Understanding how to Design Health Data Visualizations for Chilean Older Adults on Mobile Devices

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ABSTRACT

Mobile devices, including activity trackers and smartwatches, can help older adults monitor health parameters passively and unobtrusively. Most user interactions with small devices consist of brief glances at the time or notifications. Consuming information from small displays poses challenges, which have been seldom studied from the perspective of older users. In this paper, we worked with older adults towards creating health data visualizations for them for small devices. We conducted a mixed-methods study with 30 older adults, in which we (1) conducted group discussions to understand participants' opinions, (2) measured times taken to interpret health data visualizations with and without progress information, (3) measured how much information they could manage to see during brief glances. When data was visualized without progress indicators, participants took less time to understand the data and made fewer errors. Participants preferred health data visualizations that featured peaceful, and positive pictorial representations. We present design opportunities for older adults' data visualizations in small devices.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

older adults, visualization, health data, mobile devices, small devices, small screens, smartwatch

ACM Reference Format:
Gabriela Cajamarca, Valeria Herskovic, Stephannie Dondighual, Carolina Fuentes, and Nervo Verdezoto. 2023. Understanding how to Design Health Data Visualizations for Chilean Older Adults on Mobile Devices. In *Designing Interactive Systems Conference (DIS '23), July 10–14, 2023, Pittsburgh, PA, USA.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3563657.3596109

DIS '23, July 10–14, 2023, Pittsburgh, PA, USA

ACM ISBN 978-1-4503-9893-0/23/07…$15.00
https://doi.org/10.1145/3563657.3596109

1 INTRODUCTION

Older adults - especially those in digitized cultures with advanced economies - use mobile devices to assist them in daily life activities [66]. In particular, wrist-worn mobile devices, such as fitness/activity trackers and smartwatches, can be used to discreetly monitor individual's health and well-being parameters [44], e.g. physical activity and heart rate [29, 60], supporting their self-care management. Older adults in other cultures - e.g. those in the Global South - tend to use these technologies less often. In particular, older adults in Chile have significantly less experience with computers than older adults in other OECD countries [56], and their perceptions about health technologies have been seldom considered.

Mobile devices have enabled symptom monitoring for older adults with specific conditions, e.g. knee osteoarthritis [65] and pulse irregularities [19], as well as self-monitoring of personal activity [6] and support for home rehabilitation [13]. In addition, smartwatches passively and unobtrusively collect health data, and may constantly display some of it (e.g. heart rate), as well as provide notifications (e.g. cell phone notifications, prompts to do physical activity). Collected health data may be used to create data visualizations, which are valuable to older adults as a resource to stimulate discussion with their health care providers [37].

Regarding data visualization on very small screens [54], there is a need to address the efficient use of pervasive mobile devices as platforms for data visualization [38] as consuming data on for example smartwatch screens can be difficult due to factors such as screen size, interaction modalities, and typography [33, 46, 47]. Previous studies have focused on investigating user preferences in this type of screens, e.g. finding that airline personnel prefer graphical over textual data [49], or that bar graphs and pie charts should be chosen on smartwatch displays when data needs to be compared quickly [5]. Some techniques to visualize complex information such as time series have been proposed, e.g. a visualization that displays data on the screen's perimeter and in-depth information at the center [12, 50]. Although the representation of health data for older adults has been explored [7, 11, 72], there has been limited research on how older adults interpret health data visualizations in small devices.

In information visualization, *glancing* refers to the ability to quickly extract information from a screen with a glance [53]. Smartwatches in particular are interfaces in which the most common interactions consist of brief glances at the screen, generally lasting around 5 seconds [25]. The data that can be seen at a glance in a smartwatch or activity tracker is typically related to activity goals and the current progress towards that goal (e.g. goal number of steps per day, and accumulated number of steps during that day), as well as immediate values (e.g. current heart rate) or aggregated and historical data (e.g. sleep score, resting heart rate). This type of data plays a fundamental role in user decisions concerning the data [22]. In particular, data is represented in smartwatches through several visualization techniques, such as text, numbers, pictographs, animation, line graphs, bar and pie charts, or compressed versions of these visualization methods [52]. The most common data representation is an icon (e.g. a heart icon) and text (e.g. 70, for the current heart rate), while data with related goals (e.g. calories burned, step count) are commonly represented through a chart, with or without accompanying text [32]. In addition, Donut charts have been found to be an attractive, straightforward way to visualize progress towards a goal (i.e., number of steps to daily step goal) [3].

Although small devices such as smartwatches can be useful tools to support older adults' health self-management, the design of glanceable health data visualizations has seldom considered their perspectives, and existing visualizations have mainly been evaluated with younger adults. In this paper, we aim to further understand of how glanceable visualizations of health data can be designed for older adults users. In this work, we conducted a mixed-methods study with 30 older adults in Chile to assess their perception of health data visualization designs, as well as to design health data visualization according to their needs and preferences. Although a larger number of participants would possibly have a higher chance of statistical significance, studies in human-computer interaction often have less than 30 participants [10] and for mixed-methods studies, a participant group size of 30-50 is frequently advised [58].

We aimed to answer three research questions. RQ1: *Which characteristics of health data visualizations are relevant for older adults?*, RQ2: *How do older adults interpret glanceable visualizations?*, and RQ3: *Are smartwatch glanceable visualizations for older adults more effective if they have progress indicators?*.

The study was developed over the course of two phases, with 12 people participating via a zoom call and 18 participants in-person. Our results show that the highest percentage of correct responses occurred when participants visualized health information on displays without progress indicators. We also identified that participants preferred health data visualization designs that contained pictorial representations that conveyed peacefulness and tranquility (e.g., images of yoga poses). This work contributes to the literature by exploring older adults perspectives of health data visualizations in small devices, and by proposing a set of design opportunities for glanceable health data visualizations for older adults.

2 RELATED WORK

We present an overview of research on health data visualizations for older adults. Then, we discuss previous research on glanceable visualizations, focusing especially on those with very small screens (i.e. smartwatches, activity trackers), as that is the goal this paper is working towards. Finally, we discuss research on visualizations that include progress (or goal) indicators.

2.1 Visualization of health data for older adults

Health data visualization on mobile devices for older adults is beneficial. Older adults have been found to make more precise medication decisions in less time when they tracked prescriptions using a color-coded chart [61]. Also, visualization of health data has led to the increased motivation of older adults in physical therapy activities [8]. Feedback in a visual format has also helped maintain an awareness of the progress of the older adults' health goals [59], gaining a better understanding, e.g., of COVID-19 information [21].

Despite the potential benefits of visualizations for older adults, many challenges still remain [72]. First, due to information overload, older adults may have troubles understanding the language and clinical data from sensor data visualization used to monitor their activity levels [2], or become puzzled by the multitude of visual cues and occasionally choose to ignore them entirely [37]. Second, some studies have found older adults to perceive typical visualizations differently, e.g. taking longer to understand static stacked bar charts than bar charts compared to results from younger adults [35], and finding comparisons easier through radial graphs than line graphs [36]. Third, some older adults have had troubles caused by inadequate responsiveness of interactive visualizations [21]. Finally, some visualizations have been found to be complex and challenging to learn [7].

Additionally, limited research has included older adults in designing visualizations [21, 59], especially in a challenging environment such as very small screens. Therefore, if older adults' needs, context, and experiences are not considered, data visualizations may be inaccessible to them [21]. Developing appropriate visualizations for older adults can provide a valuable resource for improving access to health information with the potential of empowering them to become more involved in their own self-care management [59].

Older adults are a heterogeneous group when it comes to technology [20, 75]. Some older adults have found mobile technology and data visualizations useful and acceptable [45], while others have had little experience with technology and find it to be intrusive and noticeable [24]. When designing technologies, their focus should be the needs of the "situated communities" (of users with common interests or needs) where they will be inserted [62].

