exercise tracking. The smartwatches our participants used also carried

Tab. 4.3: Redrawn example representations from real smartwatch faces. Text color corresponds to the data type category. Bluetooth and wifi only text and only icon change color based on on/off status.

Data Types	Only Text	Only Icon	Icon + Text	Only Chart	Text + Chart
Heart rate / ECG waveform	68 bpm		 68		
Step count	3168 steps		 3168		
Sleep related info	1h 13m REM 4h 11m light		 6h 53m		
Distance traveled	1.19 Miles DISTANCE		 1 Mile		
Calories burned	64 Cal		 1,603		
Floors/Stairs climbed	31 floors		 13		
Blood pressure	SYS DIA 120 / 81		 126/78		
Weather info	PARTLY CLOUDY				
Wind speed/direction	Wind ESE at 3mph		 West		
Temperature	31°C		 14C		
Sunset/Sunrise time	6:34 PM SUNSET 7:14 AM SUNRISE				
Moon phase	Moon Age: 25.43 Days				
Humidity	40% HUMIDITY		 42%		
Bluetooth	BLUETOOTH				
Phone battery level	Mob 85%		 100%		
Location name	Paris		 Normandy		
Wifi	wi-fi		 3 bars		
Watch battery level	WATCH 44%		 88%		

a wide variety of sensors [106]: activity sensors such as accelerometers (53 models) and gyroscopes (46 models); physiological sensors such as heart rate sensors (47 models); and environmental sensors such as barometric altimeters (38 models). Many smartwatches allowed for at least bluetooth (54 models) or wifi (43 models) connectivity. By tracking which types of sensors were available on people's smartwatches, we derived the types of data their watches could track and participants could see on their watch faces (Figure 4.8).

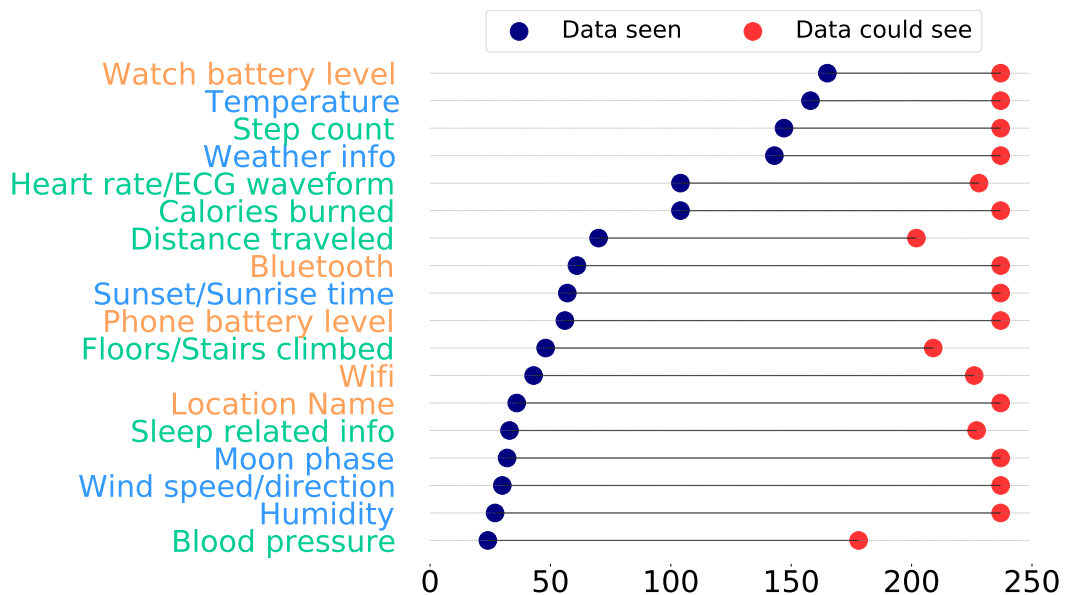


Fig. 4.8: Difference between # of watches that tracked each data type and how many participants actually saw it on their watch face.

There naturally is a mismatch between what our participants *could* see and what they *did* see: watch faces do not show all available data. Nevertheless, this mismatch varies. For example, from **health & fitness** data that almost all devices track, roughly 62.03% of participants saw *step counts*, but this percentage was less when it come to *heart rate* (45.61%), or *calories burned* (43.88%), and dropped drastically for *distance traveled* (34.65%), *floors count* (22.97%), *sleep* (14.54%), and *blood pressure* (13.48%). This list of commonly tracked data that is under-represented can serve as a starting point for visualization designers. For example, in past work [10] we found that smartwatch wearers would have liked to see sleep data but a display on their fitness tracker was not available to them.

4.3 Discussion and Future Work

It is challenging to determine a *right* vocabulary for wide-audience surveys. In our case, while we found few examples of icon only displays, participants often reported this type of representation. One possibility for these responses might be confusion about what constitutes “data.” In the survey instructions, we informed participants that we only cared about information in the form of numbers or categories, such as step count (numerical) or weather condition (categorical). We also asked participants not to consider graphics such as settings, calendar, or music app icons because they do not represent numerical or categorical information; and gave examples of graphics we cared and did not care about. Yet, participants might not have read the instructions carefully and included responses about graphical icons that do not change based on data. A second possibility for the larger frequency of Icon Only ❤️ responses might be attributed to typical Icon+Text₆₈ displays that due to missing or currently inaccessible data result in an icon-only representation (e.g.,

❤️--: heart icon with currently blank text). For our analysis reported in [Figure 4.8](#) we had to sometimes infer based on sensors whether a certain derived value such as *calories burned* would be available on a watch. The supplementary material makes our inferences transparent.

A wide variety of data types is available for our participants' watch faces. The list of frequently presented data types provides starting points for creating visual representations that could be valuable to a broad range of viewers. In addition, when designing perceptual studies in the future, it might be useful to take into account participants' familiarity with this data type.

Our participants had five data items on average on their watch faces. As five is a relatively large number for a small smartwatch display, an open research question is how to help people cope with such a dense data display. Given our analysis of common co-occurrences (especially within the categories) ([Figure 6.1-right](#)), it may be useful to consider combining them into joint representations.

Our survey results indicate that visualizations are still not as common as other representations such as text, even though they can be used to represent some of the most commonly displayed data (e.g., *step counts* and *battery levels*). Our online search of technical capabilities of smartwatches also indicates that much of the data tracked wearers do not see. This includes some [health & fitness](#) data that most devices track (e.g., *calories*, *distance*, *sleep* and *blood pressure* data). Whether these are explicit customization choices due to specific tasks they want to carry out, or due to a choice the default displays promote for the smartwatch face, remains an open question. Further research needs to investigate representation choices, to determine if the wider adoption of visualizations is a question of preference, tasks, a lack of exposure, and if it requires us to rethink visual encodings for smartwatches. In addition, future work needs to establish at which level of granularity information should be displayed. For example, are exact wind speeds important or are broad categories (stormy, light breeze, no wind) enough; presentation types would change based on this decision.

In summary, this work contributes to the understanding of the current real-world use of representation types on smartwatches and additional findings that can inform and inspire the visualization community to pursue smartwatch visualization.

Smartwatch Visualization: A Review and Design Space

In the previous chapter we set out to understand which data people currently consume on their watch faces and how it is visualized. We studied the display of data on smartwatch faces people reported to wear to ground future work on smartwatch visualizations based on the interests and preferences of wearers. This work builds on our prior chapter; we conducted an in-depth study and analysis of visualization designs for popular premium smartwatch faces according to their design styles, amount and types of data, as well as visualization styles and encodings they included. I contributed with my co-authors Tingying He, Anastasia Bezerianos, Bongshin Lee, Tanja Blascheck, and Petra Isenberg the findings of the review with 358 premium smartwatch face design as a paper and submitted at TVCG 2023. Any mention of ‘we/our’ in this chapter refers to my set of co-authors.

In this work, we focus on reviewing watch face designs, establishing a design space for smartwatch faces, and pointing to open research opportunities. As the home screen of a watch, watch faces are the most frequently seen screens of a smartwatch. One of the difficulties when designing data visualizations for smartwatch faces is that these screens typically show many types of independent data (steps, weather, battery levels, etc.) that need to be embedded in a coherent watch face design. These non-time/date data functionalities on smartwatches are called *complications* in horology [98]. As such, watch faces can be considered as small personal dashboards with distinctive design challenges. These design challenges include a limited display space due to a large number of possible complications, unique device form factors, the desire to express personality through watch face themes and design styles, as well as the mobile usage context that often requires information to be readable at a glance. In addition, watch faces require that time and/or date are readable as the primary data shown.

We conducted a first systematic investigation into the different design constraints and considerations for the design of smartwatch data representations for watch faces. Specifically, we build on our prior chapter [Chapter 4](#) in which we report on a study that asked smartwatch wearers to describe their current watch faces and the displayed data. Our prior work, however, did not systematically analyze how visualizations were integrated in a coherent watch face: we did not investigate how charts were drawn, if the watch faces used specific themes that applied to visualizations, or to what extent smartwatch face designers used graphical decorations. We address these limitations in the present work. We systematically



Fig. 5.1: The dimensions of our smartwatch face design space with examples. Watch face images (a, b, and f) indicate personal fashion preference as a factor; watch face images (c, d, and f) show examples of watch face design styles; and other watch faces (c to h) regions highlighted in magenta color are – a logo (c), a container (d), a screen border (e), a divider (f), a foreground graphic (g), and a background graphic (h). *Figure acknowledgements can be found in Section 8.1.*

analyzed 358 premium watch faces according to design dimensions, such as smartwatch components (for example: time display, number of complications, graphical decorations) and visual features (such as interface styles, animations, color). We compare our analysis to our previous work and then derive a design space (see Figure 5.1) for smartwatch face visualizations. This design space discusses design considerations related to external and device factors, watch face themes and styles, watch face components, and their visual representation. We end with a research agenda in which we summarize the most important future work on smart watch face visualizations.

5.1 A Systematic Review of Popular Smartwatch Faces

To complement our previous survey result Chapter 4 and to gain a deeper understanding about design considerations for smartwatch faces, we collected new watch face designs and conducted a systematic review. Here, we detail our methodology and report results. Throughout this section, we refer to our previous work as *the (prior) survey* to distinguish it from the new and additional work, which we call *a systematic review*.

Tab. 5.1: Codes used in the review of smartwatch faces.

	Dimensions	Values
Smartwatch Components	Time Display	digital, analog, hybrid
	No. of Complications	0, 1, 2, ...
	Types of Complications	watch battery, step counts, calories burned, ...
	Graphical Decoration	container, logo, background graphic, screen border, foreground graphic, divider
Visual Features	Number of Hues	0, 1, 2, ...
	UI Style	skeuomorphism, semi-flat, flat
	Animation	animation for graphical decoration, data-related animation (heart rate, watch battery, weather, etc.)
Representation	Data Representation in Complications	text, icon, chart, or combinations of these

5.1.1 Data Collection and Analysis

Our previous survey asked participants to describe the watch faces they currently wore. One limitation of the (prior) survey was that we relied on participants' own assessment without the capability of verifying their answers. To address this limitation, we conducted a systematic review of premium (paid) watch faces from a popular watch face app and website. We focused on premium watch faces as we considered these to exhibit an acceptable level of design professionalism. The alternative of collecting watch face screenshots from a large number of participants would have been technically infeasible and potentially privacy invasive. Screenshots are difficult to take and transfer from watch to study platform for non-tech-savvy populations and watch faces often contain privacy sensitive information, such as locations or body measurements.

Instead, we decided to collect watch faces from the Facer App [127], one of the most popular smartwatch face distribution websites. It contains a Top100 page that lists the premium or free watch faces of Apple and WearOS/Samsung smartwatches.



We manually collected the metadata in a spreadsheet of the top 100 smartwatch faces every Sunday midnight for one month because the premium list was recalculated on Sunday (00:00), starting from March 14, 2021, for WearOS/Samsung smartwatches and starting from September 18, 2022, for Apple smartwatches. When we started this work, the Apple list did not consistently contain 100 faces and we, therefore, had to collect this data later. The metadata collected for each watch face included its rank, name, link, and thumbnail.

Among the 800 top watch faces we collected, 358 were unique watch faces as several appeared in the top 100 for multiple weeks in a row. To compare and analyze these 358 watch face designs, we derived a set of codes that targeted an understanding of the watch face design overall and how data representations were integrated in it. We reviewed watch faces in the configuration shown on the Facer website and originally chosen by the watch face designer. Later configuration of watch faces, is, however, possible for some watch faces based on the features of their watch. [Table 5.1](#) lists the codes we used. On a higher level, we focused the codes on *what* is being represented on the watch face and *how* it is shown. We provide these codes as a supplementary file. In the following sections, we present our findings giving more information about the codes and, where appropriate, we contrast our findings to those of our survey (see [Chapter 4](#)).

5.1.2 Results

We conducted all analyses using the extracted image of the watch face. In case a design was not clear from the thumbnail, we went to the Facer website to look at the simulated watch face graphic. We group our results according to the components shown on a watch face and how they are shown. We compare the results relating to the number and type of complications, time display, and complication representation between the systematic review and survey. We only analyzed the results regarding graphical decorators, hues, animation, and UI style in the systematic review.

What is Displayed on a Watch Face?

Number of Complications. The watch faces from the systematic review contained a median of 4 complications, similar to our survey in which participants reported a median of 5 complications. However, we saw a difference in the number of watch faces with only one complication. While (13.41% ) of the premium watch faces contained only one complication, in our survey only (0.84% ) of the watch faces people wore contained just one data item (see [Figure 5.2](#)). The maximum number of complications per watch face drawn was similar: 16 in the systematic review and 17 in the survey.

Types of Complications. We compared the top 10 most common data types found in the systematic review to those from our survey ([Figure 5.3](#)). Watch battery level ranked first both times. In both studies, [health-fitness](#) data were the most commonly reported, followed by [weather & planetary](#) and [device-location](#) data. Moon phase, exercise or workout time, and Standing or movement time raking rise and stand out in the top 10 most common data types in the review. Moon phase was ranked 15th, exercise or workout time was ranked 19th, Standing or movement time was ranked 20th, in the survey, and ranked 7th, 9th, and 10th in the systematic review. Bluetooth was ranked 8th in the survey but did not stand out in all

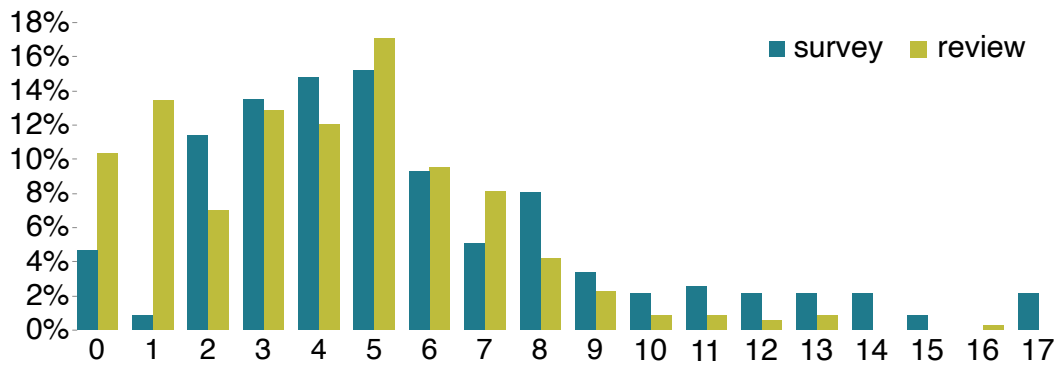


Fig. 5.2: Comparison of the percentage of respondents who saw a given number of data complications in the survey and systematic review.

the review data types, perhaps because Bluetooth icons only appear when a watch is paired to a phone and, therefore, did not show in the thumbnail simulations.

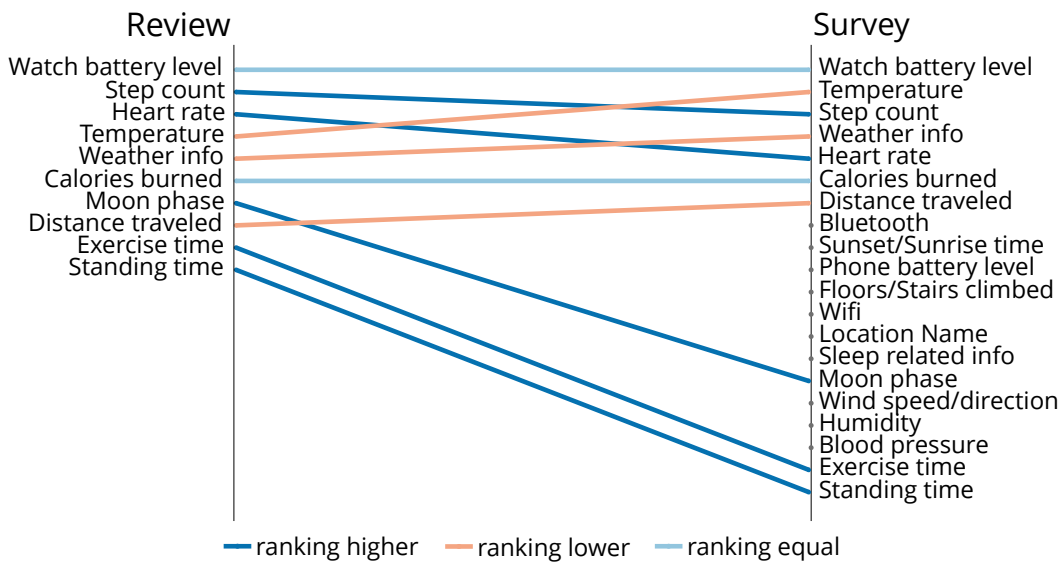



Fig. 5.3: Ranking analysis of the most common data types from the survey (shown on the right) and found on the premium watch faces review (displayed on the left).

How is the Watch Face Designed?

Watch faces consist of components representing time, complications, and decorations, each with their own representation styles.

Time display. We divide watch faces into digital, analog, and hybrid watch faces depending on the time display. Digital watch faces represent time information as HH:MM:SS for hours, minutes, and potentially seconds. Analog watch faces typically use the hour, minute, and second hands to indicate the time, to resemble conventional analog watches. Hybrid watch faces have both digital and analog time displays. Our systematic review showed that the majority of premium watch faces were digital watch faces (60.3% ), followed by analog

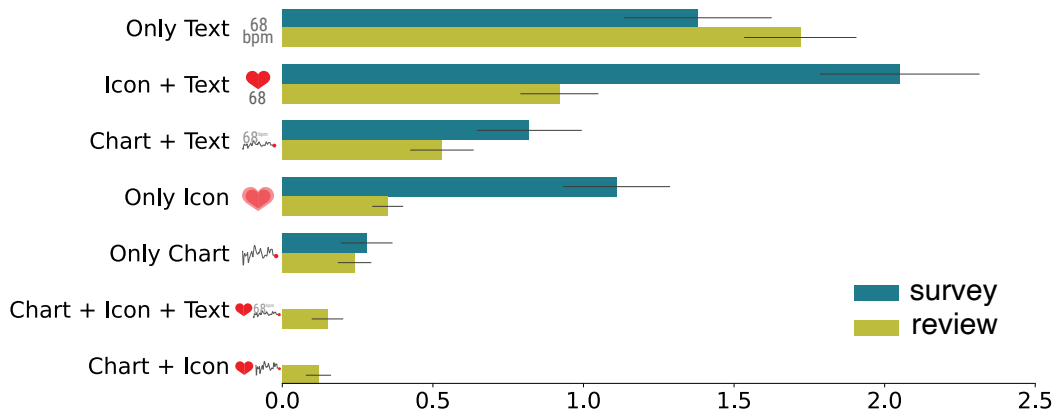








Fig. 5.4: Comparison of the average number of representation types participants saw (survey) and presented on the premium watch faces (review).

watch faces (26.3% ) and last hybrid watch faces (13.4% ). The ranking of time displays was the same as in our survey with small variations in the percentages (64.6% digital, 23.2% analog, 12.2% hybrid).

Complications Representations. We found seven ways complications were represented based on combinations of text, icons, and charts. As icons, we classified graphical content not in the strict semiotic sense and more analogously to how they are used in computing. Here icons are a type of image that represents something else. As such, our icons can be both semiotic symbols  and icons . Figure 5.4 shows the contrast of representation types on average displayed on watch faces found in our systematic review and the survey. The most common representation forms were text, icons, and chart combinations in both survey and review.

A simple text label (Text Only ^{68 bpm}) was the most common representation type for 1–2 data types on average on each watch face ($M = 1.72$, 95% CI: [1.53, 1.91]). Icons accompanied by text labels (Icon+Text ^{heart 68}) were the second most common ($M = 0.92$, 95% CI: [0.79, 1.07]). In our survey, Icon+Text had been the most common representation type, used to display two kinds of data types on average on each watch face ($M = 2.05$, 95% CI: [1.78, 2.32]) followed by Text Only ($M = 1.38$, 95% CI: [1.13, 1.66]). Both evaluations clearly show that text is the most frequent way to represent data on watch faces while charts or charts combined with text or icons are rare in practice. One notable difference in the data was the difference in Only Icon displays. Examples for representations that rely purely on a small image, such as weather icons ( ) are still rare on watch faces (see Table 4.3). Yet, in our previous survey, surprisingly a large number of participants reported seeing Only Icon displays ($M = 1.11$, 95% CI: [0.93, 1.3]), which we attributed to a potential misunderstanding of the category. In our review, Only Icon displays were, as expected, much more rare and we saw them only for weather data (99×), moon phases (23×), wind directions (3×), compass/direction finder (1×), and altitude (1×).

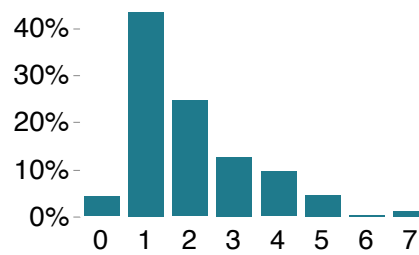













Fig. 5.5: Percentage of hues on the premium watch faces. The x-axis presents the number of hues, and the y-axis denotes the percentage of watch faces with hues.




For the following watch face components we only report results from the review as we had not asked about them in the survey:

Graphical Decorators. We define graphical decorators as graphical content on the watch face that forms a coherent unit and takes up space, similar to complications, but does not carry any data. We found six types of graphical decorators (see ?? Components): *containers* (254×)—which surround other watch face components; *background graphics* (141×)—decorations on the background of the watch face such as a wallpaper; *logos* (139×)—small images to represent the brand or designer of the watch face; *foreground graphics* (94×)—other decorations in the foreground such as small images or lines; *screen borders* (48×)—decorations on the border of watch faces such as frames; and *dividers* (31×)—the lines that split the watch face into dedicated regions.

Number of Hues. To get a better sense of the overall look of the watch faces, we analyzed the main hues used. We did not consider black, white, and gray because these dominate most backgrounds. Nearly half of the premium watch faces (43.30%  ) had only one hue (see Figure 5.5). More than a quarter (24.58%  ) had two, and only one-eighth (12.57%  ) had three hues. The maximum number of hues on one watch face was seven.

Animation. We found that (80%  ) of the top watch faces had no animated content; 20%   had animated content that did not represent data. Animations were used either on decorations or on complications to make them look more vivid and stand out. Sometimes animations were meant to make content even more iconic, such as a heartbeat animation for a heart icon .

