Beyond Screen Time: Exploring Smartwatch Interventions for Digital Well-Being

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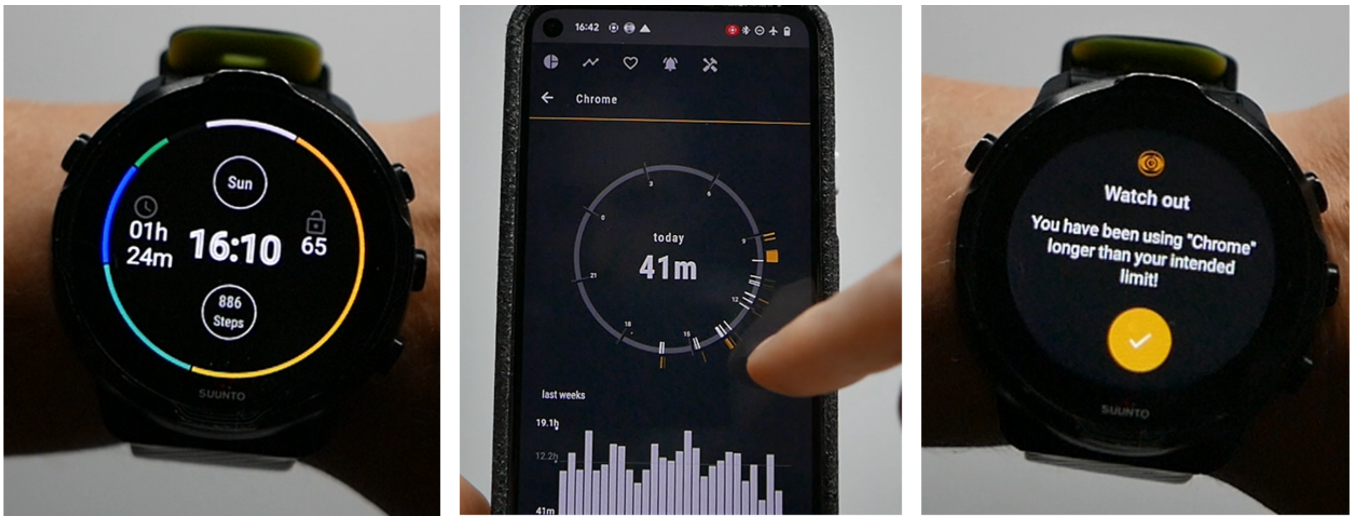

Figure 1: Application's watch face, app-specific view, and watch alarm in action.

ABSTRACT

In the digital age, technology permeates every aspect of our lives, offering connectivity but also posing risks to our well-being due to overuse. The concept of "digital detox" has emerged as a response, with smartphone apps supporting this process, yet the potential of wearable tech like smartwatches is less explored. Our study develops and tests a smartwatch-integrated digital detox aid, aiming to seamlessly blend with tech ecosystems offering a holistic solution. A preliminary mixed method user study (n=6) over two weeks assessed its efficacy in cutting down phone usage and app screen time, alongside monitoring phone interactions and physiological data. Initial results showed a decrease in screen time, which diminished in the second week, suggesting participant resistance and the intervention's perceived intrusiveness. Despite proving the concept's feasibility, the need for more user-aligned intervention methods and technical enhancements is clear, pointing to areas for future improvement.

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CCS CONCEPTS

• **Human-centered computing** → **User centered design**; **Participatory design**; **Contextual design**; **User interface toolkits**; **Empirical studies in HCI**; **HCI theory, concepts and models**; Touch screens.

KEYWORDS

Digital detox, Screen time reduction, Wearable technologies, Intervention design, Smartwatch integration, Mixed methods approach

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1 INTRODUCTION

As we delve deeper into the digital era, we witness an increasing number of individuals engaging with available technologies. However, this heightened interaction often poses risks to mental and physical well-being, as well as social relationships [7, 45, 62]. The pervasive availability of information and connectivity has led to a rise in perceived mental strain and stress. According to data from data.ai [1], users worldwide spent an average of 4.8 hours per day on their phones in 2022. Notably, social media, photo, and video

[1]https://www.data.ai/en/go/state-of-mobile-2022/?consentUpdate=updated

apps accounted for 70% of this time, aligning with predictions. This trend further highlights the dichotomy between Landes' concept of "my time," now categorized into "consumption time" versus "personal time," albeit with blurred boundaries [6]. Consequently, digital detox practices have gained widespread popularity.

Digital detox tools often come equipped with a variety of functionalities aimed at supporting users who are finding it hard to disconnect. Popular choices are smartphone applications, such as *Digital Wellbeing*, which comes with Android devices, *Screen Time*, which comes with iOS, or other various applications found in Google's Play Store or Apple's App Store. Adjusting one's habits to reduce digital consumption is inherently challenging due to the complexity of altering behaviors [25]. There are numerous ways to achieve a digital detox for smartphone addiction, spanning from basic guidelines to elaborate technical aids designed for tracking, controlling usage, and limiting apps, along with providing rewards for reduced screen time [27, 28]. According to research by Lyngs et al. [20], digital detox tools typically incorporate four main types of features to foster changes in behavior: the ability to block or remove distractions, self-monitoring capabilities, mechanisms to support progress toward goals, and systems of rewards and penalties. Albeit the array of features offered by digital detox applications to help users, an intriguing dilemma presents itself. Why use smartphone technology—the very thing from which one is attempting to detach—as a means of regulation? Or as Monge Roffarello and De Russis [28] put it: *"digital devices and services are, at the same time, the source of the problem and the platform with which the interventions are delivered to the user."* There is another piece of technology that is close to the smartphone and that can be a viable platform.