2.2 Glanceable visualizations on small screens

The visualization of health data on smartwatches can be challenging, due to several factors, such as the small screen size, reduced input capabilities [55], screen occlusion and increased 'fat finger' effects [51]. These factors especially complicate the visualization and interaction with complex data, e.g. time series [50]. In some situations, e.g. while doing physical activity, users may need to explore their data to make sure they are meeting their goals, for which designers have proposed simple visualizations, e.g. maps and standard charts, to maximize the use of available space [3].

Most interactions with activity trackers, however, are usually simpler, consisting of brief glances in which users check their progress but do not interact any further [25]. The average time of interaction in a glanceable interface is 5 seconds [25]. A study with twelve young volunteers evaluating the daily use of smartwatches revealed the average amount of time spent looking at the clock was only 3.8 seconds, while the average amount of time spent looking at alerts was around 7 seconds [60]. Another study found that the average time of user-initiated sessions is 7.94 seconds, while those initiated by notifications are approximately 10.67 seconds [76]. These brief interaction times suggest that users are checking specific indicators or their progress, rather than exploring and interacting with their data.

Studies evaluating glanceable displays measured the speed of grasping information from peripheral displays in dual-task situations while at the same time examining representations (graphical objects or text) inspired by existing displays. Some authors found that text and high visual representation were significantly better than low and medium visual representations [43]. Another study found that when data needs to be compared rapidly, bar and pie charts are preferable [5].

2.3 Visualizations with progress indicators: Challenges and Considerations

The pursuit of goals plays a fundamental role in everyday life and individuals' decision making processes [22]. For example, participants who used an awareness screen (i.e., a sensor whose data could be viewed on the phone) maintained their physical activity level over three weeks [15].

One of the proposed design features for activity tracker visualizations is that progress should be presented, in regards to a goal, which can help the user easily understand how close - or far -they are to their target [26]. How to design these progress indicators to best support users' needs is not yet clear - e.g., one recent study found that user experience was best when progress indicators included percentage information, and that ring progress bars were generally preferred [40]. Younger older adults have found visualization feedback - i.e., daily depictions of their goals - helpful as awareness of their progress [59]. However, there has not been research in the preferences and needs of older adults regarding progress indicators in small screens.

3 METHODS

This research used mixed methods to understand older adults' perceptions about health data visualizations with particular focus on small devices. The study was conducted between December 2021 and May 2022 and obtained ethical approval from University of Cardiff COMSC/Ethics/2021/126.

The aim of the study was to understand the characteristics of health data visualizations that are relevant to older adults, how they interpret them and whether visualizations for older adults should incorporate progress indicators. To achieve this, we conducted a 2-phase study (in which the first phase was online and the second phase was in-person) with six activities, which are shown in Figure 1. The activities consisted of (1) an introduction to our research, (2) a group discussion of mock data displays, (3) an activity in which we measured how much information participants got to see when we displayed health information for short periods of 5 seconds, (4) an activity in which we measured how participants interpreted information from health data visualizations, (5) an activity in which we asked our participants to design paper representations of the health data, and (6) a closing activity in which we thanked participants and asked them for their feedback. Each activity is described in detail in section 3.4.

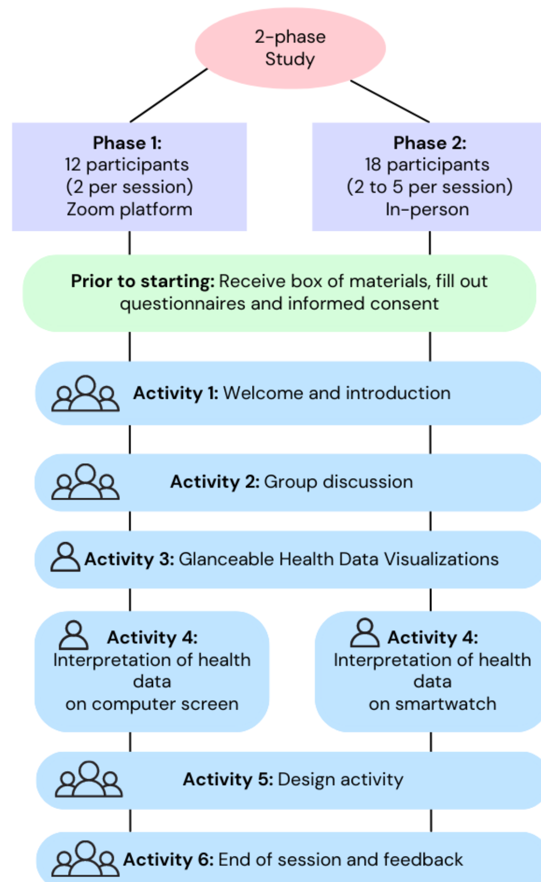


Figure 1: Activities, phases and participants of the study. Each activity includes an icon representing whether it was undertaken in a small group or for each participant individually

3.1 Research Setting

The participants in this study were older adults from Santiago, Chile, where there is limited HCI research in healthcare [67]. In Chile, older adults are usually considered to be those over 60 or over 65 [74] - e.g. retirement age is 60 for women and 65 for men [69].

Overall, appropriation of technology by older adults is lower in Chile than that observed in more developed societies. There are significant differences in the type and quality of access, the range of usage, and the technical proficiency required to benefit from an Internet connection among Chileans [16]. Age, social status, geographic locations, and education determine Internet access and usage options [39]. For example, compared to the OECD average of

31.8%, Chilean older individuals (57.9%) are significantly more likely to report having no computer experience [56]. Despite a rise in digital use among older adults in Chile between 2013 and 2016, there are significant differences based on age and education level, with people over 75 and those with less education using technology the least frequently [27]. This is therefore an understudied population, whose technological preferences have seldom been considered by existing literature in HCI research for development [67].

The COVID-19 pandemic [57] spread rapidly throughout the world, reaching Chile after it had been detected in Europe and North America. Chile declared a constitutional exception and implemented stringent preventative measures, many directed at older adults, e.g. mandatory quarantine for those over 75 years, and visit bans for older adult centers [73]. Face masks were mandatory in all closed spaces up until October 2022. Older adults were more likely to maintain measures such as physical distancing, face masks and hand washing over time [70]. For a long period of time between 2020 and 2022, older adults in Chile were reticent to participate in face-to-face research. For this reason, this research was conducted in two phases: one online, at the beginning of the study for those older adults who would not want to participate in person, and then in-person, when the COVID preventative measures were relaxed and the number of daily COVID cases had decreased. The timeline is shown in Figure 2.

3.2 Participants

First, we conducted a pilot study with two young volunteers (one female and one male aged 32 and 34) and used the data to review the visualizations and corresponding tasks and to ensure that the study procedure was appropriate. We then recruited participants through advertisements posted on social media platforms, word-of-mouth, and snowball sampling. Communication between potential participants and the researchers was done by email or phone call. During this time, we informed potential participants about the study's objectives, the activities that would be developed during the session, how long the session would last and how the provided data would be used. In addition, the time and place of the study were agreed upon.

The study was conducted in two phases: (1) we recruited 12 participants to participate in the online study using the Zoom platform. Each session had 2 participants and was facilitated by 2 researchers. In this phase, we delivered a box of materials to the participants' homes in person, using masks and maintaining physical distancing in order to comply with COVID-19 national restrictions. (2) We recruited 18 participants to execute the same study in person at a location selected by the participant: their workplace, a local park, or their own home. At this phase, there were five groups with two participants, one with three and one with five, all led by at least two researchers. Informed consent was physically or digitally obtained from participants, and participation in the study was voluntary. Participants were compensated with a $12 gift card. Each session lasted an average of 80 minutes. Online sessions were audio and video recorded, while in-person sessions were audio-recorded only.