UI Style. Through the user interface (UI) style code, we attempted to capture the overall appearance of the watch faces. We found three categories of styles: skeuomorphism, flat designs, and semi-flat designs as shown in Figure 5.1 (Style/Theme). In UI design, skeuomorphism is used to describe a graphical interface style in which elements mimic their real-world counterparts [92]. Skeuomorphism deploys gradients, shadows, or ornate details [180] and on watch faces, these design elements are often used to recreate elaborate analog watch faces, such as those of pilot or diving watches. Flat design is a term used to describe a graphical interface style in which no graphical elements attempt to create the appearances of continuous 3D depth on the interface. This style highlights simplicity by

concentrating on two-dimensional elements, clean lines, and bright colors [180]. Semi-flat designs are in-between flat design and skeuomorphism: they are flat designs with some realistic touch, such as shadows. We found flat (36.87% ) to be the most popular style in our systematic review, followed by skeuomorphism (33.80% ) and semi-flat (29.33% ) designs. However, the flat design is most frequent on Apple watch faces (56.32%) than on Android watch faces (18.48%), while the Skeuomorphism design is most frequent on Android watch faces (54.35%) than on Apple watch faces (12.07%).

5.2 Design Space

Our review of existing watch face designs gave us the opportunity to reflect deeply on the design of watch faces. In this section, we generalize our findings into a broader design space. Our goal is to systematically structure the influences on smartwatch face designs and the decisions designers need to make to create a holistic watch face. Inspired by our previous evaluations, the design space is primarily descriptive [143]. It allows to describe existing watch faces based on a variety of factors. The design space also has the potential to be generative in that its individual components could inspire new watch face ideas. However, we have not yet experimented to use the design space as such. The design space is based on our initial codes for the watch face designs listed in Table 5.1. Data collection and analysis of actual watch faces' properties led to the design space dimensions after several rounds of discussion among the co-author team.

Figure 5.1 gives an overview of our design space with examples. The figure shows four main dimensions that are important to consider in the design of a watch face. In contrast to some other design spaces, our dimensions are not independent. They are ordered in a sequence (left to right) to show the dimensions' main direction of influence. We consider watch faces to be holistic multi-view displays or data dashboards in which the designer carefully chooses what to assemble, how to style it, and how to arrange it.

5.2.1 External and Device Factors

Both internal and external factors of the watch influence the design of any watch face (Figure 5.1 Factors). The watch itself (device driven) defines the shape (form factor), display size (watch dimension), display type, and display resolution, which may influence choices made in other parts of the design space. For example, the type of display (such as OLED or E-ink) has great influence on the number of colors available to style the graphics shown on the watch face and to represent data. E-ink watch faces, for example, have fewer colors and lower display refresh rates making animations difficult. E-ink watch faces nevertheless have the potential for sport and activity smartwatches because of their paper-like characteristics, lightweight nature, low battery consumption, and readability in sunlight [8]. In contrast,

OLED displays have greater color quality than other technologies. In recent years, OLED displays have risen to prominence as the main display technology for wearable devices. Most high-end smartwatches, including Apple and Samsung, use this technology. Due to the excellent image quality, OLED displays offer great possibility for fashionable smartwatch face designs.

In addition to the display type, the display shape (form factor) has a profound impact on the layout and the graphics design on the watch face. Watch faces now mostly come with squared or circular displays; content is often shaped to match this shape and create a harmonious aesthetic. Moreover, personal factors such as use context or fashion preference play an important role in the watch's face design. Wearers prefer an appealing smartwatch appearance (casual and business look) and a smartwatch that resembles fashion when purchasing a smartwatch, as seen in previous work [171]. The designs targeting fitness, sports, weather, or style (e.g., minimal, vibrant, harmonious aesthetic) contexts may impact the overall design and look.

5.2.2 Styles, Themes, and Topics

The theme of a watch face design describes a set of design attributes applied to all elements of the watch face to create a consistent, unified, or coherent look (Figure 5.1 Style/Theme). These attributes may define a set of colors used or visual textures imitated, the overall UI style, and potential animations used. Themes can also influence other dimensions such as the components of the watch and their representation. For example, a watch face with a minimalist theme may only show few essential components such as a digital time, date, or battery life represented with simple visual features.

A theme may relate to a topic such as fitness, outdoor sports, games, and fashion. For example, Figure 5.1 (d) shows a dedicated comic theme with a flat UI style, a set of primary colors, and comic-style fonts chosen, while Figure 5.1 (f) depicts a semi-flat UI style going for an appearance of vintage-style weather components.

Watch face styles relate to themes and specify how specific components on the watch face are rendered. For example, in Figure 5.1 (d) the fonts for labels use a comic style that matches the comic theme of the watch. Specific color-related design themes and styles are common on watch faces. For example, a darker color palette for the background is used most of the time perhaps to enhance content readability without disturbing wearers with bright light during the night or to save battery [166]. The flat and skeuomorphism UI style is extremely popular, whereas semi-flat designs are used frequently when the watch face is meant to be different and unique compared to traditional watches. Themes including animation often aim for a vivid overall feel but rarely use animation to represent data.

Both themes and styles have an influence on how potential representations on a watch face can be designed. Aiming for a consistent design would affect graphical embellishments or decorations such as shading used in a visualization but also the available colors and hence potentially the types of visual channels that can be used. A watch face with a black and white theme, for example, cannot use multiple categorical color encodings based on hues.

5.2.3 Watch Face Components


We define components as any coherent object on the watch face that takes up display space, including complications, time-date-related data, graphical decorators, and input widgets (for example functional buttons) (Figure 5.1 Components). Designers have to decide which type of components to display and how many of them to put on the watch face. Only two types of components display data: time-related components (time, date, or day) and non-time-related components, called complications [7] in horology. Graphical decorators refer to elements on smartwatch faces unrelated to data, for example, logos, screen borders, or a background image. Input buttons such as settings or audio buttons are typically represented by icons on a touch-enabled smartwatch face and do not reflect any categorical or numerical data. Designers may avoid unfamiliar metaphors while designing or choosing such icons so that wearers may quickly understand their functions. The choice of type and number of watch face components is closely related to the theme of the watch. For example, an aviation-themed watch (Figure 5.1 (c)) may require specific time-related components to show the time zone, a chronograph, and a date display, and it is likely to use a skeuomorphism design style. A fitness-themed watch face (Figure 5.1 (b)) might instead require a large number of complications for showing step count, heart rate, calories burned, or distance travelled.



The choice of an analog, digital, or hybrid display of time on the watch face also has an impact on the overall design. Analog watch faces have dials that may overlap complications and make them less readable. Digital watches use fonts that need to fit the general style and typically take up a prominent position on the watch face leaving less space for other complications.

Graphical decorators also play an important role in smartwatch faces. Through them, themes can often be expressed, and they, too, can constrain the space available for complications. Containers are a particularly frequent graphical decorator that partitions the watch face into regions and gives dedicated display space to complications. For example, Figure 5.1 (d) uses a lot of space for comic-related background images and comic panel containers and constrains the complications to fit into speech bubbles. Decisions on which and how many components to display have an impact on how the components can be represented as discussed next.

5.2.4 Watch Face Representations

Each watch face component has a digital representation that has at minimum a position, size, shape, and rendering color scheme or texture (visual features). In this section, we focus our discussion on watch face complications that represent data other than time (Figure 5.1 Representation).

One of the difficulties of designing complications for smart watches is that the data category it show needs to be identifiable, for example as steps, heart rate, or calories. Designers can place signs to identify data categories or rely on wearers to learn and memorize a mapping. The types of signs that can identify a data category include—text labels that specify the category (e. g., “steps”), accompanying icons (e. g., a foot icon for step count), and text units (e. g., “km” for distance traveled). The “three rings” on the Apple Watch is instead, an example of a mapping that requires learning . It uses three concentric radial bar charts with memorable colors but without a sign to represent what each colored rings stands for: movement, exercise, and standing. One of the advantages of memorized mappings is that no display space needs to be dedicated to labels, units, or icons.

In our evaluations, we observed that most smartwatch face complications represented data with combinations of text, icons, and charts. Most data shown in smartwatch complications encodes a single data value . More complex encodings, however, are certainly possible (e. g., multiple points over time or space ) and designers can take inspiration from work on word-scale visualizations [18, 71] or data glyphs [66], for example, of complex micro visualizations.

Representations by Data Type

We divided complications according to which data type they represent as shown in Table 5.2 to discuss them in more detail: absolute numeric data, proportional data, categorical data, ordered data, temporal data, and geospatial data. Discussing complications by data type seemed more useful than by data category (e. g., steps, battery, . . .) as data in each category can easily be converted into different data types. For example, a step count can be an absolute numerical value (e. g., 6700 steps), converted to a proportion (e. g., 67% of a daily step goal), or shown as a time series. Next, we discuss representation possibilities and challenges based on the most common data types we saw represented on watch faces.

Absolute Numeric Data. Absolute numeric data on watch faces commonly appears as either a single number or a pair of numbers. For example, temperature can be a single numeric value (35°C) or a pair of a numeric value (Highest: 35°C; Lowest: 30°C). Absolute numeric data is theoretically infinite or has a large range. This data can be represented as text or in a chart but their visual representation poses major challenges when the values dynamically update. There is often not enough space for visual references such as labels, tick marks, or

Tab. 5.2: Example of common data types on watch faces for common data categories. For each data type × category combination, we show example data in text that can be turned into an appropriate visualization.

Absolute numeric

	Step count	Temperature	Heart rate	Blood pressure
Single	3500	18°C	70 bpm	
Pair		Highest: 25°C Lowest: 20°C		120/80

Proportion

	Humidity	Battery	Step count	Sleep duration
Real proportion	42%	75% (of fully charged)		
Derived proportion			80% (of 5000 steps)	80% (of 8h)

Ordered

	Battery level	Wifi signal strength	Heart Rate
Derived order	Low	Poor	Fast

Temporal

	Sunrise & Sunset time	Sleep duration	Sleep phase
Single	6:30 am & 7:30 pm	6h30min	
Multiple			REM: 1h13min Light: 4h11min Deep: 1h25min

Categorical

	Bluetooth	Weather	Moon phase	Wind direction
	On	Rainy	Full moon	NW

Geospatial

Location	Time zone
Paris	GMT+2

grids in smartwatch complications. Without these references, one would have to predict data mappings that fit in the given display space and ensure the display adjusts to the dynamic updates without confusing wearers. However, absolute numeric data often has a limitation in practice that can simplify the data representation. For example, step counts can be unlimited. Nevertheless, in reality, considering the time limit (e. g., within a day) or the limitation of human physical abilities, the value corresponding to the step count on the smartwatch face often has a potential limit. It can help to consider plausible limits for reserving display space,

calculating color scales, and identifying whether meaningful differences in values (e. g., 100 steps) should remain visible in a given chart. So far, perhaps due to these challenges, charts that visualize absolute numeric data on smartwatch faces are still rare. Only Text representations are the more common representation form.

Proportion. Proportional data displays values according to a given maximum, typically 100%. Visualizations of proportions are common on watch faces: in Table 4.3, most of the charts in the last two columns show a proportion. On watch faces, we found data in the form of real proportions and derived proportions. For real proportions, the shown value corresponding to this data category has originally been captured or measured as a proportion, such as 42% humidity or 80% power (of a fully battery charged). Derived proportions are proportions converted from absolute numeric data to a proportion according to a pre-set maximum and minimum. One of the common derived proportions is from a goal watch wearers set, such as steps—67% (of 10k steps), calories burned—67% (of 3 kCal).

Categorical. Categorical data is a type of data that does not have an implicit ordering. Categories only distinguish whether two things are the same or different [144]. Categorical data is often represented by small graphical elements. Common are icons that stand for the categorical value (weather—rainy ☁️ /sunny ☀️) or a sign with an indexical color (Bluetooth—on 🔵/off ⚪️).

Ordered. As opposed to categorical data, ordered data does have an implicit ordering [144], for example, a low/middle/high level of the smartwatch battery. Most ordered data on watch faces is quantitative or has been derived from quantitative data. Icons or charts commonly represent ordered data with an ordered color scale encoding. Often, derived ordered data is encoded together with proportions. For example, battery indicators often turn red when the battery is almost depleted and green when it is fully charged.

Temporal. Temporal data on smartwatch faces most commonly relates to specific time points such as sunrise or sunset time, time when one went to sleep or woke up, etc. Time series on a continuous scale are common for sleep data or heart rate. Designers often visualize some temporal data in conjunction with the dial of analog watch faces, such as sunrise and sunset times (Figure 5.6 shows an example of sunrise time) that are displayed as icons next to the hour numbers. Nevertheless, the variety of temporal visualizations on watch faces is still small compared to the many visualizations for time that exist [3]. Especially designs for events and intervals are still rare on watch faces and how to port past ideas to a watch should be further explored (e. g., [57]).

Geospatial Information. The most common geospatial data on smartwatch faces concerns the wearer's location and time zone. In addition to text and icons (e. g., landmarks 🏰) maps 🗺️ also sometimes represent this data.

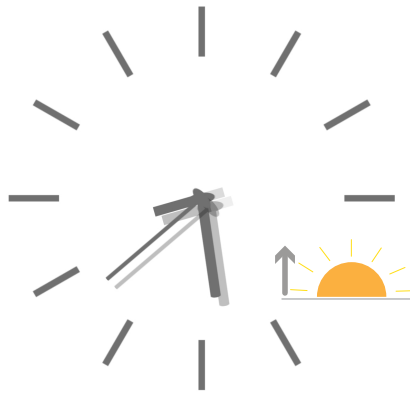


Fig. 5.6: A watch face showing sunrise time.

Representation Types

Text. Text is the most common form of data representation on watch faces. Text can be styled through font type, size, and color, which can also be used to encode additional information, for example, as in word clouds. However, we rarely saw font-size based encodings on actual watch faces despite them having been mentioned in research [5].

Icons. Icons on watch faces are widely used for labeling but rarely used to represent data. Icons can be used for categories if there are icons that meaningfully identify the categories. This is the case for weather data where viewers are familiar with icons that represent a rainy ☁️ or sunny day ☀️. It would be harder to find icons that represent REM, Light, or Deep sleep stages. There are two options to use an icon to represent quantitative data: a) designers can turn the quantity into an order or category and use a visual variable for categories such as hue, texture, or position or b) add a visual variable to the icon that can represent a quantity such as position, size, area, flicker etc. For example, suppose we want to represent quantitative data such as calories burned with an icon. In that case, we first have to choose an icon that represents calories; a fire icon is relatively common 🔥. Next, we could apply a sequential color scale (🔥 🔥 🔥), size the icon relative to a quantity (🔥 🔥 🔥), or apply animation-related variables such as flicker. Icons can also be stacked to create unit-based pictographs. Not all quantities can be turned into categories for which meaningful icons exist. Examples we saw include step counts that were represented by different shoe icons (e. g., walking, running, climbing), but examples such as this one were rare.

Charts. Charts and graphs for data representation on watch faces were rare in our survey and review. However, charts have potential to communicate information at a glance to wearers [23]. Nevertheless, they need to be carefully designed to account for the small display size [85, 93]. To design a chart for a complication, designers need to consider chart type, size, color, position and themes.

The *chart types* that are commonly used to represent data on the premium smartwatch faces were bar charts, pie charts, donut charts, gauge charts, area charts, pictographs, and sliding scales. The data type suggests the most effective chart type to use as discussed above. The chart type directly affects its possible shape, size and ultimately also its location. For example, several types of charts can be curved and then be aligned with the rim of a watch face.

The *chart size* is related to the area occupied on the watch face. Size is more closely related to the shape of a chart rather than just its bounding box due to the tight layout of components on the watch. For bar charts and sliding scales, size mainly refers to length and thickness. For pie, donut, and gauge charts, the size mainly refers to the diameter. For an area chart and pictograph, the size mainly refers to their length and width. If a chart's shape matches a watch screen's shape, the chart can fill the watch face. For example, a donut chart can use the circumference of a round watch face. We rarely saw space-filling charts (similar to Dragicevic and Huot's SpiraClock [57]). Often charts were nested inside round containers similar to complications on physical pilot or diving watch faces.

Chart color describes how many hues are used on the chart, be it to style the chart or to represent data. Black and white watch face designs exist in which hue cannot be used to represent data. In this case, textures may be used to represent categories [200] but these are difficult to design well in practice. Decorators such as gradients affect a charts' color and have to be used with care. Gradients consist of different saturation or brightness of the same hue or gradients of different hues. One difficulty of using hues for categorical color encoding on watch faces is that the hues need to match the overall theme and aesthetic of the watch face. A color scheme that might create an aesthetic design overall might not work well for encoding data and vice versa.

Chart position refers to the place of the chart on the watch face. Often charts are positions somewhere in the middle of the watch face or in the periphery. The shape of the chart affects the possible position of the chart. For round watches, ring-shaped or arc-shaped charts are most suitable for being located on the periphery of the watch face, whereas other shapes like bar- and line-charts can only be located in the middle of the watch face.

Chart theme refers to the theme of the complications, which often conforms to the overall topic of the watch face. Charts used in research rarely have a theme but for watch faces, these should be explored further. Colors, shapes, and in particular textures can represent a theme.

5.3 Discussion

In the previous section, we described a design space for smartwatch faces consisting of four dimensions—factors, styles/themes, components, and representations. We showed

example values in these categories and how design decisions in these categories might influence each other. The goal of our design space is to describe existing watch faces. These descriptions can be used to help compare different designs, to identify factors for assessing watch faces, and potentially help researchers generate new designs or variations of one design. In [Table 8.1](#), we show four descriptions of popular watch faces that have been generated with the dimensions of our design space. Next, we discuss factors related to watch faces that go beyond our design space and shed more light on external factors and interactivity. We consider watch faces as small data dashboards. Few [\[63\]](#) defines dashboards as “a predominantly visual information display that people use to rapidly monitor current conditions that require a timely response to fulfill a specific role.” Watch faces fit this definition well because they are visual displays that people glance at briefly to fulfill a specific information need. In their study on data dashboards Sarikaya et al. [\[169\]](#) survey the purpose, audience, visual features, and data semantics. Likewise, Bach et al. [\[15\]](#) propose eight groups of design patterns that provide common solutions in dashboard design. Here, we make use of their dashboard design space and discuss how it relates to ours.

Purpose. Sarikaya et al. [\[169\]](#) describe two purposes for dashboards: decision support (strategic, tactical, operational) as well as communication and learning. Bach et al. [\[15\]](#) consider dashboards as a way of communicating through visualization in which users’ needs for an information overview, control, and conciseness for decision-making are met. Our design space covers the purpose of a watch face under external factors that influence the watch face design and is able to describe how a specific purpose may influence themes, components, and their representation. Of the two purposes Sarikaya et al. mention [\[169\]](#) watch faces also concern decision support (“do I need to walk more?”, “should I leave for a meeting now?”) and communication in the wider sense by showing progress toward potential fitness goals, the current weather, or simply showing the time. However, watch faces have other purposes that were not covered in this past work, for example, entertainment (some watch faces contain games) or simply making fashion statements. Further research is needed to elicit these purposes: how people choose watch faces, and how the purpose may guide design decisions in other parts of our design space.

Audience. According to Bach et al. [\[15\]](#), novice dashboard users will need more instruction in the form of a clear layout and less information (e.g., single value, aggregated data), whereas expert or regular users will be more data literate and require more data and custom features on dashboards. Sarikaya et al. [\[169\]](#) argue that the visuals and functions of a dashboard “reflect the intended audience, their domain and visualization experience, and their agency relationship with the data.” Watch faces are “individual” dash boards in Saikaya et al.’s design space because they reside on a personal wearable device and are typically not shared with others. A broad range of the population buys smartwatches and there are now even smartwatches targeted at children. Designers of watch face visualizations, thus, cannot assume visualization literacy but many smartwatch wearers exhibit intricate familiarity with the data itself, their typical step counts, weather, or sleep patterns, for example. Most

watch faces currently seem to be designed for people with low visualization literacy in that they mostly represent data through text and use simple graphs. Past work on word-scale visualizations [18, 71], however, has shown that complex representations are possible in very small display space.

Interactivity and Visual Features. Interaction on watch faces has so far been quite restricted compared to what was found for more general dashboards [15, 169]. Types of interactions that we found relatively common were opportunities to tab through different types of data (e. g., switching from step counts to calories burned within one complication’s container). We also found some interactive games that could be played by touching a watch face. Sometimes interactive changes to watch faces were enabled through companion apps in which the layout and type of data shown on a watch face could be specified. What we have not seen are watch faces that allow to input data, correct data, or highlight specific complications.

Additional Data Semantics. Several of Sarikaya et al. and Bach et al.’s additional data semantics apply to watch faces. In particular, “benchmarks” (e. g., step counts that have been reached) are commonly represented either by colors or by specific chart choices, such as gauges and other proportion-based representations. These techniques were also mentioned in Sarikaya et al. and Bach et al.’s studies. However, Bach et al. emphasized color consistency in overall dashboard design and advocated reducing color if not required, particularly for screen fit dashboard designs. Another similarity to their dashboards was that watch faces regularly update data and provide highlights when certain thresholds have been reached (e. g., battery levels that are too low, heart rates that are too high). These updates pose visualization challenges as outlined previously, especially for watch faces that are not monitored continuously.

5.4 Research Agenda

Watch face visualizations do not only need to be small but they also need to integrate into a coherent watch face theme. As a personal data dashboard, watch faces not only make fashion statements but can also play an important role to facilitate decision making. We identified several open research questions that relate to the integration of visualizations in watch faces.

Designers Vision vs. Use in Practice. Through our survey and review, we observed a tension between a watch face design vision and the use of watch faces in practice. While a big part of the market designs included a single complication (18%), 99% of people in our previous survey reported to have more than one complication on their watch face. It is possible that people regularly pay for and try out watch faces they like, but we suspect it is more likely that they customize or personalize the watch faces to include more complications than the designer intended. Thus, while smartwatch designers may decide to follow design guidelines

and recommended practices from the visualization community in their implementations, it is possible that through customization smartwatch wearers make customization choices that violate these practices. We can try to help wearers to use a more appropriate design, for example by suggesting best locations for placing a complication depending on clutter, background color, etc. Nevertheless, smartwatches remain personal devices, and wearers are (and should) ultimately be in control. As a community, we need to consider the right balance of allowing wearers to feel empowered in their customization, without being constrictive in our attempt to guide them.

Study of the Influence of Themes. The use of embellishments around data visualizations has been heavily debated in the visualization community. Some argue that they should be avoided [189]; some argue that they do not hurt or can even help [17]. Watch face visualizations have by design a number of visual distractors surrounding them. UI styles such as skeuomorphism introduce extensive shading to give the illusion of depth, busy material textures, and color palettes that may distract from reading data. The influence of certain theme choices such as skeuomorphism vs. flat or semi-flat designs as well as the use of graphical decorators require further research. It is important to establish how they may support or hinder readability of data especially for watch face scenarios that require quick and accurate data readings.

Specific Visualization Designs for Watch Faces. Icons are useful on smartwatches as they often label the data shown. It would be useful to study how this label functionality of an icon can be combined with the display of numerical data. Possibilities exist such as using animation, generating pictographs, or sizing icons as discussed earlier but their effectiveness has not been empirically assessed for watch faces. Simplified icons with minimal color are highly recognizable [83] and potentially readable during quick glances providing motivation for studying them further.

5.5 Summary

We presented a systematic review and design space for embedding visualizations into watch faces. The design space is grounded in the collection and analysis of properties of actual watch faces. Our holistic approach looked at smartwatches not just at data displays but also as a personal accessory for which visualizations are just one of many components that need to fit within a larger visual ecosystem. This led us to consider, for the first time, dimensions like the UI style and visual themes that may have an impact on visualization design, but have not been part of visualization design considerations in smartwatch research. We discuss the interplay of these dimensions and the choices available to visualization designers, as well as pitfalls and challenges when it comes to designing visualizations for such a personal use. Our research agenda that highlights open opportunities both for visualization designers and for empirical research should inspire the visualization community to move forward.