Smartwatches have emerged as the next big innovation following smartphones [14, 44], with sales reaching 134 million units in 2023 and expected to grow by nearly 30% over the next five years [2]. These devices have the potential to transform how users engage with their phones and may help lessen dependence on them [8]. By serving as a bridge between the user and their phone, smartwatches allow for interactions that demand less of the user's attention, assisting with small tasks and providing quick access to information [60]. In spite of these benefits, there are currently few[3] examples showcasing the application and effectiveness of wearables or smartwatches in facilitating digital detox. A systematic review by Monge Roffarello and De Russis [28] investigating current work on digital self-monitoring tools lists no approach that makes use of smartwatches.

In our study, we explore the design and implementation of digital detox interventions using smartwatch technology to help users become more aware of their device usage and reduce screen time. Given the advanced functionalities and feedback mechanisms of contemporary smartwatches, numerous intervention designs are viable. A key advantage of a smartwatch is its wrist-mounted display or interface, often referred to as the *watch's face.* This placement facilitates quick interactions and enables users to easily view information with minimal cognitive strain. Smartwatches also present promising avenues for influencing physical activity behaviors and enhancing health consciousness among users [10, 48]. Given the availability of tracking data for physiological metrics, physical activity, and phone usage, we propose the following research questions:

Table 1: Research Questions

ID	Research Question
RQ 1	How could smartwatches support digital detox and reduce smartphone screen time?
RQ 2	Can health- data recordings meaningfully complement smartphone usage data?
RQ 3	How might we redesign interventions to reduce screen time based on these findings?

2 BACKGROUND

We delved into the literature on digital overload, habit formation, and implementations and designs of smartphone-based applications to help with screen-time reduction.

2.1 Excessive digital device use

The design of smartphone applications, characterized by easy accessibility, engaging interfaces, algorithms that deliver endless relevant content, and gamification features, encourages prolonged use. Excessive and frequent use of mobile devices, and social media have been linked to influencing mental and physical health [4, 51, 62], sleep [46, 53], and academic performance negatively [1, 46]. The primary reasons behind the widespread engagement with digital devices, such as smartphones and online content, internet addiction, and social media usage, are still under debate and cover research from diverse areas, such as psychology, addictive behavior and disorders and HCI [5, 17, 28]. While there is an ongoing discussion about the roots of addictive behavior, there is a general agreement that therapy could focus on either abstinence or moderated use, among other strategies. This leads to the concept of 'digital detox' as a method for managing excessive digital device use. As concerns over digital consumption grow, tools to monitor, regulate, or limit device use have been introduced. Ultimately, the responsibility falls on individuals to cultivate awareness of their device use and to integrate these tools into their daily lives [31]. A systematic review by Radtke et al. [43] sought to evaluate the effectiveness of digital detox interventions. After reviewing numerous studies, they found mixed and often conflicting results on the success of digital detox efforts. The diversity in digital detox implementations, differences in measuring outcomes, timing of assessments, selection of participants, and the randomization of study groups were cited as reasons for these inconsistent findings. Other limitations highlighted by the authors include the lack of device-based measures of user behavior, which would allow for a more reliable assessment than self-reported behavior.

Despite the awareness of digital well-being applications, a significant portion of users either stop using them after a while or never start at all. Parry et al. [36] while investigating the adoption rate of digital detox applications, found that although 80.48% of their participants indicated that they are aware of digital well-being

[2] Smartwatch market statistics, https://www.mordorintelligence.com/industry-reports/smartwatch-market
[3] e.g. RSW-TIME OFF!, https://rudolphschellingwebermann.com/en/projects/off—Accessed June 2024

applications, 63.06% of those respondents indicated that they have ceased using (16.12%) or have never (46.94%) used such applications. The mixed outcomes of digital detox efforts and the varying impact of social media on mental health highlight the nuanced relationship between digital device usage and user wellbeing. As the digital landscape continues to evolve, there is a pressing need to diversify the strategies and tools available for individuals seeking to manage their digital consumption effectively.

2.2 Digital habit formation

A habit refers to the predisposition to engage in a specific behavior, with habitual behavior stemming from this tendency [32, 37]. While individuals may be aware of their actions, they often lack insight into the habit's mechanics, rendering change difficult [59]. Dual system theory offers an explanation for how impulses emerge and decisions are made, distinguishing between two cognitive pathways: System 1 operates unconsciously, quickly, and in parallel, relying on automatic responses, learned habits, and heuristics. System 2, in contrast, is slower, conscious, and driven by goals, intentions, and rules, playing a critical role in planning, decision-making, and resisting habits and temptations. For a new, desirable behavior to become habitual, it must transition from a System 2 to a System 1 process [9, 20].

In the realm of digital detox, various strategies have been proposed to alter habits. Pinder et al. [37] suggest employing intentions and automation of self-regulation in habit formation. Monge Roffarello and De Russis [27] categorize digital well-being assistants based on their features into self-monitoring and intervention-based approaches. Despite the prevalence of tracking and data visualization in these applications, intervention features are less common, highlighting the diverse tactics each self-control tool employs. Following an exploratory study, the development of a well-being assistant revealed that although self-tracking is crucial for behavior change, it seldom fosters lasting behavioral modificationMonge Roffarello and De Russis [27]. Upon removal of the monitoring tool, individuals often revert to their original behaviors. This finding highlights the importance of grounding digital well-being tools in habit formation research to ensure sustained adherence to healthy digital behaviors [27]. Similarly, Lyngs et al. [20] analyzed Android and iOS apps and browser extensions serving as digital well-being and detox tools, examining their implementation of dual system theory. While using different methodologies and classifications compared to Monge Roffarello and De Russis [27], the analysis of feature distribution shows some degree of alignment. However, Lyngs et al. [20] identify a lack of features aimed at habit scaffolding rather than mere blocking. Furthermore, they noted a lack of delay mechanisms and expectancy components, which gauge a user's perceived likelihood of achieving their objectives.