In total, 30 older adults between 60 and 81 years old were included (M=67, SD=4.5); 19 participants were women and 11 men. All participants resided in Chile and were native Spanish speakers. Most participants were married (20/30, 66.67%), while the rest were either divorced (4/20, 20%), single (3/30, 10%), or widowed (3/30, 10%). The level of education of the participants ranged from primary school (6) and high school (5) to a bachelor's degree (19). Some participants were still active, e.g., as engineers (3), secretaries (4), or as homemakers (4), and the rest were retired (14).

Table 1 summarizes participant demographics, such as age, sex, family status, educational level, employment status, and a sum of scores on the MDPQ questionnaire (See subsection 3.5), ranging from 16 to 80, where higher scores represent higher technological competence. The results of the mobile device proficiency questionnaire (MDPQ), reveal that participants found it very easy to share images (18/30, 60%), obtain information about their interests and hobbies online (14/30, 46.67%), listen to music (13/30, 43.3%), and send mail (13/30, 43.3%).

3.3 Materials

We carried out exploratory activities in relation to designing health data visualizations on mobile devices using a box of materials that included paper, pencils, erasers, markers, yarn, play dough, screen prints from a wristwatch, and post-it notes. Participants in the in-person sessions also interacted with a physical smartwatch (Huawei watch 2). In addition, a copy of the informed consent was included in the box with the MDPQ questionnaire (See subsection 3.5). Before beginning the study, each participant was given the package of materials and instructed to read the questionnaire and informed consent instructions.

3.4 Procedure and Activities

We divided our study into 2 phases (as it was conducted online first and then in-person). Both phases had the same 6 activities, including discussion, exploratory activity of visualizations, and design activities, with minor adjustments for the online or in-person aspects. Next, we provide a detailed explanation of each step.

3.4.1 Activity 1: Welcome and Introduction. The researchers welcomed the participants and outlined the study's main goal. Following an introduction by one of the researchers, each participant talked about their background, including age, marital status, level of education, gender, and line of work. After that, to introduce the participants to data visualizations, we asked the following question: *Have you used a smartwatch to monitor health data?* Based on their responses, participants were encouraged to share their experiences using smartwatches and say what data they collected with this device or their reasons for non-use.

3.4.2 Activity 2: Group discussion. Aligned with previous research [4], we designed a variety of mock data displays of watch faces to present to the participants. For this, we examined popular watch faces from Facer [31], a watch face download and generating site for Android, Samsung, and iOS watches, to arrive at the nine suggested designs. Inspired by the data displayed on more than 100 watch faces we collected from the Facer application and Internet searches, we posited three types of health data to show participants: heart beat (bpm), steps (steps), and calories (cal). The icons used to represent these health data were those available in the Facer application.

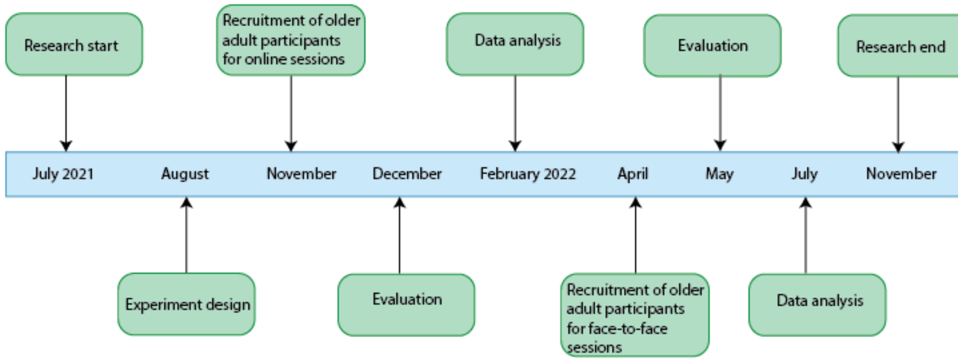


Figure 2: Chronology of the research's activities

Table 1: Participants' demographics, in addition to their responses to the MDPQ questionnaire.

Group	Participants	Age	Gender	Family status	Education	Work status	MDPQ
Group 1 (online)	P1	68	Male	Married	Bachelor	Retired	74
	P2	67	Male	Married	High school	Retired	52
	P3	66	Male	Married	High school	Retired	47
	P4	66	Female	Married	High school	Retired	63
	P5	62	Male	Married	Bachelor	Engineering	80
	P6	71	Male	Married	Bachelor	Medicine	16
	P7	63	Female	Divorced	Bachelor	Secretary	72
	P8	64	Female	Widowed	Bachelor	Secretary	71
	P9	71	Female	Married	Bachelor	Retired	40
	P10	61	Female	Divorced	Primary	Retired	29
	P11	65	Female	Married	Primary	Retired	40
	P12	69	Female	Single	Bachelor	Retired	35
Group 2 (in-person)	P13	64	Male	Married	Bachelor	Mechanical Civil Engineer	75
	P14	60	Female	Married	Bachelor	Secretary	75
	P15	65	Male	Married	Bachelor	Mechanical Civil Engineer	62
	P16	62	Male	Married	High school	Mechanical assistant	53
	P17	70	Female	Divorced	Bachelor	Retired	58
	P18	66	Female	Widowed	High school	Housemaid	51
	P19	60	Female	Married	Bachelor	Accountant	76
	P20	64	Female	Single	Bachelor	Secretary	62
	P21	66	Female	Divorced	Bachelor	Retired	40
	P22	76	Female	Married	Primary	Housemaid	35
	P23	68	Female	Married	Bachelor	Retired	70
	P24	71	Female	Single	Primary	Dressmaker	80
	P25	70	Male	Married	Primary	Retired	63
	P26	64	Female	Widowed	Bachelor	Retired	48
	P27	81	Female	Married	Primary	Housemaid	41
	P28	68	Female	Married	Bachelor	Housemaid	80
	P29	69	Male	Married	Bachelor	Mechanical Civil Engineer	48
	P30	69	Male	Married	Bachelor	Retired	40

We experimented with light, dark, and a combination of light and dark colors for screen backgrounds. As a consequence, there were 3 screens with dark backgrounds, 2 screens with light backgrounds, 2 screens with picture backgrounds, and 2 screens with a combination of light and dark backgrounds. To determine which design features older adults notice, we varied three aspects of health data visualizations: screen background colors, screen background designs, and the location of icons. For the following activities, we maintained the design features including background color, icons, and number of elements. Printouts of the health data visualizations (on coated paper, using eco-solvent ink) measuring 46x48mm and having a resolution of 1.80 x 1.88 pixels were given to participants