Smartwatch Visualization: Perceptual Study on Sleep Visualization

In our previous survey [Chapter 4](#), we found that certain types of data, particularly sleep, were not frequently shown on smartwatch faces. To better understand what smartwatch wearers would like to see and how this data could be effectively shown, I wanted to look into the readability of smartwatch visualizations, considering the impact of size and aspect ratio in the context of sleep tracking. I contributed a series of experiments with my co-authors Ranjini Aravind, Tanja Blascheck, Anastasia Bezerianos, and Petra Isenberg. Specifically, we aimed to understand the interests, preferences, and effectiveness of different sleep visualizations by smartwatch form factor. The findings of four studies related to the visualization of sleep data were published in a paper at CHI 2022 [94]. I describe this work here. Supplementary material is available at— <https://osf.io/yz8ar/> and any mention of ‘we/our’ in this chapter refers to my set of co-authors.

In this work, we focus on the visualization of sleep data on fitness trackers. Fitness trackers are wearable devices like wristbands, smartwatches, and sports watches that primarily expose data about health, and fitness activities. Fitness trackers are increasingly capable of capturing sleep data accurately [123], and sleep tracking apps have become central for many people seeking to improve their sleep behaviors [89]. Currently, sleep data is mostly checked on companion apps on smartphones, or websites rather than on the tracker itself [95]. Checking data on the tracker, however, would allow people to quickly glance at their data post-activity like they already do for other types of tracked activities without consulting alternative devices. Fitness tracker wearers also expressed this desire for in-situ consultation of sleep data and reported wanting to see sleep data on their trackers, in particular directly after waking up [10]. Our follow-up survey confirmed this desire, and



Fig. 6.1: Most preferred combinations of sleep visualizations and data from our survey for different types and granularities of sleep data.

38% of respondents mentioned checking sleep data directly after waking up. We would expect people to focus primarily on simple sleep aggregates (such as the number of hours slept) in such a quick-glance scenario. Nevertheless, we explore both simple and more complex visualizations as we expect that wearers begin to explore advanced features of their fitness trackers after extended use [47]. We have no data to explain why some device manufacturers do not expose more detailed sleep data on trackers themselves. It is possible that device manufacturers do not know the interest in this data but also that the lack of guidelines, examples, and design considerations for visualizations of detailed sleep data play a role.

Our work makes several contributions to address these concerns. First, we provide results of a survey with 108 fitness tracker wearers,¹ in which we learned how wearers track their sleep, what they wish to learn from their sleep data, and which sleep visualizations they prefer for different granularities of sleep data, and for different device form factors: smartwatch, or fitness band. Our results indicated that the most preferred visualizations were often similar for people who wore smartwatches, and those who wore fitness bands, even though the fitness band-sized visualizations were roughly half the size of the smartwatch-sized ones (Figure 6.1).

Our second contribution is three quantitative studies about the effectiveness of preferred visualizations across three types of form factors (smartwatch, horizontal, and vertical fitness band) to make recommendations about visualizations to use for sleep data.

We first conducted a detailed in-person pilot study followed by two crowdsourced perceptual studies that compared the preferred visualizations from the survey for weekly, and nightly sleep data under three different analysis tasks. Participants preferred, and were more confident with the smartwatch-sized visualizations but simple tasks could be performed equally effectively on both smartwatch, and fitness band form factors. Only the more complex tasks seemed to benefit from the larger display size.

Finally, we offer reflections on our study methodology, during which we balanced reaching a larger pool of crowdsourced participants with ecological validity, and direct experimental control, compared to our in-person pilot study; hoping to expand discussions on appropriate study methodologies for wearable visualization.

6.1 Understanding Sleep Visualization Preferences

As a first step towards recommendations for sleep data visualizations on fitness trackers, we investigated which type of sleep data people collect, and use as well as the types of visualizations they would prefer. To reach a wide audience we designed an online survey

¹Details about the questionnaire are available in the supplementary material—<https://osf.io/f3vja/>.



based on a similar survey published as part of a EuroVis Poster [10]. Our questionnaire updated answer choices to make the types of visualizations asked about more consistent, and included a randomization of answer choices, strengthening the validity of the results. The survey material is available in the supplementary material—<https://osf.io/f3vja/>.

6.1.1 Design and Analysis

We deployed our questionnaire using Google Forms. The first part of the survey included questions about the respondents' fitness tracker, and how they analyzed their sleep data. The main part of the questionnaire consisted of questions in which participants had to select a preferred visualization out of a set of four choices for a specific type of sleep data granularity (previous night, previous week, previous month, comparison to global values), and data type (sleep duration versus sleep phases). Each group of images (duration and phases) was preceded by an open-ended question, in which participants described what they would like to learn about their sleep duration and phases, respectively. The purpose of this question was to put participants in a mindset to answer the follow-up questions in the context of their own sleep data. The visualizations shown after were inspired by those found on common commercial fitness trackers and smartphone apps. The supplementary material gives additional information about our real-world inspirations and chosen encodings. In addition to having common visualizations for each data type and time granularity, we always included one option that showed the data using text. We shuffled the order of visualizations for each participant taking the survey. Table 6.2 shows all visualizations. After each choice, participants responded whether they based their preference on the amount of data shown, the design, or both.

We open-coded the free response questions, and iteratively derived answer categories. We analyzed the fixed-choice questions using Tableau.

6.1.2 Procedure

After reading the consent form, and agreeing to participate in the survey, we asked participants to validate that they own a smartwatch, or fitness band, which can track sleep data, and that they look at this data. If not, we excluded them from the survey. The accepted participants proceeded to answer the remaining questions. Based on the answer they gave regarding their used device (smartwatch, or fitness band) they saw the visualizations adapted to this form factor: Square , or Wide  (Table 6.2).

Tab. 6.1: Sleep data that respondents would like to see on their tracker. The color-coding represents the different categories, and is a visual encoding of the percentage of answers (the higher the opacity the higher the percentage of responses).

	Last Night	Weekly Overview	Monthly Overview	Social Comparison	Not Interested
Phases	88 (81%)	41 (38%)	27 (25%)	15 (14%)	10 (9%)
Duration	87 (80%)	60 (56%)	40 (37%)	19 (18%)	4 (4%)
Schedule	44 (41%)	53 (49%)	32 (30%)	9 (8%)	30 (28%)
Quality	87 (80%)	57 (53%)	39 (36%)	18 (17%)	9 (8%)
Metadata	88 (81%)	47 (46%)	28 (26%)	15 (14%)	13 (12%)

6.1.3 Results

We recruited 132 participants via Reddit, Facebook, Twitter, and personal emails. For the analysis, we included 108 valid responses, and excluded 24 people who reported not wearing a tracker, or not checking their sleep data. It took participants between 10, and 15 minutes to answer the questionnaire.





Most (86% ) of the respondents reported wearing their fitness tracker every night while sleeping. Most participants mentioned checking their sleep data only on the phone app (80.6% ) , while 4.6%  checked only their fitness tracker, and 14.6%  both devices.












Table 6.1 summarizes the answers participants gave regarding the sleep data they would like to see independent of what their current device could show. Most people were interested in data about their last night's sleep phases, duration, quality, and other metadata—all of interest to more than 80%  of respondents. Weekly sleep data was the second most preferred type but only few participants were interested in a social comparison of sleep data ($\leq 18\%$ ).

Table 6.2 summarizes the percentages of preferred visualizations for different time granularities of the sleep phases, and sleep duration while the teaser (Figure 6.1) shows the most preferred visualizations in more detail. The differences between the two top ranked visualizations for weekly sleep duration were so low that we considered them both as the winner. Table 6.2 shows the data separated for Square  and Wide  to see differences between people using a smartwatch, and those wearing a fitness band. Across all 8 groups of visualizations, the preferred visualization was mostly (5/8) the same for both types of devices. Overall, the most preferred visualization was often an area chart (Square  = 4/8, Wide  = 3/8) rated first by approximately 40–50% of respondents. Bar chart-based representations were also popular, in particular for the wide form factor (Square  = 2/8, Wide  = 4/8). A clear winner was the hypnogram (76% ) for showing last night's sleep phases, and the horizontal bars (73% ) for the social comparison of last night's sleep phases on the wide version. Only for social comparison of sleep duration, people

preferred the text version to other visualizations. In most cases, the text representation had the lowest, or second to lowest rating.

Note that while the data visualizations we showed to people were similar in color coding, the explicitly encoded information varied between designs. To understand whether people chose their “preferred” representation based on the data shown or the encoding, we asked an additional question in the survey, in which participants explained how they made their choice. On average, 49%  of the participants reported choosing the representation considering both the displayed data and the corresponding encoding. The preference information we gathered from the survey can help to inspire further studies, in which preferences based on data or visualization can be teased apart. Our results show that participants chose those visualizations that allowed them to see and infer more information than others in most cases. One clear outlier is the text representation of the comparison of social sleep duration, which shows comparatively little information as text.

6.2 Studies Comparing Sleep Visualizations

Based on our survey, we found that for five out of eight categories of sleep data, participants preferred the same type of visualization for both smartwatch, and wristband form factors. Therefore, we wanted to investigate how changes in form factor would affect the effectiveness of a visualization, and if one could expect to use the same representation type for both form factors. The main research question we investigate in the following three studies was: *How does display form factor, expressed as display size, and orientation, affect the effectiveness with which people can answer questions about sleep data?*




6.2.1 General Method

To investigate our research question, we conducted three studies: one in-person pilot study using a real smartwatch, and two studies conducted online as crowdsourced studies using peoples’ own smartphones. For all three studies, we used the same method, measuring both completion time, and accuracy of participants with a specific task, and visualization stimulus. In each study, and task, participants had a forced-choice between two answer options; therefore, we used a two-alternative forced choice (2AFC) design with a Type 1 procedure (yes/no-responses) [109]. For each trial, participants saw the stimulus, and answered the task by pushing one of two buttons; then they received feedback for 1000 ms, followed by the next stimulus visualization. There was no time limit to answer, but we instructed participants to answer as accurate as possible.

Tab. 6.2: Visualizations of sleep phases and sleep duration for smartwatch and fitness bands. Orange borders highlight the most preferred combinations of data and designs for each time granularity as well as for social comparisons.

	Sleep Phases				Sleep Duration			
	Bar		Hypnogram		Radial		Radial	
Last night								
								
Weekly Overview	Area		Bar		Area		Bar	
								
								
Monthly Overview	Area		Area		Area		Area	
								
								
Social Comparison	Horizontal Bar		Text		Horizontal Bar		Horizontal Bar	
								
								

6.2.2 Stimuli

Our stimuli used in all three studies had a display size of 320 px × 320 px (smartwatch; Square ) , 320 px × 160 px (horizontal wristband; Wide ) , and 160 px × 320 px (vertical wristband; Tall ) .

6.2.3 Data Analysis and Interpretation

To analyze the data we conducted a time, and error analysis. For all three studies, we calculated the sample mean per person, and condition for both time, and accuracy. We represent the sample mean using interval estimation with 95%-confidence intervals, which we adjusted for multiple comparisons using Bonferroni corrections [88]. We construct the confidence intervals using BCa bootstrapping (10,000 bootstrap iterations). Therefore, we can be 95% certain that the population mean is included within this given interval. We interpret the difference between two values using estimation techniques, and give the strength of the evidence about the population means as recommended in the literature [20, 21, 48, 50, 56]. A confidence interval of mean differences shows evidence if the confidence interval does not overlap with 0, which corresponds to a statistically significant result using p-value tests. The farther away from 0, and the tighter the confidence interval is, the stronger is our evidence. One can calculate equivalent p-values using the method by Krzywinski, and Altman [115].

6.3 In-person Pilot Study: Bar Charts of Weekly Sleep Durations

As a first step, we conducted an in-person pilot study in the lab using an actual smartwatch. For this in-person pilot study, we focused on visualizations representing sleep duration because participants from the survey were most interested to see sleep duration, on average, of all temporal granularities. We focused on weekly sleep data instead of last night's sleep as a richer source of data. In addition, Cai et al. [35] already tested the winning donut chart for last night's sleep patterns under varying display sizes, showing no negative effect at smaller display sizes.

6.3.1 Stimuli and Tasks

Representation Choice: The most preferred visualizations for a weekly overview of sleep durations were the area chart, and floating bar chart. We decided to use the floating bar chart, because it is the more common visualization technique for this data, and because it

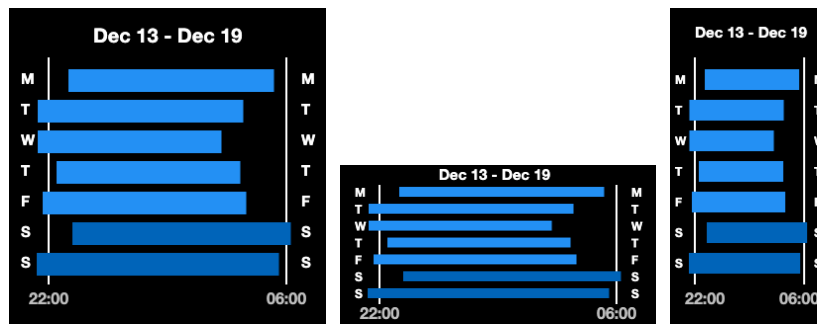


Fig. 6.2: Stimuli for the study representing weekly sleep duration with three different form factors: Square, Wide, and Tall. Sizes, when printed without scaling, correspond to the physical sizes shown during the study.

can encode more information including schedule, and sleep consistency. Moreover, it might be more affected by changes in tracker type due to the compression of bar width/length needed on the fitness band. A floating bar chart is a non-aligned bar chart, representing chosen preferred bedtimes, and wake-up times, i.e., the time when a person actually went to sleep, and woke up in the morning (Figure 6.2).

Task Choice: The floating bar chart allowed us to add more tasks that are aligned to what respondents in the questionnaire wanted to learn from their sleep data. The tasks we investigated were:

- **T1:** On which day did you sleep longer: Saturday or Sunday?
- **T2:** Did you go to bed later than planned (22:00) on 4 or more days this week?
- **T3:** Did you sleep longer on average on the weekend days (Sat, Sun) compared to the weekdays (Mon-Fri)?

Common visualization tasks [31] inspired our tasks, which required participants to analyze temporal data. T1 is an elementary task, which a participant can answer by identifying two bars (Saturday, and Sunday), and comparing their ranges in the reference set; T2, and T3 are synoptic tasks, which require participants to gain an overview of the whole reference set [6]. For T2, participants needed to summarize the set by counting the bars in relation to a reference line (22:00). T3 required participants to identify two reference subsets (weekdays, and weekend), mentally aggregate bar length for each subset, and compare the aggregates.

Data Generation: To generate the data used for the visualization stimuli, we generated values for sleep duration, and schedule for each night of the week. Each bar represented a sleep duration between 370, and 501 min of sleep that started up to 30 min before to 50 min after the preferred bedtime of 22:00. For tasks that involved comparing bars, or the average of bars, we ensured that there was a difference of a least 8 px, which corresponded to 16 min of

sleep duration. We colored the bars in two shades of blue to distinguish between weekdays, and weekend days. Stimuli of all three form factors had the same information, and text.

6.3.2 Participants

We recruited 18 participants (10 female, 8 male; 4 researchers, 14 students) with an average age of 29.27 years ($SD = 6.76$). Their highest degree was Bachelor (2), Master (12), or Ph.D. (4). They all had a background in HCI. Out of 18 participants, 17 reported having experience with visualizations. All participants had normal, or corrected-to-normal vision, and 2 of them reported to have a color vision deficiency. One participant owned a fitness tracker (Apple Watch), and two participants owned a fitness band (Fitbit). We compensated participants with chocolates, and tea at the end of the study.

6.3.3 Procedure and Apparatus

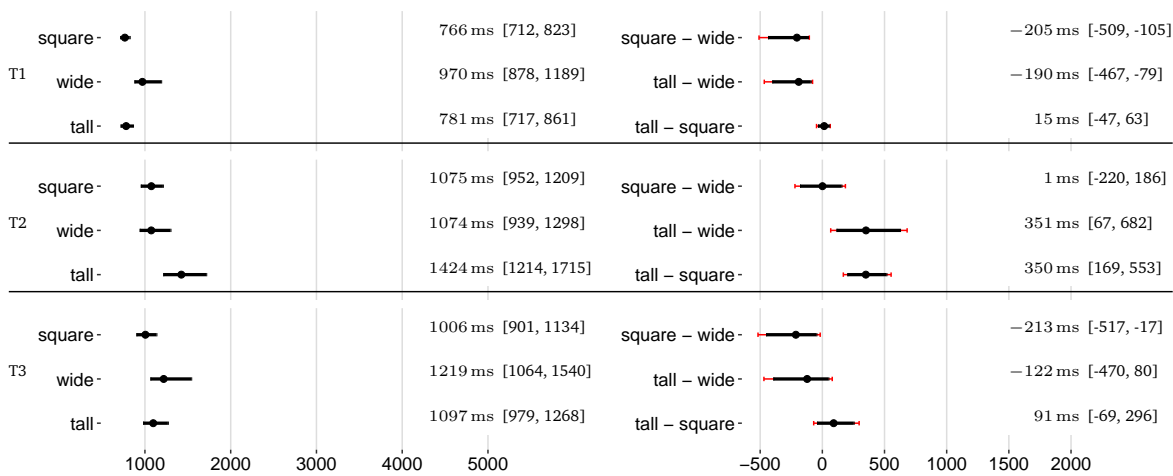
We used a within-subject design, and counterbalanced the order of the tasks, and the form factors using a Latin square. We used a Sony Smartwatch 3 with the Android Wear 2.8.0 operating system. The smartwatch's screen dimensions were $28.73\text{ mm} \times 28.73\text{ mm}$ with a resolution of $320\text{ px} \times 320\text{ px}$. We attached the smartwatch to a stand at an angle of 50 degrees [24]. We adjusted the stand so that the smartwatch was placed at 20 cm height from the table surface, and roughly 28 cm viewing distance from the participant [23]. We allowed participants to adjust their seating position during the study. To familiarize themselves with the procedure, participants did 15 practice trials, followed by a 10 s break, and 30 actual trials.

Participants answered tasks by pressing one of the four arrow keys depending on the task (up/down for T1, left/right for T2, and T3) on the keyboard placed in front of them, and below the smartwatch stand. We used a Macbook Pro laptop to run a Java program, which recorded input (key presses) of participants, saved logs, and sent feedback to the smartwatch app implemented using Android programming. We connected the smartwatch, and laptop to the same WiFi hotspot, and they communicated with each other via TCP sockets.

6.3.4 Results

In the following, we discuss the results (both time, and accuracy) of the in-person pilot study separated by task using confidence interval estimation techniques as described in Section 6.2.3. Table 6.3, and Table 6.4 show the detailed results including averages, and confidence intervals.

Tab. 6.3: *Completion Time* analysis of data from the Pilot Sleep Duration (bar) Study. Left: average completion time in milliseconds. Right: pairwise comparisons for each task, and form factor. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).



Task T1: On which day did you sleep longer: Saturday or Sunday?

Completion Time: Overall, we saw that participants were slower with Wide ■ compared to the other two form factors. We have no evidence of a difference between Tall ■ and Square ■. Completion times ranged on average between 766 ms–970 ms.

Accuracy: Accuracy was almost 100% for all form factors, and there was no evidence of a difference between the conditions.

Task T2: Did you go to bed later than planned (22:00) on 4 or more days this week?

Completion Time: Square ■ and Wide ■ had almost the same completion time with 1075 ms and 1074 ms. We have evidence for Tall ■ to be slower than the other two form factors with a completion time of 1424 ms.

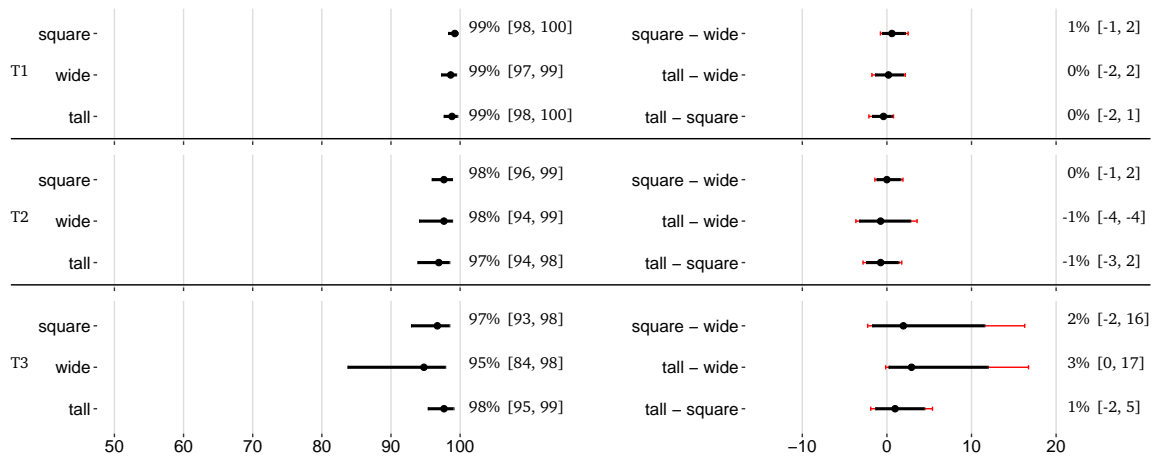
Accuracy: The accuracy in this task was only slightly lower than for T1 with 97–98%. We again see no evidence of a difference between form factors.

Task T3: Did you sleep longer on average on the weekend days (Sat, Sun) compared to the weekdays (Mon-Fri)?

Completion Time: We have weak evidence of a difference between Square ■ (faster with 1006 ms on average), and Wide ■ (slower with 1219 ms on average), but no evidence of a difference between the other form factors.

Accuracy: T3 had the highest error rate, but accuracy was still above 95% for each form factor. Again, we see no strong evidence of a difference between form factors, but there may be a trend for Tall ■ to be more accurate than Wide ■.

Tab. 6.4: *Accuracy analysis of data from the Pilot Sleep Duration (bar) Study. Left: average accuracy; right: pairwise comparisons for each task, and form factor. Error bars represent 95% bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).*



Summary: Accuracy was high in all three tasks (over 95%), and we saw no strong evidence of a difference across form factors according to how many errors participants made. Some differences were, however, visible according to completion time. For T1, Wide ■ was slower than the other two. For T2, Tall ■ was slower than the other two. In T3, we saw a potential trend for Wide ■ being slower than Square ■.

6.4 Sleep Duration (bar) Study: Bar Charts of Weekly Sleep Durations

After conducting the in-person pilot study, we re-ran the pilot as a crowdsourced study, during which participants had to use a smartphone. A crowdsourced study allowed us to access a broader pool of participants but with the tradeoff that we could no longer use smartwatches to deploy the study. Our goal was to find out whether we could reach similar results when simulating smartwatches on smartphones in a crowdsourced setting. Due to the ongoing COVID-19 pandemic in-person studies were harder to conduct, and our results have the potential to inform the design of future perception studies for smartwatches.

6.4.1 Design Specifics

We used the same study design as for the in-person pilot study described in Section 6.3. The main difference between these two studies was that we used a between-subject design to reduce the study time per participant. The between-subjects factor was the task, so

each participant saw one task but all three form factors. We preregistered the study at <https://osf.io/yz8ar/>.

To approximate the pixel density of smartwatches, we designed the study to be run on smartphones using a mobile web browser. We used a framework for running online studies [129] into which stimuli images were loaded. This ensured that images were displayed at the original aspect ratio of the Sony Smartwatch 3 used in the in-person pilot study. We used a display size of 213×213 density-independent pixels (DIP). Measuring in DIP allowed us to ensure that stimuli appear at the same physical size across screens, no matter what density those screens have. We followed the viewport size conversion of the Android developer community [49].

Participants could only participate in the study if they had a smartphone (e.g., Android mobile, iPhone) with a minimum screen resolution of $320 \text{ px} \times 480 \text{ px}$, had a web browser installed on their phone, and had a stable internet connection. We designed our study so that at the minimum screen resolution participants did not have to scroll the web page during the study. After finishing each form factor, we asked participants about their confidence when performing the task on a 5-point Likert scale (5 = completely confident, 4 = fairly confident, 3 = somewhat confident, 2 = slightly confident, 1 = not confident at all). A post-questionnaire followed after performing the task with all three form factors. There were no time constraints for giving their answers but we asked participants to answer as quickly, and accurately as possible.