2.3 Digital self-control tools

Over the years, a myriad of digital tools and companion applications have emerged to assist users in their quest to reduce application screen time, support self-monitoring and block application use. In 2013, Löchtefeld et al. [19] released an app called *AppDetox* in the Android Play store. The features provided were: One would allow users to define time frames in which opening a particular application was restricted. Breaking a rule was recorded and displayed in a separate overview. In 2016, Hiniker et al. [12] proposed the app *MyTime*, which tried to support people in achieving goals related to smartphone non-use. Three intervention nudges were implemented: First, users were asked what they wanted to accomplish today, then they could select from a catalogue of all installed applications the apps they wanted to track and set a timer for maximum daily usage. Whenever one of the tracked applications was launched, a live notification in the status bar displayed a progress bar showing how much time the user had spent with the application in relation to the set limit. When a limit was reached, a UI overlay displayed the set limit and the defined goal for the day, suggesting an alternative to using the phone. The timeout feature was partly used to gain information about usage, which was reflected in how users reacted to the 'time's up' notifications. However, participants reduced their use of applications that they perceived as 'wasting time'. With iOS 12, released in September 2018, Apple added *Screen Time* to the roster of built-in system features. With this application, it became possible to get detailed usage information, block or limit time spent with certain apps, and even get weekly reports about usage trends in iOS. Starting with 2018, Android likewise got a built-in application called *Digital Wellbeing*[4] responsible for various aspects of digital detox. Dashboards and overviews provide information on daily and weekly app usage, phone unlocks and received notifications by app. Historical data was accessible only up to four weeks, although it's possible to programmatically gather aggregated data for more extended periods in lower time resolution. The application is capable of providing settings for time limits for apps. After exceeding these goals, the app or URL will get blocked and can't be used for the rest of the day unless the limit gets removed. Given how deep third-party apps need to be integrated into systems to support restricting features, providing default built-in tools in the commonly used mobile operating systems can be seen as a sensible strategy to ensure users' privacy and security.

Okeke et al. [33] created an application for Android called *Good-Vibe* that provides users with real-time, textual feedback of how much time they have spent on a mobile application. Furthermore, a digital nudge in the form of gentle phone vibrations when a specified daily usage limit for an app is reached was added. Kim et al. [15] own application *Goalkeeper* employed several different mechanisms and proposed comparably more substantial restrictions on their users. Standard features like a timeline, the capability to define time limits for applications (daily and weekly limits are supported) and utilising the notification bar to provide quick access to usage information were included. The authors, furthermore, introduced a break and lockout mode during which only basic phone functions can be accessed. A break mode could be started voluntarily and stopped at any given time, whereas lockouts were triggered after exceeding defined usage limits for applications. Monge Roffarello and De Russis [27] had implemented *Socialize* after reviewing 42 available digital detox applications using features that were present in at least 15% of these apps: tracking, data presentation, timers and contextual interventions. Although using Socialize, participants constantly checked their phones, but they still managed to reduce

[4]Digital Wellbeing–https://www.android.com/digital-wellbeing/–Accessed June 2023

the time spent on social media significantly. However, interventions were rarely used, and even the use of Socialize did not change how they perceive problematic phone use. Purohit and Holzer [42] experimented with iOS *Shortcuts* application to create nudges to reduce the use of Instagram. Shortcuts allow users to program tasks without knowledge of any programming language and can thus theoretically be used with any app or content. The authors see the benefit of ensuring privacy and ethics by using this approach with built-in resources and mechanisms.

2.4 Challenges of self-control tools and nudges

Thaler and Sunstein [56] define a nudge as a subtle feature of choice architecture that predictably influences behavior without restricting any options or significantly altering economic incentives. Essentially, nudges gently guide individuals towards healthier choices by making those options more accessible, such as placing a basket of free fruit next to a snack machine as an encouragement for healthier snacking. Digital nudges, as described by Weinmann et al. [61], use interface elements to subtly guide user behavior in decision-making scenarios, leveraging the design of the choice presentation to influence decisions unconsciously, in line with dual-process theory. Simple changes, like altering default settings, have been shown to significantly impact choices, demonstrating the power of choice architecture [30].