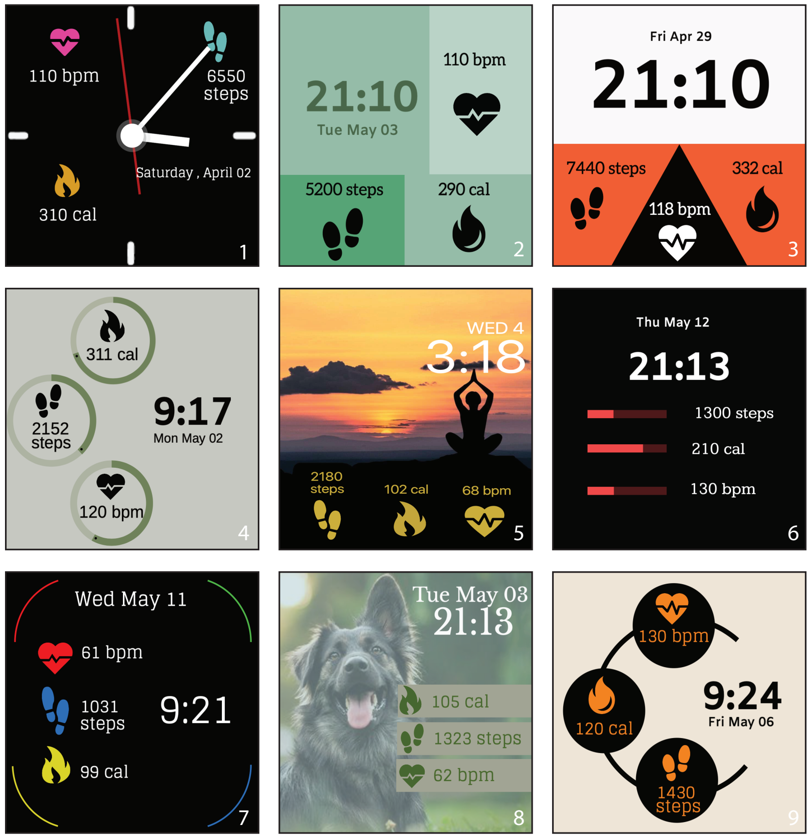


Figure 3: Visualization designs: nine visualization designs with health data, each visualization contains; date, time, number of steps, heart rate, and calories.

for activities 1 and 2. This size is a little larger -but similar to- the Apple Watch 5, which is 38x44mm.

The participants were instructed to examine nine printed health data visualization designs (see Figure 3) to elicit feedback and choose their two favorites. Then, in order to understand which design characteristics older adults focus on, we asked the following questions to each participant:

- *Which visualizations do you prefer and why?*
- *What are the positive or negative aspects of these visualizations?*
- *Which changes can be applied to the selected display layouts?*

3.4.3 Activity 3: Glanceable Health Data Visualization. This was an individual activity where participants searched for information in the mock data visualizations as part of this activity to measure how much they could manage to see during brief 5-second glances. Both the in-person and online portions of this activity were completed on a computer. First, a power point slide with questions about the health values they had to look for was presented, for example:

- *What is the number of calories?*
- *What is the number of hours of sleep?*

Next, we presented the health data visualization (see Figure 4), which included information related to the previous questions; this visualization was visible for 5 seconds, for which timed power point animations were used. The participant then answered questions about the health information they had just seen in the visualization. This activity was repeated five times per participant with variations in the design of the visualizations.

At each repetition, the mock designs of the health data displays, or *screens*, varied according to the presence or absence of progress indicators. We designed and used two **S**creens **W**ithout **P**rogress indicators (SWP), two **S**creens with **P**rogress **B**ars (SPB), and two **S**creens with **P**rogress as a **C**ircle (SPC) were used. The questions that accompanied these displays were related to the data contained in the displays so the questions varied according to the type of display. The display also showed the date, time, and three health indicators with their respective icons (see Figure 4). The order in which the visualizations were shown was previously chosen, so as to be balanced (that each visualization was shown the same number of times as first, second, third, and so on) and assigned to participants randomly. As an illustration, throughout phase 1 and 2, SPB appeared ten times as the first display, ten times as the second display, ten times as the third display, and so on to the sixth display. Each visualization is treated in this way. The number of correct and incorrect answers was counted.

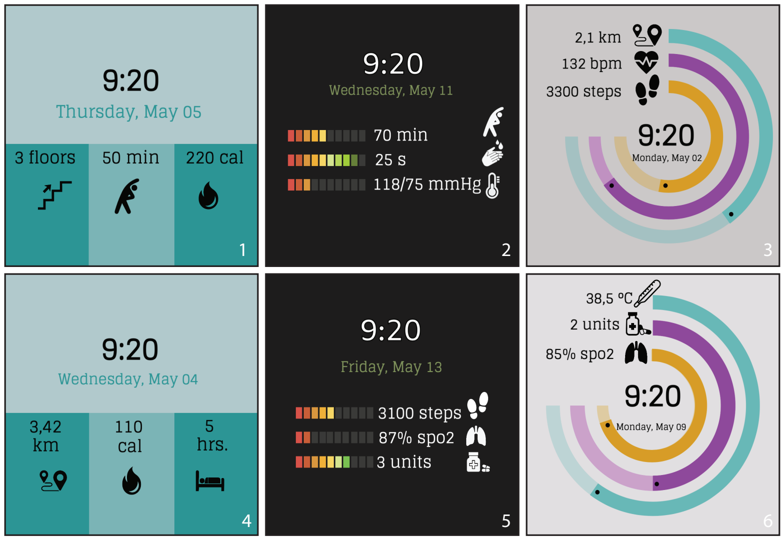


Figure 4: Health data visualizations with and without progress indicators: 1) and 4) Visualization Screen without Progress Indicators (SWP), 2) and 5) Visualization Screen with Progress Bars (SPB), 3) and 6) Visualization Screen with Progress as a Circle (SPC).

3.4.4 Activity 4: Interpretation of health data. Participants were invited to contrast the health data from the daily targets with the information collected during a typical day; this was an individual activity. Each participant was presented with a screen with mock data from the daily targets of an older adult and, at the same time, from data collected for a typical day (see Table 2). Then, we asked the participants to contrast and interpret the information presented to them. For example, in case 1 of table 2 the target goal is between 75 and 128 beats per minute, while in the visualization of a typical day a value of 133 beats per minute was depicted, to trigger interpretations and enable participants to identify that there is a exceeding the beats per minute compared to the recommended value. The time participants took to interpret the information was measured, using the time of the tape recording of the recorded audio. In the rest of the article, the time participants spent interpreting the information is considered response time. Each participant performed the activity with three visualization displays, which are shown in Table 2. For each participant, we varied the order of the visualization displays. We used the following questions to guide the interpretation of the information:

- *What do you think about the differences between health data visualization from the daily targets and the health data visualization collected during a typical day?*
- *Which suggestions do you make in light of the differences between health data from the daily targets and the health data collected during a typical day?*

The first 12 participants who attended the online session used a computer screen to observe the data for this activity. Participants who were in person carried out this activity using a physical smartwatch. In both cases, participants were shown screen designs with mock health data, date, time. Some designs also showed progress towards goals (See Table 2).

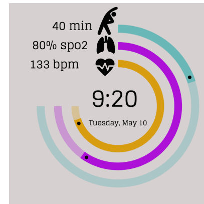
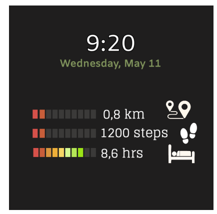
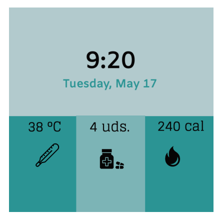
In activities 3 and 4 each participant had the support and guidance of a researcher. In order to complete the activities without interruption or distraction from their peers during the face-to-face sessions, each participant and a researcher took up a space separate from the other participants. Two researchers alternated leading activities 3 and 4 for the group of 5 participants (face-to-face sessions), and a third researcher responded to queries or comments from the other participants. In the remote session (all groups consisted of two participants), a Zoom breakout room was used, and a researcher led each participant through their activities there.

3.4.5 Activity 5: Design activity. Participants were invited to design their health data visualizations in this last activity. For this, we showed participants examples of how to represent health data in different formats, including; text, icons, or graphs. Participants were given post-it notes and markers to draw or write the representation of health data. On each post-it, we asked participants to draw three health data; blood pressure, the number of steps, and calories. We then encouraged each participant to show and explain their design, and the other participants offered suggestions for enhancements. The goal of this activity was to enable participants to draw a representation of health data that is comfortable, and suits their preferences. The following questions guided this activity:

- *In which format (text, graphic icons) would you like to represent the amount of steps?*
- *Why would you like to represent the amount of steps with this format?*
- *How does the data representation let me know if the steps are too few or too many?*

3.4.6 Activity 6: end of the study. We concluded by thanking the attendees for their time and insights. We also asked for feedback about the activities.