Training: Participants saw 15 random visualizations as training for each form factor. There were detailed instructions before each training describing the next type of visualization shown.

Study Trials: In total, participants completed 34 trials per form factor, with 30 trials in random order, and 4 trials as attention checks per section for a total of 102 trials per participant. We collected the given answer per trial, the correct answer, and the time taken to answer.



Exclusion Criteria: We excluded participants who reported having problems with the consent form, who reloaded the web browser, who did not finish the complete study, whose monitor specifications did not meet the study requirements, or who failed $\geq 50\%$ of the attention check trials. We clearly stated the exclusion criteria at the beginning of the study, notified participants if they were not able to complete the study, and terminated the study early. We also included two additional attention check questions at the end of the study asking participants to select the task they had just completed as well as which type of data they had seen during the study (sleep, as well as rainfall, or weather as distractors). If a participant failed to answer these questions, then the study was immediately terminated.

6.4.2 Participants

We recruited fluent English speakers using Prolific [161]. From the 175 total responses, 36 were incomplete, 2 failed the attention check questions, and 2 participated multiple times, and we discarded them from all our analyses. In total 135 participants completed our study. We compensated participants who completed the study with a reward of £2.63 for our 17-minute estimated study completion time, slightly higher than the French minimum wage requirements requested by our ethics committee. For T1, there were 39 participants, 42 participants for T2, and 54 participants for T3. It is difficult in crowdsourced studies to achieve an equal number of participants per condition but because we do not compare across tasks, the difference in participant numbers does not bias our findings.

Among participants, 45.9%  were female, and 54.1%  were male; 48.12%  reported to be students, the rest (51.88%) did not provide their job status (Table 6.5). All participants had normal, or corrected-to-normal vision, and the average age was 26.43 years (SD = 7.53). Among all participants, 27.06%  owned a smartwatch, 29.32%  owned a fitness band, and 6.01%  owned both. When asked to report on their familiarity with floating bar charts on a Likert scale (Figure 6.3), most participants (51.9% ) reported reading these charts occasionally.

Tab. 6.5: Details about participants for the two crowdsourced studies. Number of participants (P), location, gender (F: Female, M: Male), age (M: mean, SD: standard deviation), percentage of students, percentage of participants who reported to own a smartwatch (SW), and percentage of participants who reported to own a fitness band (FB).

Study	P	Location	Gender (F/M)	Age (M/SD)	Students	SW	FB
Sleep Duration (bar)	135		(46.7% / 53.3%)	(26.56 / 7.7)	47.4%	26.6%	29.3%
Sleep Phase (hypnogram)	117		(58.1% / 41.9%)	(26.27 / 7.02)	55.5%	33.3%	24.7%

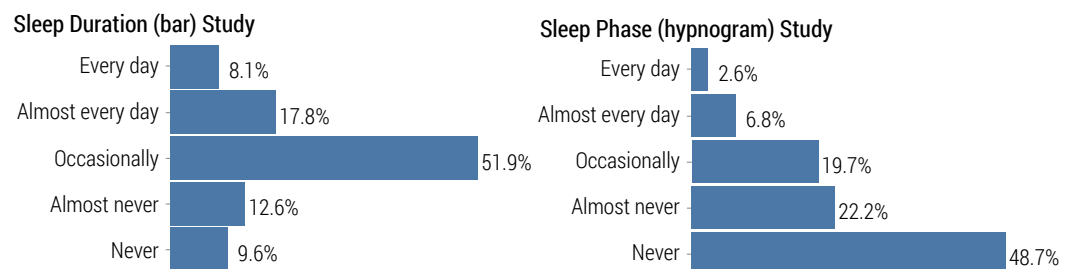
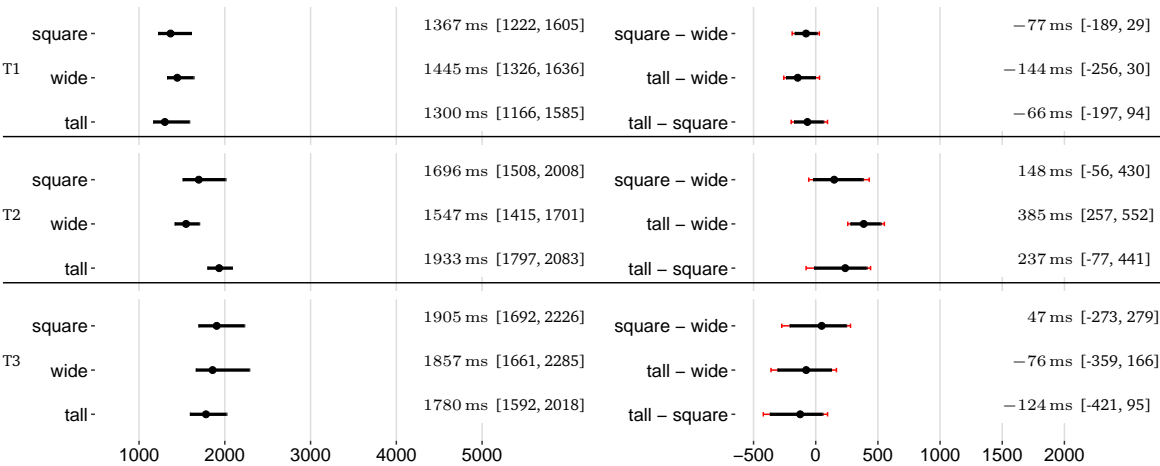


Fig. 6.3: Analysis of demographic data from the Sleep Duration (bar) Study, and the Sleep Phase (hypnogram) Study. Left: familiarity rating of participants reading floating bar charts. Right: familiarity rating of participants reading hypnogram charts.

Tab. 6.6: *Completion Time* analysis of data from the Sleep Duration (bar) Study. Left: average completion time in milliseconds for each task, and form factor. Right: pairwise comparisons for each task, and form factor. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).



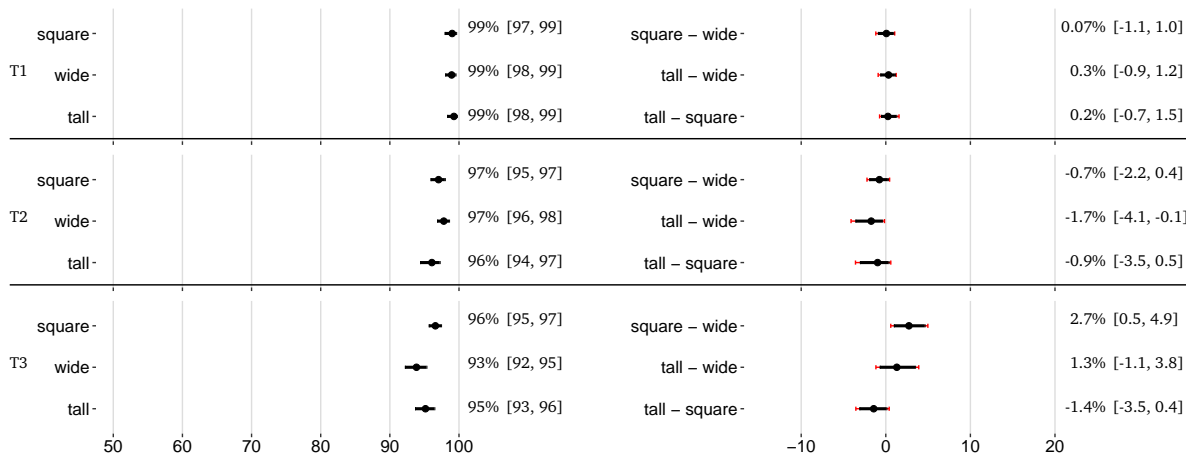
6.4.3 Results

We describe the results per task discussing completion time, accuracy, and confidence. We separate our discussion by task due to our between-subject study design (each participant saw all form factors for one task). For the data analysis, we only consider the data that was within two standard deviations of the mean answering time. We removed as outliers around 5% of the data across all tasks mostly due to a problem with our timer implementation: the first trial of each form factor took an unexpectedly long time because the time counter included page loading time. Therefore, we removed the first trial across all tasks but fixed this problem for our subsequent crowdsourced study reported in the next section. [Table 6.6](#) summarizes the results on completion time per task while [Table 6.7](#) shows the detailed results of the error analysis.

Task T1: On which day did you sleep longer: Saturday or Sunday?

Completion Time: Participants were similarly fast with all three form factors. The average of Tall ■ was fastest with 1300 ms, followed by Square ■ with 1367 ms, and Wide ■ with 1445 ms. Pairwise comparisons show no evidence of a difference between the three form factors because the corrected confidence intervals touch zero. It is nevertheless possible that there is a trend for Wide ■ being slower than the other two because the uncorrected CIs either do not cross, or are close to 0.

Tab. 6.7: Accuracy analysis of data from the Sleep Duration (bar) Study. Left: average accuracy for each task, and form factor. Right: pairwise comparisons for each task, and form factor. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).



Accuracy: In this task, correctness was high for all representations (all 99% correct). We do not have evidence of a difference between sizes.

Confidence: For T1 participants reported largely high confidence scores for all three form factors. Over 85% of respondents were at least fairly confident with each form factor: Square ■ = 95% ■■■■, Tall ■ = 92% ■■■■, Wide ■ = 87% ■■■■ (Figure 6.4 top).

Task T2: Did you go to bed later than planned (22:00) on 4 or more days this week?

Completion Time: Answer times ranged between 1547 ms (Wide ■) to 1933 ms (Tall ■), and there is strong evidence for Wide ■ being faster than Tall ■. We did not see strong evidence of a difference between Square ■ (with 1696 ms on average), and the other two form factors. Nevertheless, the uncorrected pairwise confidence intervals involving Square ■ are close to 0 that may indicate a trend of a difference between Square ■ and the other two form factors.

Accuracy: With each form factor participants were 96–97% correct. We have only some evidence that participants may be more correct with Wide ■ compared to Tall ■.

Confidence: Participants reported high confidence scores for all form factors. For Square ■ and Wide ■, 83.3% ■■■■ of participants were at least fairly confident, and for Tall ■ 90.5% ■■■■ (Figure 6.4 middle).

Task T3: Did you sleep longer on average on the weekend days (Sat, Sun) compared to the weekdays (Mon-Fri)?

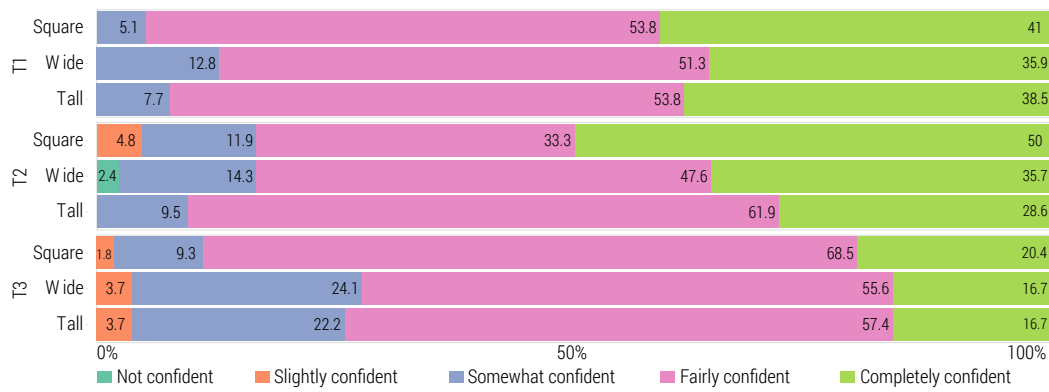


Fig. 6.4: Percentages of confidence ratings by participants of different form factors for each task for the Sleep Duration (bar) Study.

Completion Time: We saw no evidence of a difference between form factors for this task, and average completion times were similar: Tall ■ = 1780 ms; Wide ■ = 1857 ms, and Square ■ = 1905 ms.

Accuracy: Correctness for this task ranged between 93% (Wide ■), and 96% (Square ■). However, we have only evidence of a difference between Square ■ (more accurate), and Wide ■. There is possibly a trend for Square ■ to be more accurate than Tall ■ as well but the CI is close to 0.

Confidence: Participants reported the highest confidence scores for Square ■, with 89% ■ being at least fairly confident. The other confidence scores of participants reporting to be at least fairly confident in their answers also remained high with 72% ■ (Wide ■), and 74% ■ (Tall ■) (Figure 6.4 bottom).



Post-Study Questionnaire

We asked participants to pick their preferred display form factor. For each task Square ■ was the preferred representation (T1: 69.2% ■, T2: 73.8% ■, T3: 57.4% ■). When asked to compare the two wristband form factors Wide ■ was preferred for all tasks (T1: 51.3% ■, T2: 59.5% ■, T3: 53.7% ■) but the preferences for one, or the other were not strong.

Summary: The most obvious difference between form factors in this study was present in T2, for which Wide ■ was both faster, and more accurate than Tall ■. Differences in time in the other two tasks are not as prominent as in the in-person pilot study, but there are trends in T1 for Wide ■ to be slower than Square ■ and Tall ■. Accuracy was overall high (over 93%). We saw that in T3 Square ■ was more accurate than Wide ■ possibly more accurate than Tall ■ and participants felt more confident with it. We reflect more on

our methodological approach of conducting a crowdsourced study, and differences to the in-person pilot study, in Section 6.6.

6.5 Sleep Phase (hypnogram) Study: Hypnogram charts of Nightly Sleep Phases

After we identified that crowdsourced studies can help uncover insights on smartwatch perception, we expanded our exploration about whether people can use charts effectively across different form factors. Again, we focused our study on insights into sleep data, and their visualization. In this second study, we chose last night's sleep phases as one of the data sources of most interest to wearers in our survey, and because its preferred visualization was surprising to us. In particular, we were surprised by the strong preference (75.8% ) for the hypnogram chart on the wristband form factor because it is a relatively complex, and visually busy temporal chart, and we were skeptical how well it would perform in practice. In comparison, only 33.3%  of survey respondents had picked the hypnogram as preferred for the smartwatch-sized visualization. We followed the same design procedure as in our first crowdsourced study.

6.5.1 Stimuli and Tasks

A hypnogram represents the stages of sleep as a function of time. The purpose of a hypnogram is to provide a general sense of nightly sleep behaviors. It differentiates between different stages of sleep on the y -axis: rapid eye movement sleep (REM), and non-rapid eye movement sleep (NREM), sometimes separated into different levels like light, and deep sleep, during the sleep cycle [80]. A typical hypnogram on fitness trackers shows three sleep stages: light, deep, and REM together with the time a person is awake [65]. The hypnogram shows when someone transitioned from one stage to another along the x -axis.

Participants in our survey reported to be interested in learning about their sleep phases. We formulated the following three tasks to target this interest, and to remain close to the types of tasks of our Sleep Duration (bar) Study:

- **T1:** Were you in the wake phase more than or equal to 4 times?
- **T2:** Did you have 4 or more transitions from REM to light sleep?
- **T3:** Did you spend more time in REM than in deep sleep?

All three tasks required participants to analyze temporal data. While T1 is an elementary task that participants can answer by counting bar peaks, T2, and T3 are synoptic tasks, which require participants to gain an overview of the whole reference set [6]. In T2, participants needed to count patterns related to a reference set from two sleep stages. T3 requires participants to identify two reference subsets (REM, and deep sleep), calculate the aggregate bar length for each subset, and compare the aggregates.

To generate synthetic data used for the stimuli, we calculated values for the four different sleep stages. On a typical night, a person goes through four to six sleep cycles. Not all sleep cycles are of the same length, but on average, they last about 90 minutes each [155]. For the stimuli, as shown in Figure 6.5, we used five sleep cycles, and ~96 min each for an 8-hour sleep duration (22:00-06:00). For the task that involved comparing bars of the aggregates, we ensured that there was a difference of a least 8 px. Stimuli of all three form factors had the same information, and text. We colored each sleep phase differently: red-colored bars represent the *wake* sleep phase, blue-colored bars for the *REM* sleep phase, green-colored bars for the *light* sleep phase, and purple-colored bars for the *deep* sleep phase. We used the color palette Sciences Po medialab [138] generated considering color blindness. We designed the visualizations to be similar to those already found on fitness tracking apps.

6.5.2 Participants

We recruited all participants in the same way as for our first crowdsourced study via Prolific [161]. Of the 162 total responses, 45 were incomplete, and discarded from all our analyses leaving us with 117 participants in total to complete our study. We compensated participants who completed the study with a reward of £2.63 for our 17-minute estimated study completion time, slightly higher than the French minimum wage requirements requested by our ethics committee. For T1, there were 45 participants, 36 participants for T2, and 36 participants for T3. We recruited 58.1% female, and 41.9% male

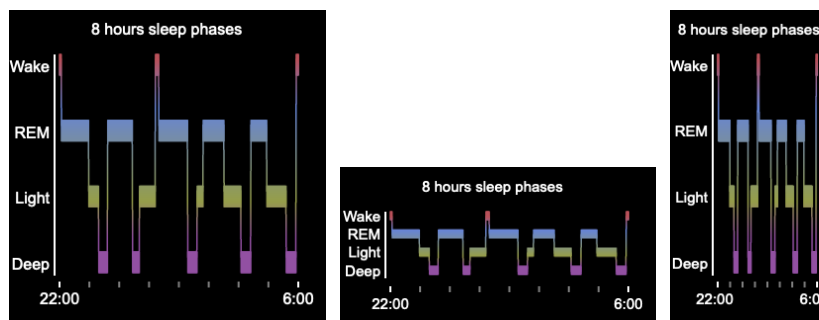
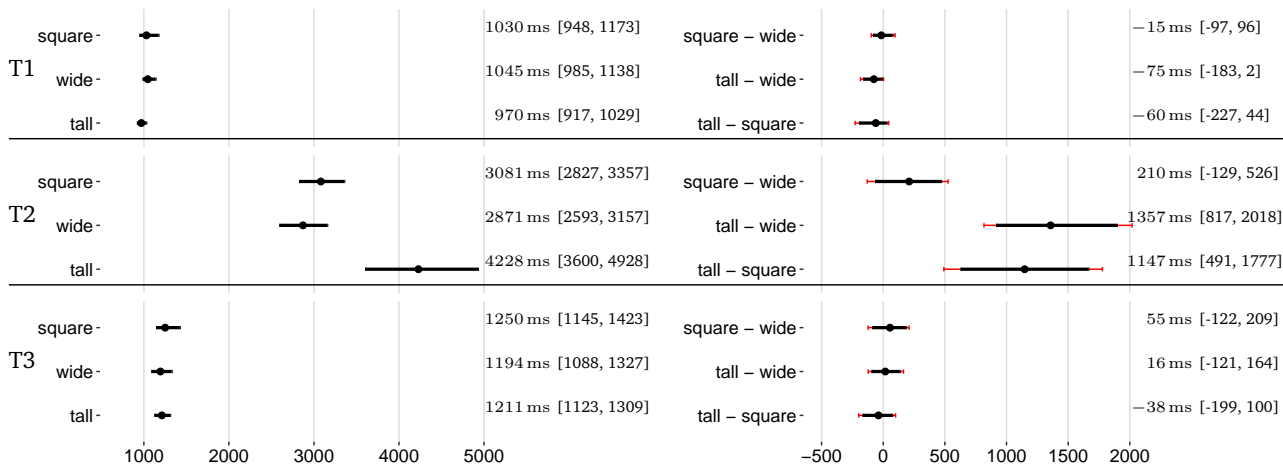


Fig. 6.5: Stimuli for the Sleep Phase (hypnogram) Study representing nightly sleep phases (wake, REM, light, deep) using three different form factors: Square, Wide, and Tall. Sizes, when printed without scaling, correspond to the physical sizes shown during the study.

Tab. 6.8: *Completion Time* analysis of data from the Sleep Phase (hypnogram) Study. Left: average completion time in milliseconds for each task; right: pairwise comparisons for each task, and form factor. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).



participants; 55.5% of the participants reported to be students, the job status of the rest (44.5%) is unknown. All participants had normal, or corrected-to-normal vision, and the average age was 26.27 years, (SD = 7.02). Among all participants, 33.3% owned a smartwatch, 24.7% owned a fitness band, and 6.83% owned both. Participants reported not to read hypnogram charts often: Never (48.7%) was the highest answer when rating hypnogram chart familiarity on a 5-point Likert scale. Figure 6.3 right, and Table 6.5 summarize background information about the participants.

6.5.3 Results

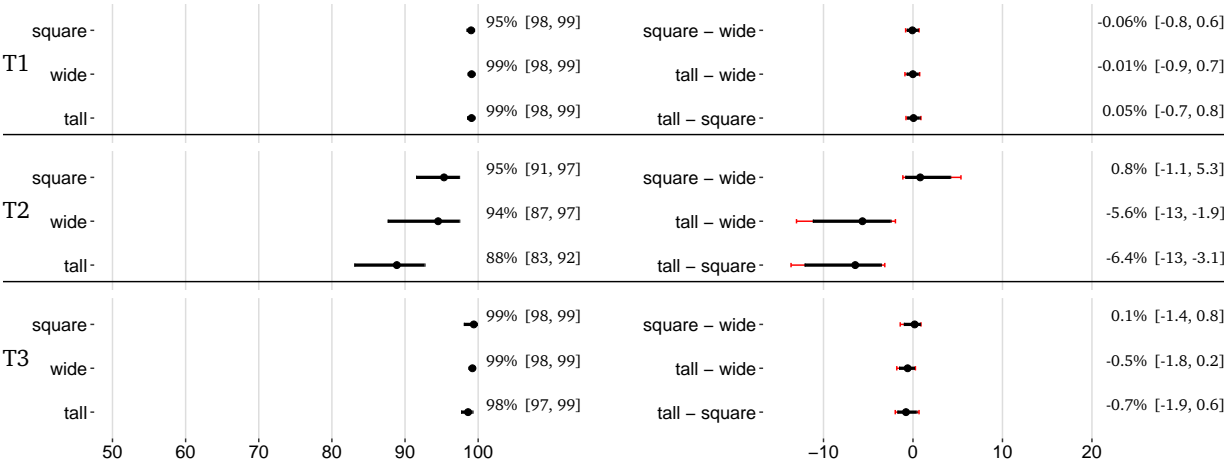
We describe the results discussing completion time, accuracy, and confidence. We separate our discussion by task due to our between-subject design. For the data analysis, we only considered the data that was within two standard deviations of the mean answering time. This means we almost uniformly removed around 5% of the data across all tasks. Table 6.8, and Table 6.9 give numerical details about the time, and accuracy results.

Task T1: Were you in the Wake phase more than or equal to 4 times?

Completion Time: The average completion times for Tall (970 ms), Square (1030 ms), and Wide (1045 ms) were similar. We saw no strong evidence for differences in the pairwise comparisons of techniques but there may be a trend for Tall to be slightly faster than Wide.

Accuracy: Correctness was high for all representations (all 99% correct on average). We do not have evidence of a difference between form factors.

Tab. 6.9: Accuracy analysis of data from the Sleep Phase (hypnogram) Study. Left: average accuracy; right: pairwise comparisons for each task, and form factor. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for three pairwise comparisons with Bonferroni correction (in red).



Confidence: Figure 6.6 top shows the confidence for all three form factors for T1. There were no participants who reported not to be confident, and confidence ratings overall were high. Most people with the Square form factor reported to be completely confident (73.3%), followed by Wide (64.4%), and Tall (57.8%).

Task T2: Did you have 4 or more transitions from REM to light sleep?

Completion Time: T2 had the largest average completion times in our study with 2871 ms for Wide up to 4228 ms for Tall. In the pairwise comparisons, we have strong evidence for this task being slower to complete with Tall than with the other two form factors (slower by over 1 s).

Accuracy: Average correctness was 94%, and 95% on average for Wide and Square respectively but dropped to 88% for Tall. We have evidence that Tall was indeed less accurate than the other two form factors, but no evidence of a difference between Wide and Square.