Building habits, according to dual-system theory, involves transitioning behaviors from conscious, deliberate actions (System 2) to automatic, subconscious processes (System 1). However, developing new habits, particularly those related to health and activity, can take months to solidify and might demand nudging. *mHealth* user studies implementing interventions to promote more active lifestyles describe three to six months until exercises become habitual behavior [18]. The challenge lies in maintaining engagement without the interventions becoming burdensome to the point of abandonment. Schwartz et al. [50] propose strategies to minimize the risk of users abandoning digital well-being tools, including adjustable interventions, combining different strategies, offering user control over chosen interventions, and ensuring consistent engagement in defiance of technological changes. Kovacs et al. [16] also suggests rotating interventions to keep users engaged, acknowledging that users may eventually overlook static nudges. However, nudges' effectiveness can vary, with their impact dependent on the context and how they're implemented [30]. The ethical dimensions of nudging, particularly regarding digital detox efforts, raise concerns over privacy, control, and the potential for manipulation, highlighting the importance of designing nudges that are transparent, easily opted out of, and genuinely aimed at improving user well-being [11, 26, 41, 57]. Critiques of self-control tools highlight the necessity for a balance between user desires and the objectives of tool designers, platform owners, and application developers [49, 50]. Ethical and usability concerns must be addressed to ensure that digital nudging tools enhance user autonomy and experience without encroaching on privacy or free choice [39, 42]. Therefore, while digital nudges and self-control tools offer promising avenues for encouraging healthier digital habits, their design and implementation must carefully consider user acceptance and the subtle balance between guiding and controlling user behavior. Monge Roffarello and De Russis [28] found in their systematic review that current digital self-control tools include a lack of theory and in general disregard ethical implications and issues. Secondly, the prevalent short-term evaluation leaves their performance in terms of building long-term sustainable habits up to speculation. Furthermore, the authors propose based on the review that future research might look into overcoming a limited perspective that focuses on technology overuse and self-monitoring tools and finally to find a way to deal with the business models of big-tech enterprises, that benefit from the continuous and frequent usage through their users and clients [28].

2.5 Towards Wearables

Wearable devices, including smartwatches, have played pivotal roles in research focused on behavior change interventions, such as encouraging more active lifestyles among sedentary individuals [23, 46, 47]. Wearable technologies offer two primary health-related applications: they can proactively correct unhealthy behaviors to prevent diseases, or they can provide diagnostic support by continuously monitoring and analyzing biomedical signals to detect medical conditions [29]. These devices incorporate a variety of compact sensors capable of tracking critical physiological indicators, including heart rate, oxygen saturation, blood pressure, skin temperature, respiration rate, and skin conductance [29, 35]. Additionally, wearables can be equipped with sensors to measure movement via accelerometers and gyroscopes and other environmental factors, such as orientation through magnetometers, location with GPS, and atmospheric conditions using barometers, humidity sensors, temperature gauges, and light sensors [29]. Raw sensor data collected by wearables can be processed and analyzed directly on the device, and then transmitted to other devices or cloud services for additional processing or storage. This analysis includes interpreting sensor signals to identify medical conditions or detect physical activities such as gait, step count, sleep patterns, and more, directly within the device [58].

Wearable technology encounters several challenges that can affect user adoption, one of which is the precision of sensor data or the accuracy of recognition outcomes. For example, Svensson et al. [55] investigated the reliability of sleep cycle detection by the Fitbit Versa smartwatch, comparing its readings against those from a validated single-channel EEG system across two weeks of nightly data from 20 participants. Although there were no significant differences in the measurements of time spent in bed and overall sleep duration, discrepancies arose in the estimation of time spent in deep sleep and awake periods, with the smartwatch both significantly overestimating and underestimating these phases. Regardless of these variances, Svensson et al. [55] concluded that the sleep tracker could still be useful for measuring sleep duration in longitudinal studies, albeit with certain caveats. Integrating data from various devices or sources to assess mental state, mental health, stress, and sleep quality is a well-established practice. Sano and Picard [47] combined accelerometer and skin conductance data from wearable sensors with mobile phone usage data to gauge overall health, mood, and stress levels. In a separate study, they gathered information from wearable sensors and phone data, as well as self-reported sleep scores and personal characteristics, to identify factors influencing academic performance, sleep quality, stress, and mental health [46]. Massar et al. [21] have shown that data from wearable sleep trackers, phone-based tappigraphy (analyzing interaction patterns), and self-reports provide both overlapping and unique insights into sleep behavior. While tappigraphy doesn't directly measure screen time or app usage, it offers indirect estimates of daily screen exposure. Past research utilized physical activity and sleep data from smartwatches, along with screen time data, to evaluate sleep quality and behavioral health, proposing methods that predict sleep quality with a high accuracy of 91%. These studies underscore the potential of combining wearable technology and digital usage data to enhance our understanding and management of health and well-being [2, 3]. Although advancements in wearable technologies for health monitoring and behavior change have been made, there's a significant gap in accurately integrating and analyzing data from various sources to fully understand health states. Furthermore, combining data from wearables with other sources to assess behavior, mental health and sleep quality is a promising direction for digital detox. Furthermore to add to this regard, findings from Cecchinato et al. [8] suggest that using smartwatches help users manage their availability and can reduce the time spent on other devices.

3 CONCEPT AND PROTOTYPE DEVELOPMENT

Based on the literature review, the paper proposes the following intervention approach.

3.1 Intervention Design

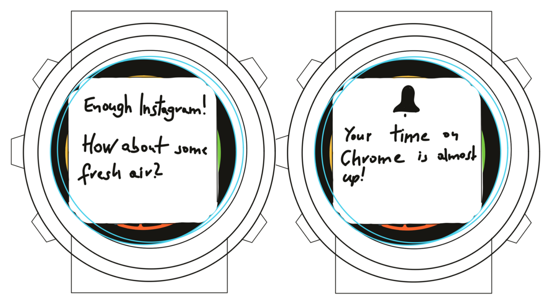
Drawing from the findings in the literature and an examination of existing reference applications, intervention designs were developed, largely inspired by the methodology outlined by Okeke et al. [33] in their work.

3.1.1 Platform selection for phone and watch. The mobile OS market [5], once diverse, is now dominated by Android (approximately 68% market share) and iOS (around 30%). For this research, Android was chosen due to existing development experience, especially since both platforms offered necessary APIs: iOS with its Screen Time API since iOS 15[6] and Android's UsageStatsManager since Android 5.0 Lollipop [7]. Choosing a smartwatch platform involved evaluating options like Garmin, Suunto, Tizen, and Wear OS. Even though initially Garmin was considered as development platform for its simplistic and features and health & sports focus, limitations in phone-watch communication led to selecting Wear OS for its seamless integration with Android. The Suunto 7 model, running Wear OS 2.5 and equipped with Google Fit, was chosen for its compatibility and comprehensive Google-backed software ecosystem, promising well-documented integration and testing.