Table 2: Health data from the daily targets matched with health data collected for a typical day.

	Health data from the daily targets	Health data collected for a typical day
Case 1	Physical activity time/day : 30 to 150 min Oxygen saturation: 95 to 99% Beats per minute: 75 to 128	
Case 2	Distance walked: 1- 4 km Steps/day: 1500 to 6000 Hours of sleep: 7 to 9 hours	
Case 3	Body temperature: 36.5 to 37.5 °C Daily medications: total 5 Calories burned/day: 200 to 350	

3.5 Data Collection

We collected the following information:

- **Mobile Device Proficiency Data:** Mobile device proficiency was assessed using the Mobile Device Proficiency Questionnaire short version (MDPQ-16) [64]. This questionnaire asks participants to rate their proficiency in performing tasks with mobile devices such as smartphones and tablets. The MDPQ-16 consists of 16 questions to assess items, such as mobile device basics, communication, data and file storage, Internet, calendar, entertainment, privacy, and software management. Each domain is assessed by two questions on task performance, measured on a Likert scale from 1 (never tried) to 5 (very quickly), resulting in a total score ranging from 16 to 80, where higher scores represent higher technological competence [30]. We applied the Spanish-translated version [48].
- **Quantitative Data:** Response times and error rates were collected from Activities 3 and 4.
- **Qualitative data**: Each session was video and audio recorded. Photographs were taken of the designs created by the participants, and the researchers who guided the sessions took field notes, writing down unexpected events and their perceptions of the activities. Audio for activities 1, 2 and 5 was transcribed.

3.6 Data Analysis

The quantitative data was analyzed by observing the Likert data's quantiles and aggregating the data of each person with the arithmetic mean and the median between the values. Proportions Z-test, Kruskal Wallis and Mann-Whitney U tests were performed to study the significance of the difference between proportions, time of response and answers with Likert data. Holm-Bonferroni correction was applied when a Post-Hoc analysis was required.

The qualitative data was analyzed by two team members, who reviewed all the captured qualitative data. The research and analysis were conducted entirely in Spanish because it is the native language of the participants and researchers. The results were then translated into English for presentation in this article.

We used a thematic analysis approach to analyze the qualitative data [34], as follows. Initially, we familiarized ourselves with the data by reading the transcripts. Then, we took an inductive approach and two researchers randomly selected two transcripts and independently generated the initial codes using an open coding procedure. All codes generated from the four transcripts were collated and form the preliminary list of codes for further exploration. Four members of the research team then iterated, reviewed, discussed, and agreed on the initial list of codes. This gave us the chance to talk about and consider the level of detail in the coding scheme. The codebook was then applied to all the transcripts including the ones used to create the preliminary codebook. After the coding process, we started searching for themes looking at how relevant codes can be grouped or combined to form overarching themes. We then reviewed the themes through several group discussions until we agreed on their names. Finally, the first author reviewed all codes and themes and created the final thematic map and report. We used the ATLAS.ti software to organize the code.

4 FINDINGS

This section describes the findings of our study, organized according to our research questions.

4.1 Which characteristics of health data visualizations are relevant for older adults?

In this section, we explore older adults' perceptions of health data visualizations and their preferences towards them. First, we discuss how older adults relate to mobile devices, such as smartwatches, in general, as this is the preferred small device that would incorporate a health data visualization. Then, we discuss the older adults' data visualization preferences.

4.1.1 Older adults and smartwatches: Current use and challenges. In Activity 1, participants answered whether they had used a smartwatch to monitor health data, and shared their experiences or reasons not to use them.

Only 4 out of 30 participants have worn a smartwatch. One participant reported using it since the pandemic began; it helps him to control his activity time and to know his physiological information. *"It lets me know if I'm sitting for a long time that I have to walk, uh, if I have a faster pulse if I'm getting very agitated. This watch is handy for me. My daughter gave it to me "* (P4). Another participant has used the smartwatch to monitor sports data such as heart rate. *"I do use a smartwatch, it can monitor health, but I don't use it much for that; in fact, what I use the most in health monitoring is heart rate, and basically, when I do sports, I use it to monitor that (...) all heart rate, nothing else"* (P15). Likewise, a participant states that there are motivations for using a smartwatch; among them is real-time monitoring. *"It would be nice to have a device that [...] I don't get home and have to resort to medical equipment to measure, so I walk more calmly, and I see what is dictating to me, let's say, my rhythm as I am walking "* (P8).

Some participants mentioned that to use a smartwatch, they might need the help of their children or family members. Also, they point out that out of about 20 mobile device functions, they could learn 4 or 5 functions, just as they do with a smartphone or computer. According to the interviewees, the absence of previous experience with smartwatches is primarily caused by a lack of need, interest, time, information about how to manage this device, or the high cost of the gadget. Additionally, some interviewees said that wearing a watch required them to change their bodies and get used to something unfamiliar.*"The only thing I wear is the wedding ring that took me a world to get used to, but nothing nothing nothing nothing, no chain or watches or anything, no, no, no, I can't stand anything that is not mine [...]. So no, I don't wear watches "* (P5).

Another participant declares little interest in wearing a smartwatch because its use implies a great challenge and a potential technological addiction.*"[...] I am not very addicted to technology, I don't like it, and it's hard for me, but I do know about phones because it is my daughter's phone that gives the heart rate and those things, the steps she walks during a day, during a certain stretch, but no, I am not addicted to technology"* (P11). A lack of time to use a smartwatch is due to daily household activities. *"So I don't use it because of you [...]. Well, you do so many things as a housewife that you spend more time taking them out than using them, so for the same reason, believe it or not, I have about five (standard watches) stored away, and there they are. So, honestly, I became more familiar with the cell phone. I see the screen and there [...]. Really, honestly, my watch is my cell phone "* (P8).

4.1.2 Data visualization preferences: Aesthetic, Hedonic and Informative qualities. In Activity 2, participants' preferences for the nine mock designs for the visualization of health data were discussed (See Figure 3). According to participant preferences, screen 5 (13/30, 43.33% participants), screen 1 (12/30, 40%), and screen 7 (9/30, 30%) were the designs that were most commonly chosen. Participants answered questions regarding their preferences. From the qualitative analysis, we created three categories to describe their comments: 1) aesthetic qualities, which are related to whether participants like what the design looks like; 2) hedonic qualities, which are related to the feelings participants have about a design; and 3) informative qualities, which are related to their expectations about which information is available on the visualization. Each category is presented below, along with quotes from participants.

Aesthetic qualities: Respondents expressed a favorable attraction to data visualization designs 5, 7, or 1. The phrases most often repeated to refer positively to the visual aesthetic of a screen were *"familiar"*, *"clear"*, and *"clean"*. Participant P2 has said, *"I liked it because it gives me the old-fashioned time, as I say (laughter)"*. Another participant expresses the clarity with which he can see the information on screen 7; for him, this screen is clean. *"I see all the information clearly, and I see it as clean; I don't have a lot of things in the background to distract me from what interests me "* (P15). Simple was also a positive characteristic that participants saw on the screens; for example, on screen 4 they said: *"Because it is straightforward. You just look at it, and you realize that it tells you the time it marks it well [...] the day, the month. And I think it is straightforward, and the simpler it is, for me, the better"* (P7). Some participants, however, have reported that they are not attracted to specific data visualization designs such as 4, 6, or 9. . Some participants described the background of the screens as *"ugly"* or *"depressing"*. One participant said, *"[...] because if you look at that color, it is very depressing... I mean, for me, I don't know about the rest, but I find those colors depressing, as well as soft or so poorly defined, because maybe if it were a greener color, or I don't know, any other color but not so ugly"* (P7).