Confidence: Confidence was lowest for this task. We see the difficulties participants had with Tall confirmed in the confidence rating; 53.3% reported being only somewhat confident, or lower. Confidence ratings for Square and Wide were similar with 80.6% of respondents reporting being fairly, or completely confident.

Task T3: Did you spend more time in REM than in Deep sleep?

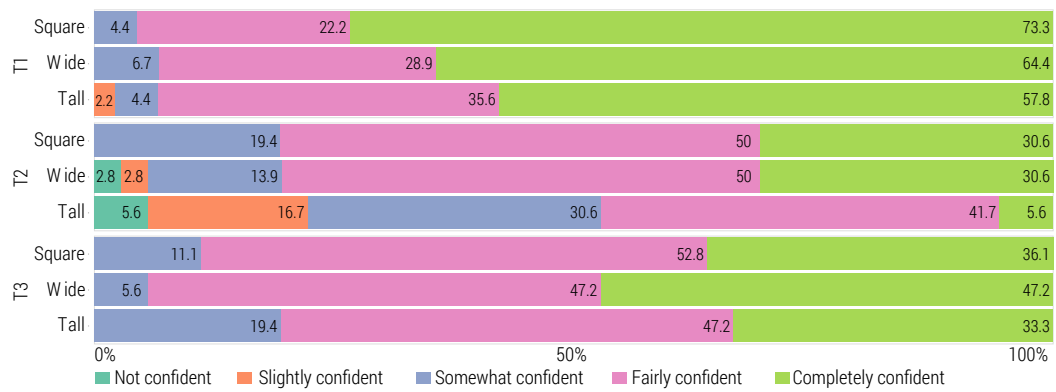


Fig. 6.6: Percentages of confidence ratings by participants of different form factors for each task for the Sleep Phase (hypnogram) Study.

Completion Time: The average completion times for this task ranged around 1.2 s with only small differences between form factors: Wide ■ 1194 ms, Tall ■ 1211 ms, and Square ■ 1250 ms. We have no evidence of a difference between form factors.

Accuracy: Participants were 98–99% correct in this task on average for all form factors. There was no evidence of a difference in the pairwise comparisons.

Confidence: The confidence scores were high for this task. Over 30% of participants reported being completely confident with each form factor, and Wide ■ having the highest response at 47.2% ■ . For each form factor, over 80% ■ of respondents were at least fairly confident: 94.4% ■ for Wide ■, 88.9% ■ for Square ■, and 80.5% ■ for Tall ■.

Post-Study Questionnaire

When asked to pick their preferred display size, participants preferred Square ■ clearly for T1 (73.3% ■). For T2 nobody chose Tall ■ and the difference between Square ■ (52.8% ■) over Wide ■ (47.2% ■) was small. The pattern was similar but reversed for T3 with participants slightly preferring Wide ■ (55.6% ■) to Square ■ (41.7% ■). When asked to decide between the two wristband form factors specifically, participants showed a clear preference for Wide ■ (T1: 86.7% ■, T2: 97.2% ■, T3: 88.9% ■).






Summary: Most differences were visible in T2, with Tall ■ performing worse than Square ■ and Wide ■ in terms of both time, and accuracy. We saw no other clear difference between the three form factors in T1, and T3. Participants tended to feel more confident with Square ■ and Wide ■ although confidence was high for all three form factors. These two were also the preferred form factors over Tall ■.

6.5.4 Methodological Reflection

The COVID-19 pandemic has prompted us to reconsider our research methods. Those of us who conduct in-person qualitative, or quantitative research have experienced substantial challenges in accessing study populations because of new social distancing regulations. In particular, research that requires specific types of technologies, such as smartwatches in our case, is challenged by the inability to run in-person studies. Our in-person pilot study, and the follow-up crowdsourced version of the pilot study, offer the opportunity to reflect on whether we can usefully run perception type studies for smartwatches in crowdsourced settings. Our approach simulated smartwatch-sized displays on smartphones, allowed us to target a wider audience, and make recommendations about smartwatch-sized displays. A recent study by Blascheck and Isenberg [25] already showed that running studies on a desktop computer with same sized stimuli leads to similar results, allowing researchers to run smartwatch studies on devices that are more available.

Summary, and Differences Between In-Person Pilot Study, and the Crowdsourced Sleep Duration (bar) Study

The crowdsourced version of our Sleep Duration (bar) Study had a few study design differences compared to the in-person pilot study that we outlined in Section 6.4.1. To answer our question whether a crowdsourced study to target fitness tracker perception is viable, we did not perform detailed statistical comparisons. Rather, we discuss how the results differ in the identified trends. In general, we would expect performance to be noisier in a crowdsourced study than in an in-person study but strong evidence should remain.

Overall, participants in the lab study had faster completion times. This can be caused by the different input methods used (keyboard vs. on-screen buttons on the smartphone), and the additional noise produced by the lack of control of the crowdsourced study environment. Several smaller effects in completion time that we observed in the in-person pilot study tended to be trends in the crowdsourced study. For example, for T1 (comparison of two adjacent bars), the evidence that Wide  was slower than the other two form factors in the in-person pilot study became only a trend in the crowdsourced study; or the completion time difference between Tall  and Square  in T2 (comparison of multiple bars) that also became a trend in the crowdsourced study. Yet, the strong evidence of Tall  being slower than Wide  in T2 was present across both the in-person pilot study, and the crowdsourced study. Measuring time accurately in crowdsourced studies is a known challenge [29], and indicates that we may need a larger number of participants to reach the same level of evidence between in-person, and crowdsourced studies. Participants in both studies were accurate in their answers, with the average accuracy for T2, and T3 (comparing averages of

groups of bars) being only slightly lower in the crowdsourced study (1–4 percentage points) but practically the same for T1.

Overall, we conclude that simulating fitness tracker displays on smartphones for crowdsourced perception studies worked well. We had engaged participants who performed similarly quickly as well as accurately, and strong evidence remained. Of course, we cannot perform all types of fitness tracker studies online by using smartphones. Any study that wishes to measure the impact of actually wearing the device, turning the wrist to look at the screen, or to measure the impact of contextual factors such as movement, still require field, or lab studies.

Recommendations for Setting up a Crowdsourced Fitness Tracker Study

Here we reflect on several of our study setup decisions, and implementation details that helped to conduct a successful crowdsourced fitness tracker perception study using smartphones.

Ensuring study participants used a smartphone: On the Prolific platform we indicated that our study had to be performed using a smartphone, and wrote dedicated instructions. Because Prolific does not itself test whether participants really used a smartphone we implemented a check that tested whether participants used a mobile browser. Checking screen resolution alone is not a good test because modern smartphones have similar resolutions compared to many desktop displays still currently in use.

Ensuring correct stimuli sizing: Smartphone environments offer a way to implement visual stimuli using density-independent pixels (DIP) to be rendered at similar physical sizes on viewers' smartphones. While we cannot control people's viewing distance from the screen in online perceptual studies, with DPIs we can at least ensure similar physical rendering sizes, and assume standard viewing distances for smartphones for the average participant.

Recording time: It is often argued that time is not a reliable measure in crowdsourced studies [29]. We set a time counter programmatically within the application: when participants changed the browser tab during the study the time counter would pause, and when participants returned to the tab the time counter would continue. However, issues with outliers in completion time remained, which we then removed from our analyses.

Ensuring engagement, and training: One of the main pitfalls of crowdsourced studies is reduced control in the assessment of participants' training [28]. We worked towards an increased willingness to engage with instructions by keeping them short, and splitting them across separate pages. The instructions were provided with text, and graphics before each training to be more engaging. Participants also needed to actively consent to understanding

each instruction before they could see the next image. In our last non-mandatory question—*“Do you have any comment about the study, for example, concerning the clarity of the instructions, or technical issues you might have experienced? (optional)”* we asked participants to give us feedback. For the Sleep Duration (bar) Study, 28 participants gave us voluntary comments, 12 of them mentioned that the instructions were clear, and explained well to them. For the Sleep Phase (hypnogram) Study, 16 participants gave us comments, 4 of them mentioned that everything was clear, and understandable to them. Some of the comments from the participants were—*“The study was enjoyable. There were no difficulties whatsoever. Everything was explained perfectly.”*, *“The instructions were simple, and clear, and the study was very interesting.”*, *“The instructions were clear, and well explained.”*, *“Very clear instructions for which I was grateful.”*, *“All was very clear, and understandable.”* As such, we are confident to recommend a similar study, and training setup.

Ensuring smooth study loading: We spent a lot of effort to reduce the loading time of the study web pages, and stimuli so that participants were not impeded by their internet speed. All graphics used in the study were produced in the Portable Network Graphics (PNG) format, or Graphics Interchange Format (GIF), and compressed to small file sizes. With a regular internet connection, the complete online study—a total of 32 web pages including all graphics—loaded within 2–4 seconds, and the first page within 7–15 milliseconds.

6.6 Discussion

In the following, we reflect on our study results, and the methodologies we used to study fitness tracker visualizations.

6.6.1 Study Results

We set out to understand how best to visualize sleep data on fitness trackers. Sleep visualizations are compelling to study because they can contain several types of data (temporal, quantitative, categorical, etc.), are relatively complex, and because many people care deeply about understanding their sleep data. From our survey, we learned that people are interested the most in short-term data (last night’s sleep, or weekly sleep patterns). Surprisingly, only about a third of our respondents were interested in comparing their sleep patterns to others.

In our survey, we asked participants which types of sleep visualizations they would prefer for different types of sleep data based on the form factor of their own fitness tracker. It was interesting to see that purely text-based representations were preferred only in one case—social comparison of sleep duration data on Square ■. More than half of our participants preferred several charts with particularly strong preferences for multiple of

the Wide ■ representations: horizontal bars for social comparison data, area charts for monthly overviews, and the hypnogram for last night's sleep phases. Due to the additional compression in the vertical direction when moving from a Square ■ to a Wide ■ form factor, we were surprised to see that independent participants often picked the same sleep visualizations (Figure 6.1) for the two form factors. The vertical compression should specifically affect vertical bar, area, or line charts, and different aspect ratios have shown in the past to affect the reading of charts [186].

Researchers can use our results to inspire the choice of dedicated sleep visualizations for fitness trackers that app developers are currently still rarely deploying on these devices. However, because the survey focused purely on visual preference we did not have evidence to recommend the use of the same types of charts on different form factors. Therefore, we conducted two follow-up studies that tested two common, and highly rated representation types for sleep duration, and sleep phase data. In our first study on sleep duration, we tested horizontal bar charts to encode weekly sleep data. We had expected that the horizontal compression of the chart, and the smaller visible differences between bars with similar start, or end positions would have a negative impact on the Tall ■ version of the chart. Nevertheless, we included Tall ■ as a condition because when worn it is more natural to read a wristband vertically, and wristbands often use a vertical layout in practice. Overall, we saw high accuracy with the visualizations for all tasks, and form factors. Surprisingly, the negative effect of horizontal compression only showed clearly for task completion time in Task 2, a synoptic task that required reading multiple bars, and comparing them to a reference line. Because we had designed differences to be at least 4 px for Tall ■ and 8 px for Wide ■ and Square ■, the negative effect of the horizontal compression seemed to be less important than we thought. We also saw a trend for Wide ■ being slower than the other two form factors for the elementary task that required comparing the length of two bars. This is interesting because the main difference of this form factor was the smaller bar width.

Next, we tested the hypnogram as a sleep phase visualization that our survey respondents strongly preferred for Wide ■. We expected again that the performance for Tall ■ would suffer due to the horizontal compression. We saw that this was only the case in Task 2, a synoptic task that required looking for specific types of transitions between phases. We had made sure that all would be visible in the Tall ■ rendering but the fact that all transitions were visually closer together negatively affected completion time, accuracy, and confidence scores. We also saw that more than half of the respondents picked Square ■ as their preferred display size for this task, giving some evidence that despite not showing as the preferred visualization in our survey for the Square ■, the chart worked well for most participants in our study.

6.6.2 Design Considerations

Based on our results, we summarize the following design considerations for sleep visualizations on fitness trackers.

Integrate sleep visualizations on fitness trackers: Overall, we saw in our survey an interest in detailed sleep data shown directly on the tracking devices themselves. Across our studies, people could solve all but one task in under 2 s with high accuracy, providing evidence that these visualizations have the potential to be glanceable, and effective at communicating sleep data to wearers [22].

Consider charts of the Tall ■ orientation for wristbands: In our studies, we tested both vertical, and horizontal wristband sized displays. When actually worn around a wrist, a wristband-sized chart would be more quickly read if rendered using the Tall ■ form factor because the wrist would have to be turned less. However, charts of this form factor did not perform well with respect to task completion time in more complex synoptic tasks. Practically, the differences in answer time might be outweighed by the additional time needed to turn the wrist to correctly orient charts of the Wide ■ form factor. In addition, Tall ■ bar, and hypnogram charts performed well according to completion time for elementary tasks, even outperforming (or trending to outperform) charts of the Wide ■ form factor.

Consider horizontal bars for social comparison data on Wide ■ form factors: In the survey, people strongly preferred bar representations. Due to the minimal compression in the vertical direction, which does not affect the data encoding, we expect these visualizations to be similarly accurately readable in social comparison tasks, as our horizontal bars in the present study on sleep duration.

Use horizontal bars for weekly overview data: We saw that participants were effective at both the elementary, and the two synoptic tasks. They also were confident, correct, and fast completing the three tasks (<2 s) with these charts at all form factors.

Do not use vertical hypnograms when wearers might want to understand sleep stage transitions: For T2, which required counting specific sleep stage transitions, we saw that participants needed the longest to answer (around 4 s), made the most errors, and were the least confident compared to the other form factors.

6.7 Conclusion

We investigated how to visualize sleep data on smartwatches, and fitness bands, through four different studies. In a first survey, we showed that wearers were mostly interested in weekly sleep duration, and nightly sleep phase data. Then, in an in-person pilot study,

and two crowdsourced studies, we selected, and tested the effectiveness of some of the most preferred visual representations for this data—bars, and hypnograms—under both elementary, and synoptic tasks. We found that despite their reduced display real estate, Tall ■, and Wide ■ performed, with a few exceptions, similarly to the larger Square ■ form factor. Accuracy was also high across tasks. This indicates that all form factors present viable platforms for displaying, and reading visualizations. Finally, we reflected on our adoption of a crowdsourced study methodology, which enabled us to reach a broader participant demographic for studies that have been traditionally lab-based.

Our work opens new questions for future research. While strong time performance trends were similar in our in-person, and crowdsourced study, the crowdsourced study seemed to highlight more differences in accuracy. It would be interesting to investigate why this is the case, and more generally conduct a systematic comparison of how in-person, and crowdsourced study results differ for such specialized wearable devices. Moreover, both types of studies remain fairly constraint, and controlled: smartwatches, and fitness bands are worn in contexts that include movement, and changing lighting conditions that may reduce readability. It remains future work to investigate these, and other factors stemming from real-use that may affect visualization reading, and comprehension. In addition, it would be useful to test the generalizability of our findings to other types of small-scale data representations, for example, the area chart, which was also often preferred.

Conclusion

My research intends to understand how to design and use micro-visualizations for pervasive and mobile data exploration. In this thesis, I started by presenting findings from an ideation workshop that can help us imagine future smartwatch visualization in the context of sight-seeing ([Chapter 3](#)). Then I discussed currently practiced data types and representations on smartwatch faces and untapped opportunities for visualization research ([Chapter 4](#)). Also, I presented a design space for smartwatch data representations which can help designers and experts to think of intuitive designs for smartwatch data ([Chapter 5](#)). Finally, I presented my work on the readability of micro-visualizations on fitness trackers (e.g., smartwatches, fitness bands), considering the impact of size and aspect ratio in sleep tracking data ([Chapter 6](#)). The initial pair of challenges concerns information needs specific to smartwatches, prompting the need for a comprehensive smartwatch face design. Drawing from the insights gained in tackling these challenges, we evaluated the efficacy of the visualization displayed on both a smartwatch and a fitness band. [Figure 7.1](#) shows the correlation between the motives driving my research pursuits and the approaches to overcome the associated challenges.

Based on the findings of all my studies, it can be concluded that smartwatch applications have the potential for contextual usage, which can enhance user engagement greatly. We also found that using data visualization techniques such as charts or graphs in smartwatch mini-dashboards is still rare, despite the fact that people can read even complex charts effectively. Through charts, users can quickly and easily understand their data and make informed decisions. These findings open opportunities both for visualization designers and for empirical research that can inspire the visualization community moving forward.

7.1 Summary and Contributions of the Thesis

Research Challenges of my Thesis. In the [Chapter 1](#), I explained the research context and the motivation of my research. I discussed why smartwatch visualization research is important to the community and the major goals of my thesis. Specifically, I highlighted the difficulties of designing a smartwatch face, a mini data dashboard of smartwatches, and the readability of smartwatch data. I mentioned four main research challenges I have been tackling during my thesis.

Related Work and Research Gaps. In the next chapter, [Chapter 2](#), I discussed related work, state-of-the-art of smartwatch use, and smartwatch data visualization. The main

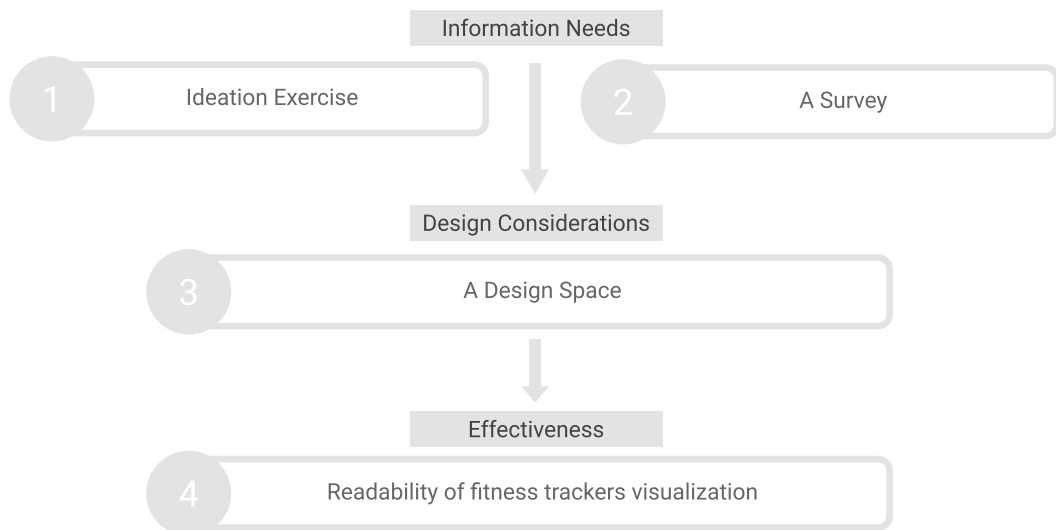


Fig. 7.1: The motives driving my research pursuits and the approaches to overcome the associated challenges.

goal of this chapter was to show the significant issues inherent in representing data on the small display of smartwatches. This chapter describes prior findings, research gaps, and how my research complements prior work. I found that despite the growing usage of smartwatches in health, fitness and self-tracking, contextual information needs, or use in sports activity, the smartwatches have great potential. However, data representation and display on fitness trackers and smartwatches have received less attention in the past. Wearers may quit smartwatch use and miss out on the benefits of this technology if there is a lack of context-specific data representation or if visualizations are inadequately designed. I discussed how my work is focused specifically on data representation on fitness trackers and smartwatches, how dedicated representations for smartwatches should be designed, and how my work complements previous recommendations. Moreover, I conducted a small systematic review to analyze papers on smartwatch face designs or application designs for data representation, and I categorized the articles according to their main research focus. I emphasized less studied topics in previous work, such as smartwatch face visualization design, despite the fact that the smartwatch face is the most frequently seen screen by wearers.

Context Specific Visualizations on Smartwatches. [Chapter 3](#) presents an analysis of the results of a full-day context-specific ideation exercise for smartwatch visualizations. Participants of the exercise created 34 sketches during a sightseeing activity. The main contribution of the chapter is a set of ideas for smartwatch motivations that highlight areas where possible micro-visualizations might be desired and that offer potential avenues for future research. The analysis of these sketches showed where visualizations could be applied and shown, what information needs they could target, and how data could be represented in the sightseeing context. The chapter also reflects our insights from the workshop and

describes the key benefits, such as— *being in-situ*, *being at the moment*, *repetition*, and the importance of the *props* to facilitate the ideation workshop for mobile data visualization.

Data and Representations on Smartwatch Face. [Chapter 4](#) presents the findings of a survey with 237 smartwatch wearers and assesses the types of data and representations commonly displayed on watch faces. This work contributes to understanding the current real-world use of representation types on smartwatches and additional findings that can inform and inspire the visualization community to pursue smartwatch visualization. We found icons accompanied by text are the most frequent representation types, dominantly displaying health and fitness data. We also found that smartwatches could capture many more data items, but currently, wearers do not see these on their watch faces. The main contribution of this study is a quantitative survey of different types of data and visual representations that smartwatch wearers saw, as well as additional findings that inspire smartwatch visualization research.

A Design Space for Smartwatch Visualization. [Chapter 5](#) presents a systematic review and proposes a design space for considering how to visualize data on smartwatch faces. This chapter builds on our prior work ([Chapter 4](#)) and contributes an in-depth study and analysis of visualization designs for popular premium smartwatch faces according to their design styles, amount and types of data, as well as visualization styles and encodings they included. From our analysis, we derive a design space to provide an overview of the most important considerations for new data displays for smartwatch faces and other small displays. Our design space can serve as an overview and inspiration for design choices and grounding for empirical work on smartwatch visualization design.

Readability of Sleep Visualization on Fitness Trackers. [Chapter 6](#) presents the findings of four studies related to the visualization of sleep data on wearables with two form factors: smartwatches and fitness bands. Our goal was to understand the interests, preferences, and effectiveness of different sleep visualizations by form factor. In a survey, we showed that wearers were mostly interested in weekly sleep duration and nightly sleep phase data. Visualizations of this data were generally preferred over purely text-based representations, and the preferred chart type for fitness bands and smartwatches was often the same. In one in-person pilot study and two crowdsourced studies, we then tested the effectiveness of the most preferred representations for different tasks and found that participants performed simple tasks effectively on both form factors, but more complex tasks benefited from the larger smartwatch size. Lastly, we reflected on our crowdsourced study methodology for testing the effectiveness of visualizations for wearables.

7.2 Limitations

Limitations were highlighted in each dedicated chapter for all of the studies done in this thesis. In this part, I will go through the more general limitations of my work.

Technical Realizations. From our ideation exercise and our later studies, we found a very large space of possibilities for smartwatch visualizations in different contexts. However, many of these might currently not be technically realizable. For example, for context-specific ideas it still needs to be determined how the context would be detected and lead to a switch on the device for the various applications. Technical limitations, therefore, might make some of the ideas less feasible.

Qualitative Insights. In both the smartwatch face survey and review, we investigated which information people display on watch faces and how. Both evaluations clearly show that text is the most frequent way to represent data on watch faces, while charts combined with text and/or icons are rare in practice. Also, in our sleep study, when we chose the designs for the tested stimuli, we prioritized real-world likeness over design consistency. However, we did not study “why” people chose the information they wanted to see or the design choices made by the designers. If the designers choose to represent data in specific representation types (e.g., text or icons), it would be useful to know why the designers picked a particular representation type. In general, our studies were less likely to analyze wearers’ opinions, expectations, or reasons for preferences for data displays. Such qualitative insights could have added a more meaningful basis for interpreting our quantitative findings. We also need to learn about the usability of current visualization on watch faces. For example, how easily can wearers navigate the visualizations on the smartwatch face design? Are the visuals clear and intuitive, or do they require excessive explanation or user training?