3.1.2 Watch face. Displaying information directly on the watch face offers a straightforward and efficient means of delivering data

(a) Standard watch face of the *Google* Pixel 2 watch[8].

(b) Draft of the prototype "watch face".



(c) Early draft of the "alarm nudge"-intervention on a watch.

Figure 2: Watch face example and early sketches.

to the user without significant interference or distraction, as illustrated in Figure 2a. This approach is common across various types of watches capable of processing data, encompassing applications in the medical field (such as blood sugar levels and heart rate monitoring), sports, daily activities (like notifications or navigation), and even entertainment (games). Watch faces possess specific characteristics that can complicate the display of sensitive information: they are openly worn and designed for quick readability. Yet, for non-standard watch interfaces, like a highly customized watch face, the data may only be interpretable to an informed observer. Accordingly, adopting the design principles outlined by Jafarinaimi et al. [13] in their development of Breakaway—a smart sculpture placed in a public space to encourage taking breaks from sitting

[5]Mobile Operating System Market Share Worldwide, https://gs.statcounter.com/os-market-share/mobile/worldwide–Accessed May 2023
[6]Screen Time API, https://developer.apple.com/documentation/DeviceActivity–Accessed May 2023
[7]UsageStatsManager, https://developer.android.com/reference/android/app/usage/UsageStatsManager–Accessed May 2023

too long—we used the following logical components to design the watch face:

- **Abstract**: We display only aggregated application data and usage totals.
- **Non-intrusive**: Watches and their faces are unobtrusive by design.
- **Public**: Data is glance-able only by the informed user as colour mappings are unique for each user. However, total usage time can be problematic but is required.
- **Aesthetic**: Customisation options are available through complications and coloring schemes.

The watch face functions as a source of near real-time feedback for the user throughout the day, independent of phone use, thereby enhancing awareness of their device usage. Figure 2b shows an early draft of this intervention. The watch face is subject to the greatest number of constraints, in line with the design principles for Google's WearOS [9]. Therefore, given that the face serves as the primary interaction hub, it is logical to extend certain design elements to the phone application. By presenting information in consistent formats across various interfaces, it simplifies the process of assimilating combined data, thereby minimizing cognitive effort. The circular design, which is a prominent feature in the initial touchpoints of both the watch interfaces, is reused in other elements to enhance design consistency. This approach is evident in the appearance of the time doughnut and the alarm-input-slider, as illustrated in the respective Figures 4c and 4d.

3.1.3 Alarm nudge. Our objective is not to develop an entirely new approach. Rather, we are drawing inspiration from the concept of digital nudges [40, 52]. Purohit et al. [40] research focused on exploring ways in which digital nudges might challenge the addictive design contexts commonly employed by social media platforms. The design also borrowed elements from Okeke et al. [33] approach, utilizing vibration as a discreet nudge on the watch. This occurs when the user exceeds a predetermined amount of daily screen time, prompting them to divert their attention from their phone and reconsider their usage patterns. To ensure the user's focus shifts from their phone, the vibration notification can only be dismissed on the watch itself. If the user persists in using a specific app beyond the daily limit, the reminder will activate once more. Accompanying the vibration is a message displayed on the watch, stating:

> You have been using "*<application name>*" longer than you intended.

This message was crafted to be straightforward and neutral. Unlike the specific limits set by Okeke et al. [33] for Facebook usage, participants have the flexibility to establish their own limits for any app they wish to use less, encouraging a personalized approach to digital well-being. Early drafts of how this visual nudge might appear on the watch are illustrated in Figure 2c.

3.1.4 Colour consistency. Colors serve as a key source of information, indicating which application was utilized in summaries and visualizations, as well as the duration and timing of its use. To maintain clarity and coherence, it's imperative that color mappings remain unaltered and consistent across all interfaces on both the phone and watch. This consistency is maintained by creating a registry of all apps, and assigning a color code that matches the primary color of the app's icon. Examples of how this color consistency is implemented across various devices, offering a unified view through the same application and color mapping scheme, are illustrated in Figure 3. Furthermore, color is incorporated as an additional attribute in all synchronization or alarm notifications to ensure uniformity across all connected devices.

3.2 Watchful phone application

3.2.1 Technical design. To ensure optimal user experiences, we adhered to Google's guidelines for modern Android development [10] across all aspects of our development. The app was developed in *Kotlin*, utilizing a single-activity architecture complemented by modular components for respective features. The UI design was inspired by Google's Rally, a material design study [11] and is implemented in Jetpack Compose. Data persistence was managed with *Room* , providing a sophisticated layer over SQLite to store app and phone usage data collected from the Android system's StatsManager API. This data served as the foundation for the app's backend, enabling UI interactions. To achieve a cohesive data presentation, a unified format was created using *Kotlin dataframe*[12], facilitating straightforward statistical calculations and to implement graphical representations against the data frame as interface. We created custom visualizations for bar and line charts and incorporated unique input methods, such as a slider for setting alarm thresholds, all realized through Jetpack Compose.

3.2.2 Data visualisation design. The phone application offers a range of visualizations focused on either usage or health data, providing insights into digital and physical well-being.