Hedonic Qualities: In this section, we have included the characteristics of how participants relate to, feel about, or appreciate health data visualizations designs. Among these characteristics, we have highlighted designs that *"convey peace"* or those that are *"understandable"*. For example, one participant (P1) indicates that looking at screen 5, which contains an image of yoga, allows him to have peace. In addition, the image in design 5 affected the participant's perception of the displayed health data. *"I like what it conveys, like a peace, let's say, of the landscape... and you see the information,* *it is clear"*. A similar idea is expressed by another participant when he looks at screen 5. *"I like it as it is because I find it very peaceful and quiet. I love sunsets, and the colors are very friendly, so I like it very much; I would not change anything. It has everything just right"* (P19).

Informative Qualities: Participants have also chosen screens according to their preferences for informative qualities. For some interviewees, the time and date must be available on the smartwatch screen when monitoring health data. For example, participant P3 mentioned the importance of having the time in the analog format. *"Something I have always liked and didn't mention before, but the time came when they changed the clocks to digital, the truth is that I prefer in.... with the hand..., with the handle, right? [...] So, 14 o'clock is two o'clock, and I know that, so I like to see it that way if it is digital; otherwise, I prefer the handle"* (P3).

4.2 How do older adults interpret glanceable visualizations?

This subsection presents general information about how older adults interacted with glanceable visualizations. First, we grouped participants according to their digital technology proficiency, to understand how those with lower technological competence - representative of most of the Chilean older adult population - interpret glanceable health data visualizations. Then, we discuss the designs older adults proposed for glanceable visualizations, which can provide information about how they interpret and process such information.

4.2.1 Glanceable visualization interpretation and technological competence. In Activities 3 and 4, participants looked at sample visualizations and answered questions about them; in the case of Activity 3 they looked at the visualization for 5 seconds and we recorded response error rates; in the case of Activity 4 the times they took to answer the questions was measured. The median technological competence (measured through the MDPQ questionnaire) in our participants was 55.8. Participants with scores below the median (55 and below) were considered to have lower technological competence (15 participants), while those with scores above the median (56 and above) were considered to have higher technological competence (15 participants). We related participants' proficiency in digital technology to the proportion of right or wrong responses and response time when they visualized at health data in SPB, SPC, and SWP.

- *Percentage of correct or incorrect answers by digital technology proficiency:* With a p-value=0.000, the Z-proportions test demonstrates that the proportion of participants with higher technological competence having correct answers is significantly higher than that of participants with lower technological competence. Also, we discovered that viewing the health data on the SWP, as opposed to the other two screens, SPB and SPC results in fewer errors for participants with high and low technological competence.
- *Response time by digital technology proficiency:* Regarding the response time concerning digital technology proficiency, we found that when participants visualize health data on the three displays, those with higher technology proficiency, on average, take less time to respond (27.76 [s]) than those with lower technological proficiency (37.18 [s]). Using the Mann-Whitney U test, we confirmed that participants with high technological competence have a significantly shorter response time than those with low technological competence ($U = 743$, $p = 0.014$).

4.2.2 Glanceable data visualization designs. In Activity 5, participants designed their own health data visualizations. Some of the designs for health data visualizations given by the participants are shown in Figure 5. Out of 30 participants, 50% indicated that the representation of health data should contain an icon plus text, while 16.7% preferred to view health data using an icon plus number plus text. Four participants (13.3%) represented their health data through an icon plus number. Other participants (5/30, 16.7%) have indicated a desire for ranges for reference to achieve goals accompanied by text, icons, or numbers. Only one participant preferred visualizing data using text plus numbers (1/30, 3.3%).

During the activity, participants elaborated on their designs. For some participants, there is no need to have text in the data representation; the text could lead to confusion and take away space for icons. *"I think that the less, well, first there is going to be professional training, but for me, the icons are indicative enough, already, so it may be difficult the first time, but the second day you will know what each one is, and if there are letters in between, you can confuse the information with the numbers, especially if at this stage of life you do not see very well then the fewer things you have that can confuse you, the better"* (P1). Other participants have expressed their desire for a dynamic data representation, where the heart (representing beats per minute) have movement. *"[...] and ending with the heart beats, maybe with a little bit of a movement effect, to the heart, let's say, like it opens and closes, to know how many beats per minute it is doing"* (P2). Also, participants have suggested representing health data in a positive way. For example, for participant P6 seeing a heart with an electrocardiogram gives him the impression of something broken and bad which discourages him. *"Ehh... maybe the heart. I would take out the electrocardiogram because it gives me the impression that it is a broken heart already, and I currently have heart disease, so at some minute I will likely have a heart attack, then that image is contradictory to me, already, so I would take out that black stripe, I would leave it [...] I would put it in positive terms"* (P6).

Some participants, such as P5, have indicated a desire to have scales or icons that change color to measure the progress of health data. Some participants are interested in seeing the level of their data (altered or average) using color-changing icons. *"So, if the temperature is correct, then the background I get is green, and if the calories which are more or less I have to do in the day or the range I have to do, if I didn't do them, I put red on it. So I could have it not static, not stiff, but I could place it variable depending on the level of compliance that I have, like this traffic light, red, yellow, green, right?"*. P14 also expresses his idea of integrating context information when visualizing health data. *"The technological device should indicate where it is, right? that is, painted or with numbers (...), or with sound (...) also say what the goal is, so I can know, "ah, I have to get there, I'm getting there, I have this much to go" (...) the same with the steps and the calories"* (P14).

Figure 5: Examples of health data visualization designed by participants.

4.3 Are smartwatch glanceable visualizations for older adults more effective if they have progress indicators?

This section presents the results of our study, when comparing response times and error rates in visualizations that showed progress indicators and those that did not. The analyzed data corresponds to activities 3 and 4.

4.3.1 Error rates. Table 3 displays the overall correct and wrong answers for each type of visualization. The results indicate no significant difference between the percentage of correct answers between SPB and SPC ($Z = -0.64, P = 0.51$), while the percentage of correct responses of SWP is significantly higher than SPC ($Z = 4.03, P < .001$) and SPB ($Z = 3.41, P < .001$) visualizations.

Table 3: Number and percentage of correct and wrong answers as per visualization type (SPB, SPC, and SWP).

Screen Type	Correct [n (%)]	Wrong [n (%)]	Total
SPB	62 (51.7%)	58 (48.3%)	120
SPC	67 (55.8%)	53 (44.2%)	120
SWP	92 (76.7%)	28 (23.3%)	120
Total	221 (61.3%)	139 (38.7%)	360

4.3.2 Response times. We show the participants' response times when interpreting the health data. We will start by displaying the reaction time distribution by participant group and visualization type. The difference in response times between group 1 and group 2 participants for each visualization type will then be presented.

The participants in the online meeting were members of group 1, and they looked at health data on a computer or smartphone screen. Group 2 consists of those who participated in the face-to-face session, and the visualization of health information collected from a typical day was displayed on a physical smartwatch. Figure 6 shows time box plot by participant group and visualization type, and Table 4 the response time statistics. In Table 4, we can see that the average response time in group 1 is similar among all types of screens. However, the SPB and SWP screens have greater response time variation than the SPC screens. In group 2, both the average and the variation in response time are higher in SPB than in the other two displays (SPC and SWP).

- *Distribution of response time by participant group and screen type:* There were no significant differences in response time variances when participants examined each of the three visualizations SPB, SPC and SWP ($W = 1.8$, $P = 0.16$), according to Levene's test. There was no difference between the overall response time between the different screen types ($H = 1.6$, $P = .44$) see Table 4 When the data were broken down by participant groups, it was found that group 1 shows a very slight difference in response time ($H = 4.3$, $P = 0.11$), however group 2 does not show a difference at all ($H = 0.1$, $P = 0.94$).
  The response time trend when participants visualized health data on the SPC screen in Group 1 (online participation) is higher than when participants visualized health data on the other two visualizations (SPB, SWP). In addition, we observed that participants' response times in group 2 (face-to-face participation) were not different when viewing health data using SPC, SPB, or SWP.