Real-world Evaluation. Our own ideas and the results of our studies have yet to be translated into real-world applications. For example, in [Chapter 6](#), our results show that sleep visualizations on fitness bands can be effectively read for different tasks even though they display a lot of data. It would be useful to deploy such visualizations in a real-world context, test them, and collect feedback from actual use outside the lab. Besides, our smartwatch face design space (described in [Chapter 5](#)) is primarily descriptive and has the potential to be generative. However, we are still determining how our design space will impact the smartwatch face designers or practitioners’ vision. Evaluating it in real-world practice makes it easier to determine whether this design space helps to generate ideas for smartwatch visualization design practitioners.

Approximating Smartwatch Usage. In our ideation workshop, we gave every participant a physical paper prop (see [Figure 3.1](#) in the shape of a smartwatch. Two partners combinedly drew ideas on paper props without being worn on the arm. In a real-life scenario, wearing the smartwatch and looking at the data requires considerations such as hand posture,



(a) driving context



(b) cycling context

Fig. 7.2: (a) & (b) Examples of prop and ideation workshop setting according to the context.

visualization size, rotation, or the gaze's angle to the vis. In our current work (see [Figure 7.2](#)), I have adapted the initial methodology from [Chapter 3](#) such that a single participant is wearing the prop and sketches draft ideas in a given setting. We consider that by wearing a prop, the designer will get more insights to approximate real smartwatch usage.

For the sleep visualization study, during the covid pandemic, we changed our initial study design from an in-person one to a crowdsourced one where we simulated smartwatches and fitness band screens on mobile phones. This worked well in general, and trends and evidence of differences across conditions were mostly similar. Nevertheless, we cannot perform all types of fitness tracker studies online by using smartphones, for example, those that require actually wearing the device. Nevertheless, for our perception-type experiments simulating smartwatches and fitness tracker screens on a smartphone worked well.

7.3 Future Work

While we have previously hinted at some possible future research directions and research agenda, here, I highlight what I consider to be the most important and promising research directions for smartwatch visualization.

Scalability: The Number of Complications and Their Complexity. For small data representations, it is intuitive to recommend that their designs should be simple and should encode only a few data values or dimensions. However, it would be helpful to study the encoding limits in more depth empirically. Studies could investigate two scenarios of increasing visualization complexity: (1) adding more dimensions, more data values, and more encoding types while keeping the same (small) display space and (2) decreasing the display space while keeping the same level of data complexity. Some of the past studies on visualization size (e.g., [35, 85, 86, 100, 157]) have consistently shown that people prefer larger visualizations

but we have also seen that participants could quite effectively and correctly complete certain tasks with appropriate encodings [23]. In addition to questions regarding the scalability (or miniaturization) of visualizations, scalability questions also arise regarding the number of visualizations to show on watch faces. Should all data be represented with a visualization? If not, what would be a good number to have? Both our survey and review show that wearers have 3–5 complications on average, including time on their watch faces. The highest number of complications was 17. How many complications on a small smartwatch display can effectively communicate with the wearers needs future research. In summary, there are several avenues of scalability to explore: more data, smaller size, and more visualizations.

Understanding How Context Matters. The primarily intended context of a fitness tracker’s use needs to be considered in its graphical and interaction design. The default for some Garmin watches, for example, is to show data during exercise using a large black font on a white background. No visualizations are shown. Is this the most effective way to communicate data to wearers or the one that ensures the most safety during other primary tasks? Especially contexts with divided attention, for example, glancing during driving, cycling, or running, require further research attention. Here, viewers can only afford quick glances at watch faces. Visualizations in these settings are difficult to evaluate and test, and future work is needed not only on which visualizations are glanceable but also on study methodologies to actually measure glanceability during activities while wearers are on the move.

Another important factor is the intended task context for watch faces. So far, most research has focused on watch face representations for improving personal health (Figure 2.2). Yet, we also saw commercial watch faces target contexts of use that we had not seen in research, such as entertainment, festival, or military usage. In Chapter 3, we showed that with dedicated ideation exercises, watch faces could be easily envisioned that target specific usage contexts such as sightseeing. Digital watch faces are easy to switch, and studying the impact of dedicated but changing watch faces on wearers would be interesting. Furthermore, it would be useful to investigate how to create a design to be context-aware for the real world. For example, a design on the watch face would adjust the display based on the time of day, the user’s location, or other relevant factors.

Understanding the Influence of Motion. When fitness trackers are worn during sports activities and involve moving one’s arms (e.g., walking, running, swimming, skiing, climbing), the displays will be in motion relative to the wearer’s gaze [97]. Depending on the activity, the relative motion will be more or less predictable and more or less quick, and the wearer will have different information needs. Motion characteristics such as speed, acceleration, trajectories, or direction may impact the readability of visualizations. Yao et al. [197] conducted two first evaluations about how donut charts’ moving speed and trajectory affected reading accuracy. Their results showed that participants’ performance was better on linear trajectories and slow speed than on irregular trajectories and fast speed. However,

in their experiment, all participants were stationary and sat in front of a screen larger than 13 inches. Because fitness trackers have a much smaller display size and many application scenarios involve moving viewers, the impact of motion characteristics for reading data on smartwatches requires further research in this context.

In addition, motion in realistic indoor and outdoor scenarios will entail additional challenges, such as changing lighting conditions, the presence of equipment, and a primary task. The type of sport itself will largely determine the types of motion characteristics and the extent of secondary factors; as such dedicated research is likely necessary. The characteristics of the different sports types determine the continuity of the viewer's movement, and the presence of required sports equipment can directly affect the viewer's ability to read or even attach a fitness tracker. For example, swimming goggles may filter certain light, reduce the field of view, or having to wear heavy coats while skiing might make it difficult to access a wrist-worn smartwatch screen. Finally, the needed concentration on primary tasks determines the length of time the viewer can read from their fitness tracker.

Smartwatch Display Types. The capabilities of the technology chosen to display visualizations in motion may significantly impact how well athletes can focus on their performance. Heller et al. [87] discussed a design space for wearable displays with two main dimensions: on-body placement and display content. As they showed, branching out from commercial fitness trackers to wearable accessories, clothing, or skin and body projections is a possibility, and ample research opportunities for visualization design exist—not only for performance-oriented displays but also for ambient visualization [69]. In the future, we will see displays of different shapes emerge for which potentially dedicated watch face designs have to be developed. First prototypes of watch strap displays [112] and curved displays [34, 111] have emerged already. Similarly, other types of embedded screens in clothing or wristbands will emerge, and we have to understand how watch faces can be designed for these non-flat displays.

Smartwatch Interaction. An issue related to display technology is how wearers can interact with the shown content. Few interactions with visualizations on watch faces have been implemented to mitigate the “fat finger problem” (e.g., Bezel Interaction [147], EdgeSelect Interaction [150]). At this point, mostly simple swipes and taps are used on touch-enabled watch faces. These allow, for example, switches between different representations or time intervals. Yet, more complex interactions have been explored for touch interactions on desktop-sized or tablet-sized charts (see [30, 119] for a summary). If they would be useful and how they can be used in the context of smartwatches when the “fat finger problem” becomes even more acute is an interesting avenue for research. In addition, interaction with these displays could be taken into account. Burstyn et al. [34], for example, presented an interactive wrist-worn device prototype in which the display could adjust to the wearer's body pose. As hand and arm postures can change rapidly during an activity, fitness trackers

that are body-pose aware could change the rotation, size, and location of a visualization to be most readable.

In summary, I envision that smartwatch technologies will continue to be great tools for monitoring people's health, improving daily life contextual needs, and improving functionality for those with accessibility needs. I want to contribute more to the broader topic of micro visualization research in my coming years.

Bibliography

- [1] Mario Aehnel and Bodo Urban, “Follow-Me: Smartwatch Assistance on the Shop Floor”, in: Springer International Publishing, 2014, pp. 279–287, DOI: 10.1007/978-3-319-07293-7_27 (cit. on p. 13).
- [2] Meeshu Agnihotri, Reema Upadhyaya, Katherine Kenna, and Chen-Dah Chiang, “Rist: An Interface Design Project for Indoor Navigation”, in: *Proceedings of the Conference on Communications in Computer and Information Science*, vol. 714, Springer, 2017, pp. 327–334, DOI: 10.1007/978-3-319-58753-0_48 (cit. on p. 13).
- [3] Wolfgang Aigner, Silvia Miksch, Heidrun Schumann, and Christian Tominski, *Visualization of Time-Oriented Data*, 1st ed., Springer, 2011 (cit. on p. 47).
- [4] Danielle Albers, Michael Correll, and Michael Gleicher, “Task-Driven Evaluation of Aggregation in Time Series Visualization”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2014, pp. 551–560, DOI: 10.1145/2556288.2557200 (cit. on p. 12).
- [5] Fereshteh Amini, Khalad Hasan, Andrea Bunt, and Pourang Irani, “Data Representations for In-Situ Exploration of Health and Fitness Data”, in: *Proceedings of the Conference on Pervasive Computing Technologies for Healthcare*, ACM, 2017, pp. 163–172, DOI: 10.1145/3154862.3154879 (cit. on pp. 11, 13, 14, 48).
- [6] Natalia Andrienko and Gennady Andrienko, *Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach*, Springer, 2005 (cit. on pp. 60, 70).
- [7] Android developer guides, *Watch face complications*, <https://developer.android.com/training/wearables/watch-faces/complications/>, Accessed: March, 2022 (cit. on p. 44).
- [8] Leonardo Angelini, Maurizio Caon, Stefano Carrino, Luc Bergeron, Nathalie Nyffeler, Mélanie Jean-Mairet, and Elena Mugellini, “Designing a Desirable Smart Bracelet for Older Adults”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing Adjunct Publication*, ACM, 2013, pp. 425–434, DOI: 10.1145/2494091.2495974 (cit. on p. 42).
- [9] Apple Inc. 2015, *Apple Watch User Guide – Version 1.0*, https://manuals.info.apple.com/MANUALS/1000/MA1708/en_US/apple_watch_user_guide.pdf, Accessed: September, 2022 (cit. on pp. 25, 108).
- [10] Ranjini Aravind, Tanja Blascheck, and Petra Isenberg, “A Survey on Sleep Visualizations for Fitness Trackers”, in: *Posters of the European Conference on Visualization (EuroVis)*, ed. by João Madeiras Pereira and Renata Georgia Raidou, The Eurographics Association, 2019, DOI: 10.2312/eurp.20191152 (cit. on pp. 33, 53, 55).

- [11] Eirik Årsand, Miroslav Muzny, Meghan Bradway, Jan Muzik, and Gunnar Hartvigsen, “Performance of the First Combined Smartwatch and Smartphone Diabetes Diary Application Study”, in: *Journal of Diabetes Science and Technology*, vol. 9, no. 3, 2015, pp. 556–563, DOI: 10.1177/1932296814567708 (cit. on p. 13).
- [12] Amir-reza Asadi, “iParallel: A SmartWatch-based Serious Game for Organizational Learning”, in: *International Serious Games Symposium (ISGS)*, 2020, pp. 68–73, DOI: 10.1109/ISGS51981.2020.9375157 (cit. on p. 13).
- [13] Stavros Asimakopoulos, Grigorios Asimakopoulos, and Frank Spillers, “Motivation and User Engagement in Fitness Tracking: Heuristics for Mobile Healthcare Wearables”, in: *Informatics*, vol. 4, no. 1, 2017, p. 5, DOI: 10.3390/informatics4010005 (cit. on p. 9).
- [14] S. K. Awan, E. J. Dunoyer, K. E. Genuario, A. C. Levy, K. P. O’Connor, S. Serhatli, and G. J. Gerling, “Using voice recognition enabled smartwatches to improve nurse documentation”, in: *Proceedings of the Symposium on Systems and Information Engineering Design*, 2018, pp. 159–164, DOI: 10.1109/SIEDS.2018.8374728 (cit. on p. 13).
- [15] Benjamin Bach, Euan Freeman, Alfie Abdul-Rahman, Cagatay Turkay, Saiful Khan, Yulei Fan, and Min Chen, “Dashboard Design Patterns”, in: *IEEE Transactions on Visualization and Computer Graphics*, 2022, pp. 1–11, DOI: 10.1109/TVCG.2022.3209448 (cit. on pp. 50, 51).
- [16] Magnus Bang, Katarina Solnevik, and Henrik Eriksson, “The Nurse Watch: Design and Evaluation of a Smart Watch Application with Vital Sign Monitoring and Checklist Reminders”, in: *AMIA Annual Symposium Proceedings*, vol. 2015, Nov. 2015, pp. 314–319 (cit. on p. 13).
- [17] Scott Bateman, Regan L. Mandryk, Carl Gutwin, Aaron Genest, David McDine, and Christopher Brooks, “Useful Junk? The Effects of Visual Embellishment on Comprehension and Memorability of Charts”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2010, pp. 2573–2582, DOI: 10.1145/1753326.1753716 (cit. on p. 52).
- [18] Fabian Beck and Daniel Weiskopf, “Word-sized Graphics for Scientific Texts”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 6, 2017, pp. 1576–1587, DOI: 10.1109/TVCG.2017.2674958 (cit. on pp. 45, 51).
- [19] Yannick Bernaerts, Matthias Druwé, Sebastiaan Steensels, Jo Vermeulen, and Johannes Schöning, “The Office Smartwatch: Development and Design of a Smartwatch App to Digitally Augment Interactions in an Office Environment”, in: *Proceedings of the Companion Publication on Designing Interactive Systems*, ACM, 2014, pp. 41–44, DOI: 10.1145/2598784.2602777 (cit. on p. 13).
- [20] Lonni Besançon and Pierre Dragicevic, “The Continued Prevalence of Dichotomous Inferences at CHI”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2019 (cit. on p. 59).
- [21] Lonni Besançon and Pierre Dragicevic, “The Significant Difference between p-values and confidence intervals”, in: *Proceedings of the Conference on l’Interaction Homme-Machine*, 2017, pp. 53–62 (cit. on p. 59).

- [22] Tanja Blascheck, Frank Bentley, Eun Kyoung Choe, Tom Horak, and Petra Isenberg, “Characterizing Glanceable Visualizations: From Perception to Behavior Change”, in: *Mobile Data Visualization*, CRC Press, 2021, pp. 151–176, DOI: 10.1201/9781003090823-5 (cit. on p. 78).
- [23] Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, and Petra Isenberg, “Glanceable Visualization: Studies of Data Comparison Performance on Smartwatches”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, 2019, pp. 630–640, DOI: 10.1109/TVCG.2018.2865142 (cit. on pp. 3, 11, 25, 48, 61, 85).
- [24] Tanja Blascheck, Anastasia Bezerianos, Lonni Besançon, Bongshin Lee, and Petra Isenberg, “Preparing for Perceptual Studies: Position and Orientation of Wrist-worn Smartwatches for Reading Tasks”, in: *Proceedings of the Workshop on Data Visualization on Mobile Devices held at ACM CHI*, 2018 (cit. on p. 61).
- [25] Tanja Blascheck and Petra Isenberg, “A Replication Study on Glanceable Visualizations: Comparing Different Stimulus Sizes on a Laptop Computer”, in: *Proceedings of the Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications-Volume 3 IVAPP*, SCITEPRESS-Science and Technology Publications, 2021, pp. 133–143 (cit. on p. 74).
- [26] William K Bodin, David Jaramillo, Sanjeev Kumar Marimekala, and Matt Ganis, “Security challenges and data implications by using smartwatch devices in the enterprise”, in: *Proceedings of the Conference on Emerging Technologies for a Smarter World*, 2015, pp. 1–5, DOI: 10.1109/CEWIT.2015.7338164 (cit. on p. 13).
- [27] Niall Bolger, Angelina Davis, and Eshkol Rafaeli, “Diary methods: Capturing life as it is lived”, in: *Annual review of psychology*, vol. 54, no. 1, 2003, pp. 579–616 (cit. on p. 17).
- [28] Rita Borgo, Bongshin Lee, Benjamin Bach, Sara Fabrikant, Radu Jianu, Andreas Kerren, Stephen Kobourov, Fintan Mcgee, Luana Micallef, Tatiana Landesberger, Katrin Ballweg, Stephan Diehl, Paolo Simonetto, and Michelle Zhou, “Crowd-sourcing for Information Visualization: Promises and Pitfalls”, in: Sept. 2017, pp. 96–138, DOI: 10.1007/978-3-319-66435-4_5 (cit. on p. 75).
- [29] Rita Borgo, Luana Micallef, Benjamin Bach, Fintan Mcgee, and B. Lee, “Information Visualization Evaluation Using Crowdsourcing”, in: *Computer Graphics Forum*, vol. 37, June 2018, pp. 573–595, DOI: 10.1111/cgf.13444 (cit. on pp. 74, 75).
- [30] Matthew Brehmer, Bongshin Lee, John Stasko, and Christian Tominski, “Interacting with Visualization on Mobile Devices”, in: *Mobile Data Visualization*, Chapman and Hall/CRC, 2021, pp. 67–110 (cit. on p. 86).
- [31] Matthew Brehmer and Tamara Munzner, “A Multi-Level Typology of Abstract Visualization Tasks”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, 2013, pp. 2376–2385, DOI: 10.1109/TVCG.2013.124 (cit. on p. 60).
- [32] Nathalie Bressa, Kendra Wannamaker, Henrik Korsgaard, Wesley Willett, and Jo Vermeulen, “Sketching and Ideation Activities for Situated Visualization Design”, in: *Proceedings of the Conference on Designing Interactive Systems*, ACM, 2019, pp. 173–185, DOI: 10.1145/3322276.3322326 (cit. on p. 16).

- [33] Jeffrey Browne, Bongshin Lee, Sheelagh Carpendale, Nathalie Riche, and Timothy Sherwood, “Data Analysis on Interactive Whiteboards Through Sketch-based Interaction”, in: *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, ACM, 2011, pp. 154–157, DOI: 10.1145/2076354.2076383 (cit. on p. 16).
- [34] Jesse Burstyn, Paul Strohmeier, and Roel Vertegaal, “DisplaySkin: Exploring Pose-Aware Displays on a Flexible Electrophoretic Wristband”, in: *Proceedings of the International Conference on Tangible, Embedded, and Embodied Interaction*, ACM, 2015, pp. 165–172, DOI: 10.1145/2677199.2680596 (cit. on pp. 7, 86).
- [35] Xiwen Cai, Konstantinos Efstathiou, Xiao Xie, Yingcai Wu, Y. Shi, and Lingyun Yu, “A Study of the Effect of Doughnut Chart Parameters on Proportion Estimation Accuracy”, in: *Computer Graphics Forum*, vol. 37, no. 6, 2018, pp. 300–312, DOI: 10.1111/cgf.13325 (cit. on pp. 59, 84).
- [36] Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman, eds., *Readings in Information Visualization: Using Vision to Think*, 1999 (cit. on p. 3).
- [37] Carpendale, Isenberg, Perin, Blascheck, Daneshzand, Islam, Currier, Buk, Cheung, Quach, and Vermette, “Mobile Visualization Design: An Ideation Method to Try”, in: *Mobile Data Visualization*, Chapman and Hall/CRC, Nov. 2021, pp. 241–261, DOI: 10.1201/9781003090823-8 (cit. on pp. 13, 15).
- [38] Carme Carrion, Maurizio Caon, Stefano Carrino, Liliana Arroyo Moliner, Alexandra Lang, Sarah Atkinson, Marco Mazzola, Paolo Perego, Carlo Emilio Standoli, Conxa Castell, and Mireia Espallargues, “Wearable Lifestyle Tracking Devices: Are They Useful for Teenagers?”, in: *Proceedings of the Conference and Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, ACM, 2015, pp. 669–674, DOI: 10.1145/2800835.2809442 (cit. on pp. 7, 9).
- [39] Marta E. Cecchinato, Anna L. Cox, and Jon Bird, “Always On(Line)? User Experience of Smartwatches and Their Role within Multi-Device Ecologies”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2017, pp. 3557–3568, DOI: 10.1145/3025453.3025538 (cit. on p. 9).
- [40] Marta E. Cecchinato, Anna L. Cox, and Jon Bird, “Smartwatches: The Good, the Bad and the Ugly?”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2015, pp. 2133–2138, DOI: 10.1145/2702613.2732837 (cit. on p. 1).
- [41] Liqiong Chang, Jiaqi Lu, Ju Wang, Xiaojiang Chen, Dingyi Fang, Zhanyong Tang, Petteri Nurmi, and Zheng Wang, “SleepGuard: Capturing Rich Sleep Information Using Smartwatch Sensing Data”, in: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 3, 2018, DOI: 10.1145/3264908 (cit. on p. 11).
- [42] Yang Chen, “Visualizing Large Time-series Data on Very Small Screens”, in: *Short Papers of the European Conference on Visualization (EuroVis)*, The Eurographics Association, 2017, DOI: 10.2312/eurovisshort.20171130 (cit. on p. 11).
- [43] Eun Kyoung Choe, Bongshin Lee, and m.c. schraefel m.c., “Characterizing Visualization Insights from Quantified Selfers’ Personal Data Presentations”, in: *IEEE Computer Graphics and Applications*, vol. 35, no. 4, 2015, pp. 28–37, DOI: 10.1109/MCG.2015.51 (cit. on p. 9).

- [44] Lucio Ciabattoni, Francesco Ferracuti, Sauro Longhi, Lucia Pepa, Luca Romeo, and Federica Verdini, “Real-time mental stress detection based on smartwatch”, in: *Proceedings of the International Conference on Consumer Electronics (ICCE)*, IEEE Computer Society Press, 2017, pp. 110–111, DOI: 10.1109/ICCE.2017.7889247 (cit. on p. 10).
- [45] Franceli L. Cibrian, Kimberley D. Lakes, Arya Tavakoulia, Kayla Guzman, Sabrina Schuck, and Gillian R. Hayes, “Supporting Self-Regulation of Children with ADHD Using Wearables: Tensions and Design Challenges”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2020, pp. 1–13, DOI: 10.1145/3313831.3376837 (cit. on pp. 13, 18).
- [46] Céline Clavel, Steve Whittaker, Anaïs Blacodon, and Jean-Claude Martin, “Wenner: A Theoretically Motivated Approach for Tailored Coaching about Physical Activity”, in: *Proceedings of the Conference and Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, ACM, 2018, pp. 1669–1675, DOI: 10.1145/3267305.3274190 (cit. on p. 13).
- [47] James Clawson, Jessica A. Pater, Andrew D. Miller, Elizabeth D. Mynatt, and Lena Mamykina, “No Longer Wearing: Investigating the Abandonment of Personal Health-Tracking Technologies on Craigslist”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing*, ACM, 2015, pp. 647–658, DOI: 10.1145/2750858.2807554 (cit. on p. 54).
- [48] Andy Cockburn, Pierre Dragicevic, Lonni Besançon, and Carl Gutwin, “Threats of a Replication Crisis in Empirical Computer Science”, in: *Communications of the ACM*, vol. 63, no. 8, 2020, pp. 70–79 (cit. on p. 59).
- [49] Android developer community, *Support different pixel densities*, <https://developer.android.com/training/multiscreen/screendensities>, Accessed: September, 2022 (cit. on p. 64).
- [50] Geoff Cumming, *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*, Routledge, 2013 (cit. on p. 59).
- [51] Katherine Currier, Søren Knudsen, Miriam Sturdee, and Sheelagh Carpendale, “Combining Ideation and Journaling to Explore to New Possibilities for Visualization on Mobile Devices”, in: *ACM CHI Workshop on MobileVis*, 2018 (cit. on p. 16).
- [52] Max Doan, Franceli L. Cibrian, Agnes Jang, Nihar Khare, Sean Chang, Aiyuan Li, Sabrina Schuck, Kimberley D. Lakes, and Gillian R. Hayes, “CoolCraig: A Smart Watch/Phone Application Supporting Co-Regulation of Children with ADHD”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2020, pp. 1–7, DOI: 10.1145/3334480.3382991 (cit. on p. 13).
- [53] Remus A. Dobrican and Denis Zampunieris, “A Proactive Solution, using Wearable and Mobile Applications, for Closing the Gap between the Rehabilitation Team and Cardiac Patients”, in: *Proceedings of the Conference on Healthcare Informatics (ICHI)*, IEEE Computer Society Press, 2016, pp. 146–155, DOI: 10.1109/ICHI.2016.23 (cit. on p. 13).
- [54] Pierre-Yves Donzé, “Dynamics of Innovation in the Electronic Watch Industry: A Comparative Business History of Longines (Switzerland) and Seiko (Japan), 1960–1980”, in: *Essays in Economic and Business History*, 2019, pp. 120–145 (cit. on p. 1).