Usage Data. : Derived from Android's UsageStatsManager API, usage data informs several graphical displays within the app:

- **Daily Overview:** The main feature of the overview screen is a doughnut chart displaying application screen time and the number of phone unlocks since midnight, as illustrated in Figure 4a. This layout closely mirrors the design of the Digital Wellbeing dashboard.
- **Daily Overview Over Time:** Swiping the doughnut chart switches to a 24-hour clock-like graph with colored segments for app usage, helping identify heavy usage periods, as shown in Figure 4b.
- **App-Specific Overview:** Displays a 24-hour usage breakdown for a selected app, including alarm triggers as white marks and a list of timestamps, as shown in 4c. Beneath the clock display, a bar chart presents the weekly aggregate of screen time over recent weeks.

[8]Google Pixel 2, https://store.google.com/gb/product/pixel_watch_2–Accessed January 2024
[9]WearOS design principles: https://developer.android.com/design/ui/wear/guides/foundations/design-principles–Accessed August 2023
[10]Modern Android Development, https://developer.android.com/modern-android-development–Accessed July 2023
[11]Rally Material Design, https://m2.material.io/design/material-studies/rally.htm and https://github.com/android/compose-samples/tree/main/Rally–Accessed July 2023
[12]Kotlin Dataframe, https://github.com/Kotlin/dataframe–Accessed July 2023

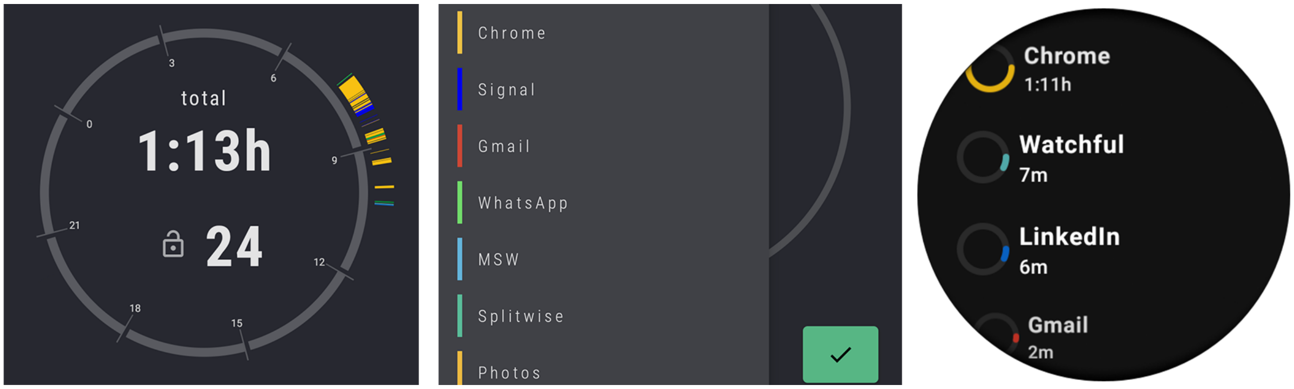


Figure 3: Colour consistency per application across views and devices.

- **Historical Data Overview:** Offering a long-term usage perspective, another view presents weekly screen time totals as a bar chart.

Health Data Visualizations. : Health data sourced from Google Fit includes the last 24 hours of activity:

- **Heart Rate:** Displayed in 5-minute intervals on a line graph, with app usage and sleep data integrated for a comprehensive health overview, as shown in Figure 5a.
- **Steps Data:** Step counts are aggregated into 5-minute intervals and displayed as a bar chart, with app usage shown on a separate axis, depicted in Figure 5b.
- **Sleep Data:** Sleep duration is shown in the heart rate and step charts as large grey blocks, indicating bed and wake times without detailing sleep cycles for simplicity and accuracy concerns.

3.3 Watchful watch application

3.3.1 Technical design. Similar to the phone app, the companion app for the watch was developed using *Kotlin* and Jetpack Compose. A backend app manages communication and data storage, utilizing protocol buffers for efficient data handling [13]. Additionally, distinct activities were crafted for alarm functionalities, illustrated in Figure 7c and to furnish detailed data visualizations. The watch face component, depicted in Figure 7a, is built on a *WatchFace Service*, displaying the current data from the storage layer. For a detailed breakdown of the watch face's displayed information, refer to Figure 6. Notifications on the watch are activated via the phone application once a usage limit is initially exceeded. If the participant persists in using the app beyond this point, an alarm is set off after a 10-second threshold period.

3.3.2 User interface implementation. The watch face features a doughnut chart showcasing the top five applications by screen time, along with a sixth 'other' category, mirroring the central design element of the phone app (refer to Figure 4a and 7a). To the left of the time display, the total daily screen time is shown in hours and minutes, while to the right, the cumulative count of phone unlocks is presented. Additionally, two complication slots above and below the time display offer customization options, potentially used to show information like the date, battery level, weather conditions, and more (as detailed in Figure 6). The watch app includes an additional activity beyond the watch face, designed to provide a more detailed view of data in a list format, which displays up to six items (the top 5 applications by screen time and an 'other' category), as seen in Figure 7b. Each item in the list displays the application's name, its daily screen time, and a doughnut chart indicating its share of the total daily screen time. The alarm screen, illustrated in Figure 7c, features a design highlighted by the color of the application that triggered the alarm, including both the app's logo and the OK button.