Table 4: Response time statistics

	Group 1			Group 2			Overall		
Screen Type	SPB	SPC	SWP	SPB	SPC	SWP	SPB	SPC	SWP
Mean [s]	26.0	28.7	26.0	40.1	34.3	33.8	34.6	32.1	30.6
STD [s]	17.9	8.2	22.2	26.5	14.1	17.4	24.3	12.2	19.6
Median [s]	20.8	30.5	17.5	25.0	29.0	30.0	25.0	29.0	28.0

- *Examining the differences in response time according to the type of screen in group 1 and group 2:* Group 1 had slightly lower response times when viewing health data on the SPC visualization than with the SPB visualization ($U = 39.5$, $P = .063$) and SWP ($U = 44$, $P = .063$), according to the Holm-Bonferroni correction ($\alpha = .1$). When health information is visualized on the SWP, SPB, and SPC display in group 2, there is no conclusive proof that participants' response times differ. Additionally, comparing response time between groups found strong evidence that the response time in group 1 was slower than in group 2 when participants viewed the information on the SWP screen ($U = 56$, $P = .021$).

5 DISCUSSION

Few studies have studied how to design and evaluate health data visualizations on small devices such as smartwatches for older adults. Previous studies have evaluated characteristics of smartwatch data visualizations focused on users with extensive experience with

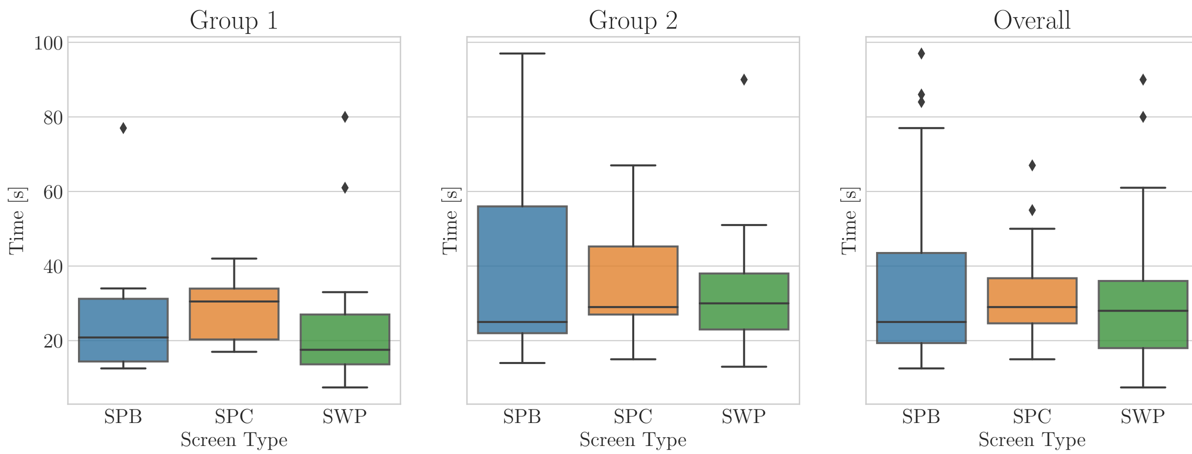


Figure 6: Time box plot per participants' group and visualization type

tracking tools and applications [3]. Others have evaluated for example smartwatch data representations (bar graphs, pie charts, or donuts) are preferable for quickly comparing information [5]. Our study explored how older adults perceived health data visualizations in small devices such as smartwatches and how they interacted with glanceable visualizations. We also present an overview of how our participants relate to technology in general and smartwatches and visualizations in particular. In addition, we involved older adults in designing the visualizations and collected their perspectives on health data visualization designs to understand their preferences and what they expect from health data representations on small screens. Matching visual designs to users' expectations by following their knowledge and experiences could enable creation of technologies that are more accessible to older adults [21]. However, there is limited discussion in the literature about how to show older adults their health data on mobile devices with small screens. In this section, we discuss (1) the results of the exploration of health data visualizations (2) the factors to consider while designing health data visualizations on small devices (e.g., smartwatches) for older adults and (3) challenges in working with older adults in Chile.

5.1 Reflection on the evaluation of smartwatch health data visualizations

The design of the data visualizations influenced older adults' understanding of health data. Our results show that when older adults visualized health data on the SWP, the percentage of correct responses was higher than with the SPB and SPC. Unlike SPB and SPC, the SWP did not include progress indicators. Previous work showed that older adults are disturbed by the various visual cues on the screen and are confused about which screen components to pay attention to [37]. Also, when older adults used interactive displays, the researchers detected that those visual elements (e.g., lines or bars), when densely distributed, posed a challenge because of participants' lack of fine motor skills and good eyesight to navigate them [21].

Based on our results, we advise caution with the use of progress indicators to display health data on small screens for older adults. The presence of progress indicators in a bar or circular style may draw older users' attention to elements used in progress representation, such as color variation, direction, and progress length, decreasing their ability to search and focus on the actual data values. Previous work showed that varying colors and element lengths in data visualizations slowed down the visual search for a target, i.e., affected user performance [5, 28]. However, some authors suggest that older adults make sense of the rate of alertness in the context of good and bad values when using colors to display data from implantable electronic devices [1]. Aligned to [72], some older adults stated that they wanted to see their data in context (e.g. to 'good' values or their goals), so perhaps it is necessary to create more subtle ways to indicate progress. Therefore, it remains challenging to fit progress indicators into the health data visualization on small devices such as smartwatches for older adults.

In addition, our findings indicate that when older adults participated online, visualization of progress indicators in a circular style (see Figure 4) required more time to interpret the health information than the other visualizations (SPB and SWP) . Representing progress information using circles could provide additional analysis features for older users to understand the data (e.g., identifying the direction of progress information). Previous studies demonstrated when older adults use radial graphs for visual representations, the shapes of these graphs are seen as distracting, and the colors of this format are challenging to contrast [37]. However, other researchers discovered that when older adult users had to compare components within the visualization and comprehend granular data, the radial graph was more straightforward to understand than the line graph [36]. For users with extensive experience with tracking tools and applications, it has also been attractive and easy to visualize progress toward a goal (e.g., the number of steps toward the daily steps goal) using donuts charts [3].

Participants with high digital technology proficiency showed shorter response times and lower error rates in viewing health data at a glance. There is evidence from the literature that older adults who are less educated, have lower incomes, have impairments or long-term health issues, or live in rural regions have less access to knowing how to use digital technologies [33, 39]. Most of the participants in this research had professional degrees, and half had high digital technology proficiency, indicating that they had better access to it than older adults who lived in less privileged situations. The meanings of social and cultural aspects must be considered because they are crucial to creating technology [9]. Furthermore, data visualizations should be evaluated not only for their effectiveness but also for their appropriateness to older adult user experiences [21] and even to older adults' styles, tastes, and fashion sense [11]. Therefore, more research is required to determine how older adults in Latin America evaluate and perceive health data visualization on mobile devices.

5.2 Design Opportunities

We suggest three design opportunities for developing health data visualizations for small devices such as smartwatch for older adults.

5.2.1 Tailor data visualization designs with older adults' expectations by understanding and leveraging their existing experiences. In terms of visualization preferences, the phrase that can summarize the sentiment of the study group is "the simpler, the better," which reinforces what was found in previous studies [7, 37, 72], where the need for simplicity in visualization is expressed. Participants favored designs that show accurate information without distraction and appreciated having classic clock information, i.e., displaying the date and the time in an analog format.