- [55] Steven Dow, Julie Fortuna, Dan Schwartz, Beth Altringer, Daniel Schwartz, and Scott Klemmer, “Prototyping dynamics: sharing multiple designs improves exploration, group rapport, and results”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2011, pp. 2807–2816 (cit. on p. 17).
- [56] Pierre Dragicevic, “Fair Statistical Communication in HCI”, in: *Modern Statistical Methods for HCI*, ed. by Judy Robertson and Maurits Kaptein, Springer, 2016, chap. 13, pp. 291–330 (cit. on p. 59).
- [57] Pierre Dragicevic and Stéphane Huot, “SpiraClock: A Continuous and Non-Intrusive Display for Upcoming Events”, in: *Extended Abstracts on Human Factors in Computing Systems (CHI)*, ACM, 2002, pp. 604–605, DOI: 10.1145/506443.506505 (cit. on pp. 47, 49).
- [58] Daniel A. Epstein, Monica Caraway, Chuck Johnston, An Ping, James Fogarty, and Sean A. Munson, “Beyond Abandonment to Next Steps: Understanding and Designing for Life after Personal Informatics Tool Use”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2016, pp. 1109–1113, DOI: 10.1145/2858036.2858045 (cit. on p. 9).
- [59] Daniel A. Epstein, Jennifer H. Kang, Laura R. Pina, James Fogarty, and Sean A. Munson, “Reconsidering the Device in the Drawer: Lapses as a Design Opportunity in Personal Informatics”, in: *Proceedings of Conference on Pervasive and Ubiquitous Computing*, ACM, 2016, pp. 829–840, DOI: 10.1145/2971648.2971656 (cit. on p. 7).
- [60] Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson, “A Lived Informatics Model of Personal Informatics”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing*, ACM, 2015, pp. 731–742, DOI: 10.1145/2750858.2804250 (cit. on p. 9).
- [61] Andrey Esakia and Lindah Kotut, “Smartwatch-Centered Design and Development in Mobile Computing Classes”, in: *IEEE Frontiers in Education Conference (FIE)*, 2020, pp. 1–7, DOI: 10.1109/FIE44824.2020.9274280 (cit. on p. 13).
- [62] Catrin Feron, Tina Ekhtiar, and Ruben Gouveia, “Transitions in Personal Informatics: Investigating Self-Tracking During Moments of Change”, in: *Proceedings of the Nordic Human-Computer Interaction Conference*, ACM, 2022, DOI: 10.1145/3547522.3547686 (cit. on p. 10).
- [63] Stephen Few, *There’s Nothing Mere About Semantics*, <https://www.perceptualedge.com/blog/?p=2793>, Blog Post (cit. on p. 50).
- [64] Leah Findlater, Bonnie Chinh, Dhruv Jain, Jon Froehlich, Raja Kushalnagar, and Angela Carey Lin, “Deaf and Hard-of-Hearing Individuals’ Preferences for Wearable and Mobile Sound Awareness Technologies”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2019, pp. 1–13, DOI: 10.1145/3290605.3300276 (cit. on p. 10).
- [65] Sleep Stage by Fitbit, *REM, Light, Deep: How Much of Each Stage of Sleep Are You Getting?*, <https://blog.fitbit.com/sleep-stages-explained/>, Accessed: September, 2022 (cit. on pp. 9, 69).

- [66] Johannes Fuchs, Petra Isenberg, Anastasia Bezerianos, and Daniel Keim, “A Systematic Review of Experimental Studies on Data Glyphs”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 7, 2017, pp. 1863–1879, DOI: 10.1109/TVCG.2016.2549018 (cit. on p. 45).
- [67] Ombretta Gaggi, Claudio E. Palazzi, Matteo Ciman, and Armir Bujari, “StepBy-Watch: A smartwatch-based enhanced navigation system for visually impaired users”, in: *Proceedings of the Conference on Consumer Communications and Networking (CCNC)*, 2018, pp. 1–5, DOI: 10.1109/CCNC.2018.8319311 (cit. on p. 13).
- [68] M.J. Geier, “Tools & Toys: It’s All On The Wrist”, in: *IEEE Spectrum*, vol. 42, no. 8, 2005, pp. 57–58, DOI: 10.1109/MSPEC.2005.1491230 (cit. on p. 2).
- [69] Çağlar Genç, Yavuz Ali Ekmekçioğlu, Fuat Balci, Hakan Ürey, and Oguzhan Özcan, “Howel: A Soft Wearable with Dynamic Textile Patterns as an Ambient Display for Cardio Training”, in: *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, ACM, 2019, pp. 1–6, DOI: 10.1145/3290607.3312857 (cit. on p. 86).
- [70] Christos Gkournelos, Panagiotis Karagiannis, Niki Kousi, George Michalos, Spyridon Koukas, and Sotiris Makris, “Application of Wearable Devices for Supporting Operators in Human-Robot Cooperative Assembly Tasks”, in: *Proceedings of the Conference on Assembly Technologies and Systems*, vol. 76, 2018, pp. 177–182, DOI: 10.1016/j.procir.2018.01.019 (cit. on p. 13).
- [71] Pascal Goffin, Jeremy Boy, Wesley Willett, and Petra Isenberg, “An Exploratory Study of Word-Scale Graphics in Data-Rich Text Documents”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 10, 2017, pp. 2275–2287, DOI: 10.1109/TVCG.2016.2618797 (cit. on pp. 45, 51).
- [72] Steven Goodman, Susanne Kirchner, Rose Guttman, Dhruv Jain, Jon Froehlich, and Leah Findlater, “Evaluating Smartwatch-Based Sound Feedback for Deaf and Hard-of-Hearing Users Across Contexts”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2020, pp. 1–13, DOI: 10.1145/3313831.3376406 (cit. on p. 10).
- [73] Rúben Gouveia, Evangelos Karapanos, and Marc Hassenzahl, “How Do We Engage with Activity Trackers? A Longitudinal Study of Habito”, in: ACM, 2015, pp. 1305–1316, DOI: 10.1145/2750858.2804290 (cit. on p. 11).
- [74] Rúben Gouveia, Fábio Pereira, Evangelos Karapanos, Sean A. Munson, and Marc Hassenzahl, “Exploring the Design Space of Glanceable Feedback for Physical Activity Trackers”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing*, ACM, 2016, pp. 144–155, DOI: 10.1145/2971648.2971754 (cit. on pp. 2, 11, 13, 14, 18, 25).
- [75] Saul Greenberg, Sheelagh Carpendale, Nicolai Marquardt, and Bill Buxton, *Sketching user experiences: The workbook*, Elsevier, 2011 (cit. on p. 16).
- [76] Saul Greenberg, Sheelagh Carpendale, Nicolai Marquardt, and Bill Buxton, *Sketching user experiences: The workbook*, Elsevier, 2011 (cit. on p. 17).
- [77] Fairouz Grioui and Tanja Blascheck, “Study of Heart Rate Visualizations on a Virtual Smartwatch”, in: *Proceedings of the Symposium on Virtual Reality Software and Technology*, ACM, 2021, DOI: 10.1145/3489849.3489913 (cit. on p. 13).

- [78] Agnes Gruenerbl, Gerald Pirkel, Eloise Monger, Mary Gobbi, and Paul Lukowicz, “Smart-Watch Life Saver: Smart-Watch Interactive-Feedback System for Improving Bystander CPR”, in: *Proceedings of the International Symposium on Wearable Computers*, ACM, 2015, pp. 19–26, DOI: 10.1145/2802083.2802086 (cit. on p. 13).
- [79] Sibel Deren Guler, Madeline Gannon, and Kate Sicchio, “A Brief History of Wearables”, in: *Crafting Wearables: Blending Technology with Fashion*, Apress, 2016, pp. 3–10, DOI: 10.1007/978-1-4842-1808-2_1 (cit. on p. 8).
- [80] Helena Hachul, Cristina Frange, Andréia Bezerra, Camila Hirotsu, Gabriel Pires, Monica Andersen, Lia Bittencourt, and Sergio Tufik, “The effect of menopause on objective sleep parameters: Data from an epidemiologic study in São Paulo, Brazil”, in: *Maturitas*, vol. 80, Nov. 2014, DOI: 10.1016/j.maturitas.2014.11.002 (cit. on p. 69).
- [81] Katrin Hänsel, Akram Alomainy, and Hamed Haddadi, “Large Scale Mood and Stress Self-Assessments on a Smartwatch”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing*, ACM, 2016, pp. 1180–1184, DOI: 10.1145/2968219.2968305 (cit. on p. 13).
- [82] Tian Hao, Chongguang Bi, Guoliang Xing, Roxane Chan, and Linlin Tu, “MindfulWatch: A Smartwatch-Based System For Real-Time Respiration Monitoring During Meditation”, in: *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 1, no. 3, 2017, DOI: 10.1145/3130922 (cit. on p. 11).
- [83] Steve Haroz, Robert Kosara, and Steven L. Franconeri, “ISOTYPE Visualization: Working Memory, Performance, and Engagement with Pictographs”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2015, pp. 1191–1200, DOI: 10.1145/2702123.2702275 (cit. on p. 52).
- [84] Hayati Havlucu, Idil Bostan, Aykut Coskun, and Öuzhan Özcan, “Understanding the Lonesome Tennis Players: Insights for Future Wearables”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2017, pp. 1678–1685, DOI: 10.1145/3027063.3053102 (cit. on p. 11).
- [85] Christopher G. Healey and Amit P. Sawant, “On the Limits of Resolution and Visual Angle in Visualization”, in: *ACM Transactions on Applied Perception*, vol. 9, no. 4, Oct. 2012, DOI: 10.1145/2355598.2355603 (cit. on pp. 48, 84).
- [86] Jeffrey Heer, Nicholas Kong, and Maneesh Agrawala, “Sizing the Horizon: The Effects of Chart Size and Layering on the Graphical Perception of Time Series Visualizations”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2009, pp. 1303–1312, DOI: 10.1145/1518701.1518897 (cit. on p. 84).
- [87] Florian Heller, Kashyap Todi, and Kris Luyten, “An Interactive Design Space for Wearable Displays”, in: *Proceedings of the Conference on Mobile Human-Computer Interaction*, ACM, 2021, DOI: 10.1145/3447526.3472034 (cit. on pp. 4, 8, 86).
- [88] James Higgins, *Introduction to Modern Nonparametric Statistics*, Thomson Learning, 2004 (cit. on p. 59).

- [89] Alexandra Hosszu, Daniel Rosner, and Michael Flaherty, “Sleep Tracking Apps’ Design Choices: A Review”, in: *Proceedings of the Conference on Control Systems and Computer Science (CSCS)*, 2019, pp. 426–431, DOI: 10.1109/CSCS.2019.00078 (cit. on p. 53).
- [90] Giulio Iacucci, Kari Kuutti, and Mervi Ranta, “On the move with a magic thing: role playing in concept design of mobile services and devices”, in: *Proceedings of the 3rd conference on Designing interactive systems: processes, practices, methods, and techniques*, 2000, pp. 193–202 (cit. on p. 17).
- [91] IDEO., *IDEO Method Cards: 51 ways to inspire design*, William Stout, 2003 (cit. on p. 17).
- [92] Interaction design foundation, *Skeuomorphism*, <https://www.interaction-design.org/literature/topics/skeuomorphism/>, Accessed: March, 2022 (cit. on p. 41).
- [93] Petra Isenberg, “Micro Visualizations: Design and Analysis of Visualizations for Small Display Spaces”, Habilitation, Université Paris-Saclay, Dec. 2021 (cit. on pp. 1, 3, 48).
- [94] Alaul Islam, Ranjini Aravind, Tanja Blascheck, Anastasia Bezerianos, and Petra Isenberg, “Preferences and Effectiveness of Sleep Data Visualizations for Smartwatches and Fitness Bands”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2022, DOI: 10.1145/3491102.3501921 (cit. on p. 53).
- [95] Alaul Islam, Anastasia Bezerianos, Bongshin Lee, Tanja Blascheck, and Petra Isenberg, “Visualizing Information on Watch Faces: A Survey with Smartwatch Users”, in: *Proceedings of the IEEE Visualization Conference – Short Papers*, IEEE, 2020, pp. 156–160, DOI: 10.1109/VIS47514.2020.00038 (cit. on pp. 25, 53).
- [96] Alaul Islam, Tanja Blascheck, and Petra Isenberg, “Context Specific Visualizations on Smartwatches”, in: *Posters of the European Conference on Visualization (EuroVis)*, The Eurographics Association, 2022, DOI: 10.2312/evp.20221122 (cit. on p. 15).
- [97] Alaul Islam, Lijie Yao, Anastasia Bezerianos, Tanja Blascheck, Tingying He, Bongshin Lee, Romain Vuillemot, and Petra Isenberg, “Reflections on Visualization in Motion for Fitness Trackers”, in: *Proceedings of the New Trends in HCI and Sports Workshop at MobileHCI*, 2022 (cit. on p. 85).
- [98] Wallace Jackson and Pao, *SmartWatch Design Fundamentals*, Springer, 2019 (cit. on pp. 3, 35).
- [99] Pradthana Jarusriboonchai and Jonna Häkkinä, “Customisable Wearables: Exploring the Design Space of Wearable Technology”, in: *Proceedings of the Conference on Mobile and Ubiquitous Multimedia*, ACM, 2019, DOI: 10.1145/3365610.3365635 (cit. on p. 7).
- [100] Waqas Javed, Bryan McDonnel, and Niklas Elmqvist, “Graphical Perception of Multiple Time Series”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 16, no. 6, 2010, pp. 927–934, DOI: 10.1109/TVCG.2010.162 (cit. on p. 84).
- [101] Jawbone, *Jawbone tracker*, [https://en.wikipedia.org/wiki/Jawbone_\(company\)](https://en.wikipedia.org/wiki/Jawbone_(company)), Accessed: October, 2022 (cit. on p. 9).
- [102] Robert W Jellicorse, “2015–2016 Pebble Smartwatch Advertising Campaign”, in: 2015 (cit. on p. 2).

- [103] W.D. Jones, “EE gifts for the holidays”, in: *IEEE Spectrum*, vol. 37, no. 12, 2000, pp. 31–35, DOI: 10.1109/6.887593 (cit. on p. 2).
- [104] H. Kalantarian, N. Alshurafa, E. Nemati, T. Le, and M. Sarrafzadeh, “A smartwatch-based medication adherence system”, in: *Proceedings of the Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 2015, pp. 1–6, DOI: 10.1109/BSN.2015.7299348 (cit. on p. 10).
- [105] Aida Kamišalić, Iztok Fister, Muhamed Turkanović, and Sašo Karakatič, “Sensors and functionalities of non-invasive wrist-wearable devices: A review”, in: *Sensors*, vol. 18, no. 6, 2018, p. 1714, DOI: 10.3390/s18061714 (cit. on p. 7).
- [106] Aida Kamišalić, Iztok Fister, Muhamed Turkanović, and Sašo Karakatič, “Sensors and functionalities of non-invasive wrist-wearable devices: A review”, in: *Sensors*, vol. 18, no. 6, 2018, p. 1714, DOI: 10.3390/s18061714 (cit. on p. 32).
- [107] Rushil Khurana, Nikola Banovic, and Kent Lyons, “In Only 3 Minutes: Perceived Exertion Limits of Smartwatch Use”, in: *Proceedings of the Symposium on Wearable Computers*, ACM, 2018, pp. 208–211, DOI: 10.1145/3267242.3267285 (cit. on p. 2).
- [108] Joohee Kim and Byung-Chull Bae, “A Smartwatch-Based Feedback System for Eating Rate Guidance”, in: *Proceedings of the Conference and Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, ACM, 2018, pp. 384–387, DOI: 10.1145/3267305.3267669 (cit. on pp. 11, 13).
- [109] Frederick Kingdom and Nicolaas Prins, *Psychophysics: A Practical Introduction*, 1st, Elsevier, 2010 (cit. on p. 57).
- [110] Konstantin Klamka and Raimund Dachzelt, “Bendable Color EPaper Displays for Novel Wearable Applications and Mobile Visualization”, in: *The Publication of the Symposium on User Interface Software and Technology*, ACM, 2021, pp. 6–10, DOI: 10.1145/3474349.3480213 (cit. on p. 13).
- [111] Konstantin Klamka and Raimund Dachzelt, “Bendable Color ePaper Displays for Novel Wearable Applications and Mobile Visualization”, in: *Proceedings of the Symposium on User Interface Software and Technology*, ACM, 2021, DOI: 10.1145/3474349.3480213 (cit. on p. 86).
- [112] Konstantin Klamka, Tom Horak, and Raimund Dachzelt, “Watch+Strap: Extending Smartwatches with Interactive StrapDisplays”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2020, pp. 1–15, DOI: 10.1145/3313831.3376199 (cit. on pp. 7, 86).
- [113] Milan Kosanović and Slavimir N. Stosovic, “THE CONCEPT FOR THE “SMART HOME” CONTROLLED BY A SMARTWATCH”, in: *Facta universitatis. Series electronics and energetics*, vol. 31, 2018, pp. 389–400, DOI: 10.2298/FUEE1803389K (cit. on p. 13).
- [114] John Krumm, Gerry Cermak, and Eric Horvitz, “RightSPOT: A Novel Sense of Location for a Smart Personal Object”, in: *UbiComp 2003: Ubiquitous Computing*, Springer Berlin Heidelberg, 2003, pp. 36–43, DOI: 10.1007/978-3-540-39653-6_3 (cit. on p. 2).
- [115] Martin Krzywinski and Naomi Altman, “Points of Significance: Error bars”, in: *Nature Methods*, vol. 10, 2013, pp. 921–922 (cit. on p. 59).

- [116] Stefan Langer, Dennis Dietz, and Andreas Butz, “Towards Risk Indication In Mountain Biking Using Smart Wearables”, in: *Extended Abstracts of the Conference on Human Factors in Computing Systems*, ACM, 2021, DOI: 10.1145/3411763.3451746 (cit. on pp. 10, 13).
- [117] Bongshin Lee, Rubaiat Habib Kazi, and Greg Smith, “SketchStory: Telling More Engaging Stories with Data through Freeform Sketching”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, 2013, pp. 2416–2425, DOI: 10.1109/TVCG.2013.191 (cit. on p. 16).
- [118] Bongshin Lee, Greg Smith, Nathalie Henry Riche, Amy Karlson, and Sheelagh Carpendale, “SketchInsight: Natural data exploration on interactive whiteboards leveraging pen and touch interaction”, in: *PacificVis 2015*, Apr. 2015, pp. 199–206, DOI: 10.1109/PACIFICVIS.2015.7156378 (cit. on p. 16).
- [119] Bongshin Lee, Arjun Srinivasan, Petra Isenberg, John Stasko, et al., “Post-wimp interaction for information visualization”, in: *Foundations and Trends® in Human-Computer Interaction*, vol. 14, no. 1, 2021, pp. 1–95 (cit. on p. 86).
- [120] Boon Giin Lee, Jae-Hee Park, Chuan Chin Pu, and Wan-Young Chung, “Smartwatch-Based Driver Vigilance Indicator With Kernel-Fuzzy-C-Means-Wavelet Method”, in: *IEEE Sensors Journal*, vol. 16, no. 1, 2016, pp. 242–253, DOI: 10.1109/JSEN.2015.2475638 (cit. on p. 13).
- [121] Boon-Giin Lee, Boon-Leng Lee, and Wan-Young Chung, “Wristband-Type Driver Vigilance Monitoring System Using Smartwatch”, in: *IEEE Sensors Journal*, vol. 15, no. 10, 2015, pp. 5624–5633, DOI: 10.1109/JSEN.2015.2447012 (cit. on p. 13).
- [122] Juncheol Lee, Yeongtak Song, Jaehoon Oh, Youngjoon Chee, Chiwon Ahn, Hyunggoo Shin, Hyunggoo Kang, and Tae Ho Lim, “Smartwatch feedback device for high-quality chest compressions by a single rescuer during infant cardiac arrest: a randomized, controlled simulation study”, in: *European Journal of Emergency Medicine*, vol. 26, no. 4, 2019, pp. 266–271, DOI: 10.1097/MEJ.0000000000000537 (cit. on p. 13).
- [123] Jung-Min Lee, Wonwoo Byun, Alyssa Keill, Danae Dinkel, and Yaewon Seo, “Comparison of Wearable Trackers’ Ability to Estimate Sleep”, in: *International Journal of Environmental Research and Public Health*, vol. 15, no. 6, 2018, DOI: 10.3390/ijerph15061265 (cit. on p. 53).
- [124] SinJae Lee, SangBin Kim, and JungHyun Han, “Promoting Stretching Activity with Smartwatch - A Pilot Study”, in: *Entertainment Computing – ICEC*, ed. by Günter Wallner, Simone Kriglstein, Helmut Hlavacs, Rainer Malaka, Artur Lugmayr, and Hyun-Seung Yang, Springer International Publishing, 2016, pp. 211–216 (cit. on p. 13).
- [125] Gang Li, Boon-Leng Lee, and Wan-Young Chung, “Smartwatch-Based Wearable EEG System for Driver Drowsiness Detection”, in: *IEEE Sensors Journal*, vol. 15, no. 12, 2015, pp. 7169–7180, DOI: 10.1109/JSEN.2015.2473679 (cit. on p. 13).
- [126] Zilu Liang, Bernd Ploderer, and Mario Alberto Chapa-Martell, “Is Fitbit Fit for Sleep-Tracking? Sources of Measurement Errors and Proposed Countermeasures”, in: *Proceedings of the Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth ’17*, Barcelona, Spain: ACM, 2017, pp. 476–479, DOI: 10.1145/3154862.3154897 (cit. on p. 7).

- [127] Little Labs, Inc., *Facer - Thousands of FREE watch faces for Apple Watch, Samsung Gear S3, Huawei Watch, and more*, <https://www.facer.io/>, Accessed: September, 2022 (cit. on pp. 25, 26, 37, 106).
- [128] Guillaume Lopez, Shohei Abe, Kengo Hashimoto, and Anna Yokokubo, “On-Site Personal Sport Skill Improvement Support Using Only a Smartwatch”, in: *International Conference on Pervasive Computing and Communications Workshops*, IEEE Computer Society Press, 2019, pp. 158–164, DOI: 10.1109/PERCOMW.2019.8730681 (cit. on p. 10).
- [129] Yvonne Jansen Luiz Augusto Morais Pierre Dragicevic, *Framework for Running Online Experiments*, <https://github.com/yvonnejansen/FROE/>, Accessed: September, 2022 (cit. on p. 64).
- [130] Deborah Lupton, *The Quantified Self: A Sociology of Self-Tracking*, First, Polity Press, 2016 (cit. on p. 9).
- [131] Kent Lyons, “Visual Parameters Impacting Reaction Times on Smartwatches”, in: *Proceedings of Conference on Human-Computer Interaction with Mobile Devices and Services*, ACM, 2016, pp. 190–194, DOI: 10.1145/2935334.2935344 (cit. on p. 11).
- [132] Kent Lyons, David Nguyen, Daniel Ashbrook, and Sean White, “Facet: A Multi-Segment Wrist Worn System”, in: *Proceedings of the ACM Symposium on User Interface Software and Technology*, ACM, 2012, pp. 123–130, DOI: 10.1145/2380116.2380134 (cit. on p. 7).
- [133] Ilias Maglogiannis, George Spyroglou, Christos Panagopoulos, Maria Mazonaki, and Panayiotis Tsanakas, “Mobile reminder system for furthering patient adherence utilizing commodity smartwatch and Android devices”, in: *Proceedings of the Conference on Wireless Mobile Communication and Healthcare*, 2014, pp. 124–127, DOI: 10.1109/MOBIHEALTH.2014.7015925 (cit. on p. 10).
- [134] Steve Mann, “Wearable computing as means for personal empowerment”, in: *Proc. 3rd Int. Conf. on Wearable Computing (ICWC)*, 1998, pp. 51–59 (cit. on p. 8).
- [135] Steve Mann, *Wristwatch-Based Videoconferencing System*, <http://wearcam.org/smartwatch/>, Accessed: September, 2022 (cit. on p. 1).
- [136] Sean McKenna, Alexander Lex, and Miriah D. Meyer, “Worksheets for Guiding Novices through the Visualization Design Process”, in: *CoRR*, vol. abs/1709.05723, 2017 (cit. on p. 16).
- [137] Donald McMillan, Barry Brown, Airi Lampinen, Moira McGregor, Eve Hoggan, and Stefania Pizza, “Situating Wearables: Smartwatch Use in Context”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2017, pp. 3582–3594, DOI: 10.1145/3025453.3025993 (cit. on pp. 9, 11).
- [138] Sciences Po medialab, *i want hue*, <https://medialab.github.io/iwanthue/>, Accessed: September, 2022 (cit. on p. 70).
- [139] Jochen Meyer, Anastasia Kazakova, Merlin Büsing, and Susanne Boll, “Visualization of Complex Health Data on Mobile Devices”, in: *ACM*, 2016, pp. 31–34, DOI: 10.1145/2985766.2985774 (cit. on p. 11).