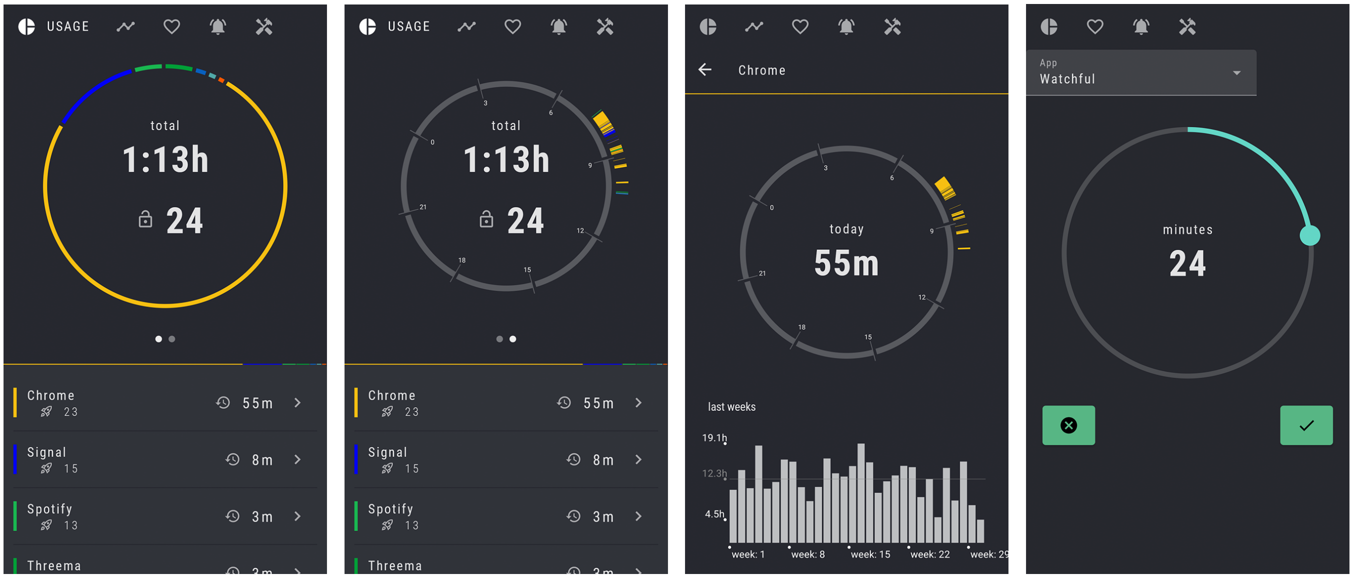
3.3.3 Watchful's components communication. Figure 8 illustrates how data is exchanged among the key components of the prototype's architecture. The diagram includes the WearOS data layer: the phone and wearable device communicate through Bluetooth. If Bluetooth is unavailable or turned off, the system automatically switches to using a Google Service via WiFi or LTE for data exchange [14]. Interactions between the phone and the watch app, rely on WearOS APIs, such as the data layer, to push latest usage figures or send notifications. To conserve bandwidth and battery life on both devices, the system is designed to transmit only essential updates. This means no data is sent if there's no new phone usage activity, minimizing unnecessary communication. The system ensures that application or health data remains on the device, only leaving if participants choose to export their data upon completion of the study.

4 EVALUATION - USER STUDY

To evaluate the prototype's impact, a preliminary user study was conducted, where quantitative data regarding phone usage was gathered. As shown in Table 2, the study was divided into three phases. Participant interviews offered a deeper understanding of their individual experiences.

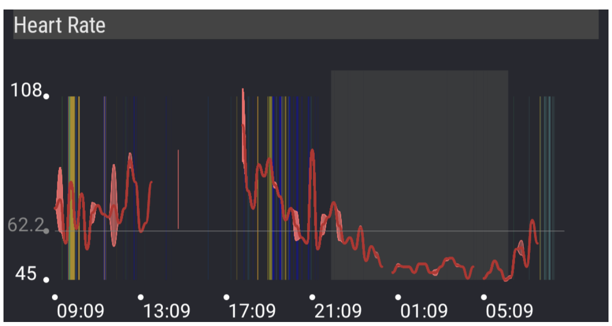
[13]protobuf,https://github.com/protocolbuffers/protobuf–Accessed July 2023,

[14]WearOS data layer, https://developer.android.com/training/wearables/data/data-layer–Accessed July 2023

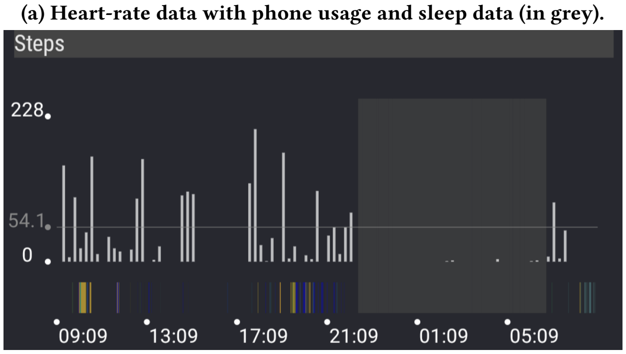


(a) **Total daily usage overview** (b) **Daily historic overview** (c) **App-specific view** (d) **Configuring alarms**

Figure 4: User interface of *Watchful* Application.



(a) Heart-rate data with phone usage and sleep data (in grey).



(b) Step data with phone usage and sleep data (in grey).

Figure 5: Health data visualisations for the last 24 hours.

4.1 Study Design

Nine students (2 females, 7 males) were recruited from a pool of bachelor course participants using the word of mouth. Selection criteria included their willingness to undergo digital detox and ownership of an Android smartphone. Participating students received bonus points as compensation. Those interested had to read an information sheet and sign a consent form before joining the study. Participants in the study were provided with smartwatches and guided through the setup process during the briefing meeting, which always took place on Mondays. Instructions for the first week involved wearing the watch as much as possible, including during sleep, to acclimate to it and familiarize themselves with the watch face. The application observed their behavior during this time. At the end of the first week, participants received an email reminder to begin using the nudging functionality for selected applications during the second part of the study. The email also included a brief survey to gather initial impressions and address any technical difficulties or questions. Upon completion of the two-week study period, participants returned to the lab to submit their data and hardware exports and participate in interviews about their experiences. The interviews were audio-recorded using a handheld recorder.