Data visualizations that match older adults' expectations, knowledge, and experiences can decrease their cognitive load, and learning effort [21]. Our study shows that the progress indicators representation should have defined colors that are easy to interpret, such as green for a standard health value, yellow to warn of slightly altered values, and red to indicate out-of-normal values. The gradient colors used in health data visualization (Figure 4-2) to represent progress information levels did not favor the data reading in the visualizations, so the gradient colors in the progress information representation in the health data visualization could lead to misinterpretations and meanings challenging to remember by older adults. In addition, this data representation could require users to acquire a new way of evaluating the values of the representation, adding cognitive effort. Our participants suggested creative representations of the progress indicators in health data visualizations, for example, partially filling an icon with color (Figure 5-1) or gradually filling the space (Figure 5-6). A previous study on the design of wellness visualizations among older adults determined that participants preferred vivid colors rather than graded shading for longitudinal views and comparisons of holistic wellness [37]. Also, some authors have demonstrated that older adults are able to understand the red, yellow, and green traffic light metaphor when it comes to designing health data [1].

5.2.2 Visualizations of health data that are aesthetically pleasant and inspire good feelings. The outcome of the data display on screen 5 (see Figure 3) demonstrates that, in addition to delivering health information, the group liked the screen visually. The image on this screen "conveyed tranquility," according to a few participants, and they valued the screen since it gave them the necessary information plus the added benefit of making them feel peaceful. Older adults prefer to read health information with graphics that evoke pleasant feelings rather than images or colors that could depress or discourage them.

There is no doubt that the variables to consider when designing health data visualizations for older adults are related to the cues represented by the visualization icons, as demonstrated by the requirements expressed by our participants. For instance, several participants stated that they would prefer the icons to be happier or to portray the information in a more positive light because it is unpleasant for older adults to check their health information frequently. Therefore, agreeing with previous studies, if the icons were more stimulating, for example, if they had a color for each health data [60], if there was movement in them [8], or if the icons changed color to show the status of the progress information [3] the data values of the visualizations could be more pleasant to view and easier to remember. One prominent example was the heart icon with the ECG line, which caused participant P6 to have a negative memory of walking around the hospital and seeing that icon on all the machines. Given that some older people may find it comfortable for symbols to mimic those used on medical devices or in hospitals, while others may find it off-putting, interface designs for healthcare devices must offer both possibilities. For example, it has been discovered that older persons prefer non-medicalized, discrete wearable technology since trackers with a medical aesthetic may cause anxiety or result in early discouragement [71].

5.2.3 Include data representation in text and icon format to facilitate understanding of health data visualizations. Following the guidelines for the design of health data visualizations on mobile devices, 50% of participants preferred the representation of health data with an icon and text, indicating that this way, they understood it better because sometimes icons alone did not give them enough information to know what the health data corresponded to, agreeing with previous studies [43]. Previous research points out that for older adults, to the extent possible, smartphone user interfaces should use icons alongside textual labels to improve the affordances of the elements [17]. However, in some situations, users may need to explore the smartwatch's health data in-situ to ensure they are meeting their goals, for which designers have proposed "clean" data visualization designs with minimal use of text that would allow information to be extracted quickly [3]. More research is needed to explore what features of smartwatch health data visualizations enable older adults to understand information quickly.

5.3 Challenges in working with older adults

Working with older adults has particular challenges. For example, older adult participants may need help acting in experimental settings due to their lack of experience [18]. In this study, it was necessary to describe the exercises before the sessions because the participants were concerned that they would not be able to finish them. The researchers emphasized that we do not require participants with experience with technology and that we were interested in their opinions regardless of technological knowledge. They described in simple and understandable terms precisely the activities involved, what the participants would use and who would intervene in the sessions. A welcoming and trusting environment is essential when planning an intervention for older people.

The time needed to offer instructions should be flexible, which has been noted as a further challenge in the literature and our research. Additionally, several participants became anxious because we tested their memory. Providing other forms of support (for example, a greater degree of researcher involvement when participants want it, providing encouragement) and exchanging high-level information with participants are some recommendations made by some authors [23]. Additionally, it has been demonstrated that including older adults in the development of technologies may present challenges when coping with hypothetical new technology [41, 42]. However, the option to share their experiences by designing their own health data visualizations generally pleased these study participants. Even if some of their design proposals would need adjustments to be implemented (e.g., to be scaled down to fit in a smartwatch screen), involving older adults in the design of health data visualizations provided valuable insights.

6 LIMITATIONS

We would like to acknowledge the limitations of this study. First, the sample size of the study is small and the study was conducted at a single location with a limited follow-up period. As such, the results of this study may not be generalizable to older adults in other locations and different populations.

Out of 30 participants, 26 were not smartwatch users, citing diverse reasons including lack of interest, unwillingness to learn, and lack of technological knowledge. This may mean that perhaps other solutions - and not glanceable visualizations in small screens - are more appropriate for this population.

The visualizations we used were health-related; it remains an open question how older adults would understand other types of data visualizations (for example, emotional status data) and how design guidelines would need to be adapted to the socio-cultural context. In this study, the design, color, and presence of progress indicators in the visualizations varied. However, for data analysis, only the presence or absence of progress information was taken into account. However, all activities were undertaken in the same order and the questions were asked in the same order, so we acknowledge that, especially with older adults, there may be a fatigue effect when answering questions that were not at the beginning of the experiment.

Due to COVID-related restrictions, twelve participants undertook the study through the Zoom videoconferencing platform. They used their own computers or mobile devices, which increases variability of the experience during their participation. They occasionally needed the assistance of their relatives to connect to this platform. With this modality, we had little control over their devices, including screen size and quality, Internet access, and environmental factors (e.g., lighting conditions). Previous research shows that device characteristics can be problematic because visualizations need screen real estate and mouse-based interaction [14, 63]. Although 18 participants joined the study face-to-face using a laptop computer with adjustable screen quality and size for health data visualization, more long-term research is needed where environmental factors and screen characteristics are controlled. COVID-related restrictions also caused some participants to interact with paper prototypes and not a smartwatch, so screen sizes and resolution were not exactly accurate and could also affect the participants' experiences.

Finally, since the qualitative data analysis of this study was interpretive, it could be biased by our assumptions, attitudes, and opinions.

7 CONCLUSION AND FUTURE WORK

Mobile devices may positively impact older adults' health self-care management, however, presenting health data to older adults using small screens such as smartwatches is challenging. This study investigates how to visualize health data on smartwatches targeted at older adults. We conducted activity-based evaluations of different health data visualization designs to explore older adults' experiences and perspectives. The evaluation includes a quantitative analysis of the proportion of correct answers and data interpretation completion time. Additionally, we conducted a qualitative analysis of users' preferences and feedback on the visualization designs. The outcome of this evaluation helps to identify design opportunities for health data visualizations for older adults.

The designs of the health data visualizations we suggest in this research are intended to be familiar to older adults, allowing them to scan and retrieve important information at a glance. However, regardless of literacy level, all individuals have a limited amount of working memory to learn new knowledge [68]. Therefore, materials that convey new information in a way that reduces cognitive load will make learning easier. The designs proposed in this study that obtained the highest percentage of correct responses were when they lacked progress indicators. Participants preferred health data visualization designs containing pictorial representations that conveyed calmness and reassurance; however, this needs to be evaluated in other socio-cultural contexts.

ACKNOWLEDGMENTS

This study was partially funded by ANID Fondecyt 1211210, National Center for Artificial Intelligence CENIA FB210017, Basal ANID, and ANID-PFCHA/Doctorado Nacional/2018-21180784. We would like to acknowledge the participation of Francisco Vásquez in the analysis of quantitative data.

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