- [140] Matthias Mielke and Rainer Brück, “A Pilot Study about the Smartwatch as Assistive Device for Deaf People”, in: *Proceedings of the Conference on Computers & Accessibility*, ACM, 2015, pp. 301–302, DOI: 10.1145/2700648.2811347 (cit. on p. 10).
- [141] Chulhong Min, Seungwoo Kang, Chungkuk Yoo, Jeehoon Cha, Sangwon Choi, Younghwan Oh, and Junehwa Song, “Exploring Current Practices for Battery Use and Management of Smartwatches”, in: *Proceedings of the International Symposium on Wearable Computers*, ACM, 2015, pp. 11–18, DOI: 10.1145/2802083.2802085 (cit. on p. 7).
- [142] Manuel Eugenio Morocho Cayamcela, Wansu Lim, and Donguk Kwon, “Using body-measurement indices and wrist-type photoplethysmography signals to categorize consumer electronic users’ health state through a smartwatch application”, in: *Proceedings of the Conference on Electronics, Information, and Communication*, 2018, pp. 1–4, DOI: 10.23919/ELINF0COM.2018.8330573 (cit. on p. 13).
- [143] Tamara Munzner, *Developing Design Spaces for Visualization*, Stanford HCI Seminar Talk Slides, <https://www.cs.ubc.ca/~tmm/talks.html#stanf22>, Talk held on March 4th, 2022. Slides accessed: March, 2022 (cit. on p. 42).
- [144] Tamara Munzner, *Visualization analysis and design*, CRC press, 2014 (cit. on p. 47).
- [145] S. M. Neis and M. I. Blackstun, “Feasibility analysis of wearables for use by airline crew”, in: *Proceedings of the Conference on Digital Avionics Systems*, IEEE Computer Society Press, 2016, pp. 1–9, DOI: 10.1109/DASC.2016.7778023 (cit. on pp. 11, 13).
- [146] Ali Neshati, Fouad Alallah, Bradley Rey, Yumiko Sakamoto, Marcos Serrano, and Pourang Irani, “SF-LG: Space-Filling Line Graphs for Visualizing Interrelated Time-Series Data on Smartwatches”, in: *Proceedings of the International Conference on Mobile Human-Computer Interaction*, ACM, 2021, pp. 1–13, DOI: 10.1145/3447526.3472040 (cit. on pp. 11, 12).
- [147] Ali Neshati, Bradley Rey, Ahmed Shariff Mohommed Faleel, Sandra Bardot, Celine Latulipe, and Pourang Irani, “BezelGlide: Interacting with Graphs on Smartwatches with Minimal Screen Occlusion”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2021, DOI: 10.1145/3411764.3445201 (cit. on pp. 7, 86).
- [148] Ali Neshati, Yumiko Sakamoto, and Pourang Irani, “Challenges in Displaying Health Data on Small Smartwatch Screens”, in: *Studies in Health Technology and Informatics*, vol. 257, 2019, pp. 325–332, DOI: 10.3233/978-1-61499-951-5-325 (cit. on pp. 11–13).
- [149] Ali Neshati, Yumiko Sakamoto, Launa C Leboe-McGowan, Jason Leboe-McGowan, Marcos Serrano, and Pourang Irani, “G-Sparks: Glanceable Sparklines on Smartwatches”, in: *Proceedings of the Graphics Interface Conference on Proceedings of Graphics Interface*, Canadian Human-Computer Communications Society, 2019, DOI: 10.20380/GI2019.23 (cit. on p. 11).
- [150] Ali Neshati, Aaron Salo, Shariff Am Faleel, Ziming Li, Hai-Ning Liang, Celine Latulipe, and Pourang Irani, “EdgeSelect: Smartwatch Data Interaction with Minimal Screen Occlusion”, in: *Proceedings of the Conference on Multimodal Interaction*, ACM, 2022, pp. 288–298, DOI: 10.1145/3536221.3556586 (cit. on pp. 7, 86).

- [151] Jasmin Niess, Kristina Knaving, Alina Kolb, and Paweł W. Woźniak, “Exploring Fitness Tracker Visualisations to Avoid Rumination”, in: *Proceedings of the Conference on Human-Computer Interaction with Mobile Devices and Services*, ACM, 2020, DOI: 10.1145/3379503.3405662 (cit. on p. 11).
- [152] Jasmin Niess and Paweł W. Woźniak, “Supporting Meaningful Personal Fitness: The Tracker Goal Evolution Model”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2018, pp. 1–12, DOI: 10.1145/3173574.3173745 (cit. on p. 9).
- [153] Simon Olberding, Kian Peen Yeo, Suranga Nanayakkara, and Jurgen Steimle, “AugmentedForearm: Exploring the Design Space of a Display-Enhanced Forearm”, in: *Proceedings of the Conference on Augmented Human*, ACM, 2013, pp. 9–12, DOI: 10.1145/2459236.2459239 (cit. on p. 7).
- [154] Antti Oulasvirta, Esko Kurvinen, and Tomi Kankainen, “Understanding contexts by being there: case studies in bodystorming”, in: *Personal and Ubiquitous Computing*, vol. 7, 2003, pp. 125–134, DOI: 10.1007/s00779-003-0238-7 (cit. on p. 17).
- [155] Araujo JF Patel AK Reddy V, *Physiology, Sleep Stages*, <https://www.ncbi.nlm.nih.gov/books/NBK526132/>, Accessed: September, 2022 (cit. on p. 70).
- [156] Ömer Pektaş, MURAT Köseoğlu, Miroslav Muzny, Gunnar Hartvigsen, and Eirik Årsand, “Design of an Android Wear Smartwatch Application as a Wearable Interface to the Diabetes Diary Application”, in: *Academic Platform - Journal of Engineering and Science*, vol. 9, no. 1, 2021, pp. 126–133, DOI: 10.21541/apjes.660490 (cit. on pp. 12, 13).
- [157] Charles Perin, Romain Vuillemot, and Jean-Daniel Fekete, “SoccerStories: A Kick-off for Visual Soccer Analysis”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, 2013, pp. 2506–2515, DOI: 10.1109/TVCG.2013.192 (cit. on p. 84).
- [158] Christian Piguet, *Low-power electronics design*, CRC press, 2004, pp. 1–10, DOI: 10.1201/9781420039559 (cit. on p. 1).
- [159] Stefania Pizza, Barry Brown, Donald McMillan, and Airi Lampinen, “Smartwatch in Vivo”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2016, pp. 5456–5469, DOI: 10.1145/2858036.2858522 (cit. on pp. 7, 9, 11).
- [160] Lorenzo Porzi, Stefano Messelodi, Carla Mara Modena, and Elisa Ricci, “A Smart Watch-Based Gesture Recognition System for Assisting People with Visual Impairments”, in: *Proceedings of the Workshop on Interactive Multimedia on Mobile & Portable Devices*, ACM, 2013, pp. 19–24, DOI: 10.1145/2505483.2505487 (cit. on p. 10).
- [161] Prolific, *Prolific – Online participant recruitment for surveys and market research*, <https://www.prolific.co/>, Accessed: September, 2022 (cit. on pp. 65, 70).
- [162] Juan C. Quiroz, Min Hooi Yong, and Elena Geangu, “Emotion-Recognition Using Smart Watch Accelerometer Data: Preliminary Findings”, in: *Proceedings of the Conference and Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, ACM, 2017, pp. 805–812, DOI: 10.1145/3123024.3125614 (cit. on p. 11).

- [163] Amir Bahman Radnejad, Michael F Ziolkowski, and Oleksiy Osiyevskyy, “Design thinking and radical innovation: enter the smartwatch”, in: *Journal of Business Strategy*, vol. 42, no. 5, 2021, pp. 332–342, DOI: 10.1108/JBS-02-2020-0044 (cit. on p. 1).
- [164] M. T. Raghunath and Chandra Narayanaswami, “User Interfaces for Applications on a Wrist Watch”, in: *Personal Ubiquitous Comput.*, vol. 6, no. 1, 2002, pp. 17–30, DOI: 10.1007/s007790200002 (cit. on p. 7).
- [165] Jonathan C. Roberts, Panagiotis D. Ritsos, Sriram Karthik Badam, Dominique Brodbeck, Jessie Kennedy, and Niklas Elmqvist, “Visualization beyond the Desktop—the Next Big Thing”, in: *IEEE Computer Graphics and Applications*, vol. 34, no. 6, 2014, pp. 26–34, DOI: 10.1109/MCG.2014.82 (cit. on pp. 16, 17).
- [166] Maurits van Rossum, “Patient empowerment via a smartwatch activity coach application: Let the patient gain back control over their physical and mental health condition”, in: 2020, Accessed: October, 2022 (cit. on pp. 12, 13, 43).
- [167] Sirat Samyoun, Abu Sayeed Mondol, and John A. Stankovic, “CoPED: A Smartwatch Based Voice Cognitive Assistant for the Pandemic and beyond: Demo Abstract”, in: *Proceedings of the Conference on Embedded Networked Sensor Systems*, ACM, 2020, pp. 605–606, DOI: 10.1145/3384419.3430431 (cit. on p. 13).
- [168] J. Sanford, K. Yamazaki, C. Narayanaswami, T. Inoue, N. Kamijoh, S. Venkiteswaran, E. Schlig, V. Kulkarni, T. Cipolla, D. Guniguntala, and M. Raghunath, “IBM’s Linux Watch: The Challenge of Miniaturization”, in: *Computer*, vol. 35, no. 01, 2002, pp. 33–41, DOI: 10.1109/2.976917 (cit. on p. 2).
- [169] Alper Sarikaya, Michael Correll, Lyn Bartram, Melanie Tory, and Danyel Fisher, “What Do We Talk About When We Talk About Dashboards?”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, 2019, pp. 682–692, DOI: 10.1109/TVCG.2018.2864903 (cit. on pp. 50, 51).
- [170] Alexander Schiewe, Andrey Krekhov, Frederic Kerber, Florian Daiber, and Jens Krüger, “A Study on Real-Time Visualizations During Sports Activities on Smartwatches”, in: *Proc. of the International Conference on Mobile and Ubiquitous Multimedia*, 2020, pp. 18–31, DOI: 10.1145/3428361.3428409 (cit. on p. 12).
- [171] Steven Schirra and Frank R. Bentley, ““It’s Kind of like an Extra Screen for My Phone”: Understanding Everyday Uses of Consumer Smart Watches”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2015, pp. 2151–2156, DOI: 10.1145/2702613.2732931 (cit. on pp. 9, 43).
- [172] Michael Sedlmair, Miriah Meyer, and Tamara Munzner, “Design study methodology: Reflections from the trenches and the stacks”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, 2012, pp. 2431–2440 (cit. on p. 16).
- [173] Sougata Sen, Vigneshwaran Subbaraju, Archan Misra, Rajesh Krishna Balan, and Youngki Lee, “The case for smartwatch-based diet monitoring”, in: *International Conference on Pervasive Computing and Communication Workshops*, IEEE Computer Society Press, 2015, pp. 585–590, DOI: 10.1109/PERCOMW.2015.7134103 (cit. on p. 11).

- [174] Suranga Seneviratne, Yining Hu, Tham Nguyen, Guohao Lan, Sara Khalifa, Kanachana Thilakarathna, Mahbub Hassan, and Aruna Seneviratne, “A Survey of Wearable Devices and Challenges”, in: *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, 2017, pp. 2573–2620, DOI: 10.1109/COMST.2017.2731979 (cit. on pp. 7, 8).
- [175] Teddy Seyed, Xing-Dong Yang, and Daniel Vogel, “Doppio: A Reconfigurable Dual-Face Smartwatch for Tangible Interaction”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2016, pp. 4675–4686, DOI: 10.1145/2858036.2858256 (cit. on p. 7).
- [176] M. Al-Sharrah, A. Salman, and I. Ahmad, “Watch Your Smartwatch”, in: *Proceedings of the Conference on Computing Sciences and Engineering (ICCSE)*, IEEE, 2018, 1:1–1:5, DOI: 10.1109/ICCSE1.2018.8374228 (cit. on p. 9).
- [177] Misfit Shine, *Misfit Shine Review*, <https://www.tomsguide.com/us/misfit-shine-fitness-tracker-review,review-1990.html>, Accessed: October, 2022 (cit. on p. 9).
- [178] Pekka Siirtola, “Continuous Stress Detection Using the Sensors of Commercial Smartwatch”, in: *Proceedings of the Conference and Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, ACM, 2019, pp. 1198–1201, DOI: 10.1145/3341162.3344831 (cit. on p. 10).
- [179] Katta Spiel, Fares Kayali, Louise Horvath, Michael Penkler, Sabine Harrer, Miguel Sicart, and Jessica Hammer, “Fitter, Happier, More Productive? The Normative Ontology of Fitness Trackers”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2018, pp. 1–10, DOI: 10.1145/3170427.3188401 (cit. on pp. 7, 10).
- [180] Konstantinos Spiliotopoulos, Maria Rigou, and Spiros Sirmakessis, “A Comparative Study of Skeuomorphic and Flat Design from a UX Perspective”, in: *Multimodal Technologies and Interaction*, vol. 2, no. 2, 2018, DOI: 10.3390/mti2020031 (cit. on pp. 41, 42).
- [181] Simon Stankoski, Nina Reščič, Grega Mežič, and Mitja Luštrek, “Real-Time Eating Detection Using a Smartwatch”, in: *Proceedings of the Conference on Embedded Wireless Systems and Networks (EWSN)*, Junction Publishing, 2020, pp. 247–252 (cit. on p. 11).
- [182] Thad Starner, “How Wearables Worked their Way into the Mainstream”, in: *IEEE Pervasive Computing*, vol. 13, no. 4, 2014, pp. 10–15, DOI: 10.1109/MPRV.2014.66 (cit. on p. 8).
- [183] Statista, *Statista—Empowering people with data*, <https://www.statista.com/forecasts/1314339/worldwide-users-of-smartwatches>, Accessed: September, 2022 (cit. on p. 2).
- [184] Marc Steen, “Tensions in human-centred design”, in: *CoDesign*, vol. 7, no. 1, 2011, pp. 45–60, DOI: 10.1080/15710882.2011.563314 (cit. on p. 17).
- [185] Andrei Corneliu Suciu and Jakob Eg Larsen, “Active Self-Tracking and Visualization of Subjective Experience using VAS and Time Spirals on a Smartwatch”, in: *Proceedings of the Data Visualization on Mobile Devices Workshop held at the Conference on Human Factor in Computing Systems*, ACM, 2018 (cit. on pp. 11, 13).

- [186] Justin Talbot, John Gerth, and Pat Hanrahan, “An Empirical Model of Slope Ratio Comparisons”, in: *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, 2012, pp. 2613–2620, DOI: 10.1109/TVCG.2012.196 (cit. on p. 77).
- [187] Lie Ming Tang, Margot Day, Lina Engelen, Philip Poronnik, Adrian Bauman, and Judy Kay, “Daily & Hourly Adherence: Towards Understanding Activity Tracker Accuracy”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2016, pp. 3211–3218, DOI: 10.1145/2851581.2892438 (cit. on p. 7).
- [188] Aneesh P. Tarun, Byron Lahey, Audrey Girouard, Winslow Burleson, and Roel Vertegaal, “Snaplet: Using Body Shape to Inform Function in Mobile Flexible Display Devices”, in: *CHI Extended Abstracts on Human Factors in Computing Systems*, ACM, 2011, pp. 329–334, DOI: 10.1145/1979742.1979701 (cit. on p. 7).
- [189] Edward Tufte, *Envisioning Information*, Graphics Press, 1990 (cit. on p. 52).
- [190] Aku Visuri, Zhanna Sarsenbayeva, Niels van Berkel, Jorge Goncalves, Reza Rawasizadeh, Vassilis Kostakos, and Denzil Ferreira, “Quantifying Sources and Types of Smartwatch Usage Sessions”, in: *Proceedings of the Conference on Human Factors in Computing Systems*, ACM, 2017, pp. 3569–3581, DOI: 10.1145/3025453.3025817 (cit. on pp. 11, 26).
- [191] Jagoda Walny, Sheelagh Carpendale, Nathalie Henry Riche, Gina Venolia, and Philip Fawcett, “Visual Thinking In Action: Visualizations As Used On Whiteboards”, in: *IEEE TVCG*, vol. 17, no. 12, 2011, pp. 2508–2517, DOI: 10.1109/TVCG.2011.251 (cit. on p. 16).
- [192] Wei-Ching Wang, Chun-Ching Chen, and Tzu-Heng Chiu, “An Initial Exploration into the Design of Visualized Interfaces to Help Children Search for Books Using Smartwatches”, in: *Posters of the IFLA World Library and Information Congress Conference*, 2017 (cit. on p. 13).
- [193] Withings, *Withings Pulse HR Health & fitness tracker*, <https://www.withings.com/us/en/pulse-hr>, Accessed: October, 2022 (cit. on p. 9).
- [194] Jed R Wood and Larry E Wood, “Card sorting: current practices and beyond”, in: *Journal of Usability Studies*, vol. 4, no. 1, 2008, pp. 1–6 (cit. on p. 21).
- [195] Cheng Xu and Kent Lyons, “Shimmering Smartwatches: Exploring the Smartwatch Design Space”, in: *Proceedings of the Conference on Tangible, Embedded, and Embodied Interaction*, ACM, 2015, pp. 69–76, DOI: 10.1145/2677199.2680599 (cit. on p. 13).
- [196] Rayoung Yang, Eunice Shin, Mark W. Newman, and Mark S. Ackerman, “When Fitness Trackers Don’t ‘Fit’: End-User Difficulties in the Assessment of Personal Tracking Device Accuracy”, in: *Proceedings of the Conference on Pervasive and Ubiquitous Computing*, ACM, 2015, pp. 623–634, DOI: 10.1145/2750858.2804269 (cit. on p. 7).
- [197] Lijie Yao, Anastasia Bezerianos, Romain Vuillemot, and Petra Isenberg, “Visualization in Motion: A Research Agenda and Two Evaluations”, in: *IEEE Transactions on Visualization and Computer Graphics*, 2022, DOI: 10.1109/TVCG.2022.3184993 (cit. on p. 85).

- [198] Steffen Zenker and Sebastian Hobert, “Design and implementation of a collaborative smartwatch application supporting employees in industrial workflows”, in: *Proceedings of the European Conference on Information Systems*, 2019 (cit. on p. 13).
- [199] Hailong Zhang, Haowei Wu, and Atanas Rountev, “Detection of Energy Inefficiencies in Android Wear Watch Faces”, in: *Proceedings of the Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ACM, 2018, pp. 691–702, DOI: 10.1145/3236024.3236073 (cit. on p. 25).
- [200] Yuanyang Zhong, Tobias Isenberg, and Petra Isenberg, *Black-and-White Textures for Visualization on E-ink Displays*, Posters of IEEE Visualization, Poster, IEEE, 2020 (cit. on p. 49).



8.1 Figure Acknowledgements

Smartwatch face examples come from Facer [127]). From left to right: a) Pixel-like Analog / Digital (clayton), b) Big step 6000 (MB-Watch), c) B# – Open Heart (B Sharp Watches), d) Comic Pro! (Round or Square; Roch: Platinum Designs), e) Legion – ctOS (Watch Dogs), f) MOD-486 Weather Watch (Michael O'Day), g) Fall Mandala (Linlay Designs), h) WorldMap-Blue-S7 (Slumtek).

Tab. 8.1: Four examples of smartwatch faces describing design space dimensions.

Smartwatch face	Design space dimensions
<p>a)</p> 	<p>Factors: This watch face (designed by–Faster Studio, Facer) was designed for full color round watch displays. It is meant to show relatively basic smart watch data and to serve primarily as a time piece.</p> <p>Style/Theme: This watch face imitates but updates some of the oldest retro digital watches which is visible through the choice of the overall color scheme that matches old digital watches and the semi-flat design.</p> <p>Components: The watch face chose only three complications: battery life, step count, and heart rate next to the time and date display. Graphical decorators are used to give the impression of an old digital watch.</p> <p>Representations: The overall theme of the watch has a direct influence on the size and representations of components. A large amount of space is dedicated to decorators that give the graphical context of digital watches. The largest components in the square central container show time and date. The more modern smart watch functions are displayed as text with small icons as labels using old digital watch fonts.</p>
<p>b)</p> 	<p>Factors: This watch face (designed by–BERGEN, Facer) compactly assembles necessary health information that quickly grabs health & fitness-conscious people’s attention. This design is meant to fit in both square, and round shape watch faces.</p> <p>Style/Theme: This watch face has a modern, stylish look with a vibrant presentation on a skeuomorphism interface. It used three hues on a black theme color palette, including red, neon blue, and green. The neon blue color does not only reflect the trend but also gives a luxurious touch to the watch face.</p> <p>Components: Six complications, i.e., heart rate, step count, battery charge, distance traveled, calories burned, moon phase, including timestamp, make this watch face informative but at the same time displays a lot of data to the wearers.</p> <p>Representations: It is interesting to observe some visualization complications; for example, heart rate and step count represent data with the combination of Icon+Text+Chart.</p>

Tab. 8.1: Four examples of smartwatch faces describing design space dimensions (cont.).

Smartwatch face	Design space dimensions
<div>c)</div> 	<p>Factors: This watch face (designed by–Apple [9]) is aimed at helping wearers relax in sync with soothing animation. Style/Theme: The patterns in the animated image with the calming color palette are meant to create a soothing feel. Wearers inhale while the animation grows and exhales as the animation shrinks. Components: The watch face only shows time data as an analog watch representation on a semi-flat interface. Representations: This watch face has no other complications except time and only uses an animated background image.</p>
<div>d)</div> 	<p>Factors: This watch face (designed by– JN Watch-Faces, Facer) was designed for both round and square type watch displays. The left side arc disappears when it displays on a round-shaped watch face. Style/Theme: The unique second dial makes this watch face different; while its minimalistic color palette creates an aesthetically pleasing result. The sparing use of vibrant red color in one complication enforces the minimalistic design. Components: It shows heart rate, step count, temperature, sky condition, calories burned, distance traveled, and battery charging complications, including a timestamp. Representations: Two complications, step count and watch battery charging, are represented with chart+icon+text, where the Icon is used as a label. For others, sky condition is represented with Icon only, heart rate with Icon+Text and other complications are represented with simple text.</p>