In contrast to previous studies [33, 39, 41], the week preceding the study's commencement served as the baseline reference for comparing subsequent two-week periods of usage. Due to the limited number of watches, only three participants could participate simultaneously. This approach proved beneficial, particularly in the initial phase, as it facilitated the streamlining of briefing and setup procedures and enabled prompt resolution of technical issues. For instance, certain Android distributions' manufacturer-specific characteristics necessitated consideration to prevent system processes or unique UI widgets from skewing usage statistics and disrupting user experiences. Software patches could swiftly be developed and disseminated to participants via Android's Play Store to address minor issues.

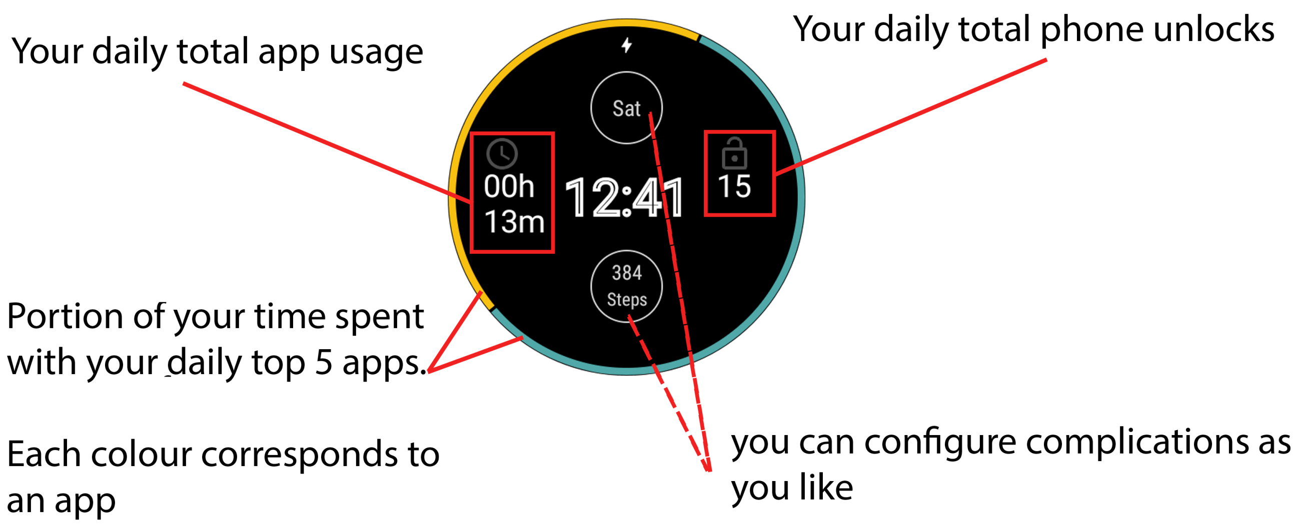


Figure 6: Explanation of the available fields of the *Watchful* watch face that was supplied to the participants.

Table 2: Study Phases Description

Phase	**Description**
Baseline Phase	• 7 days prior to the beginning of the study. • Extraction of screen-time only as a reference.
Passive Phase	• First 7 days. • Participants should accommodate themselves to the watch. • Only monitoring of screen-time through *Watchful* applications. • **No alarm intervention**.
Active Phase	• Last 7 days. • Continuation of monitoring. • **Active alarm intervention**.

4.2 Measurement

Using the participant's phone usage history, the following metrics were extracted to assess behavior throughout the study period and at least seven days before its commencement:

- Start and end timestamps of applications running in the foreground.
- Timestamps of phone unlock events.
- Timestamps and application origin of alarm events.
- Timestamps, application, and nature of alarm-settings changes (e.g., creation, deletion, or update of limits).

Additionally, with the integration of *Google*'s Google Fit[15] into the watch, additional physical metrics were accessible for use in phone-application visualizations and post-study analysis:

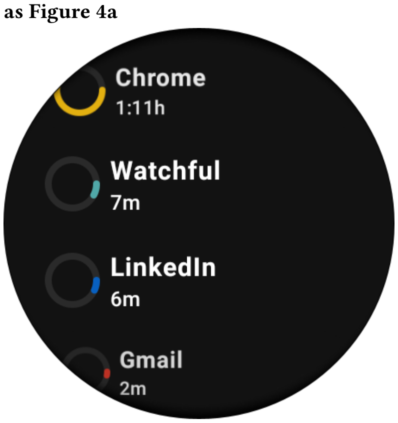
- Heart rate (time series data).
- Steps (time series data).
- Sleep activities (beginning, end, and sleep cycle).

Participants were instructed to export their data at the study's conclusion using a feature integrated into the phone application. This application collects data from a local database, while remote Google Fit services generate domain-specific CSV files labeled with a UUID on the phone's internal storage. Finally, to facilitate sharing through a participant-selected channel, a zip archive was created as a final step. An import routine was utilized to transfer the zip-archived files into a dedicated timescaleDB[16] database, which was running locally on the moderator's notebook. This database served as a centralized repository for all the study's data. Leveraging the powerful tools provided by TimescaleDB for interacting with time series data, event data describing ongoing user interaction with

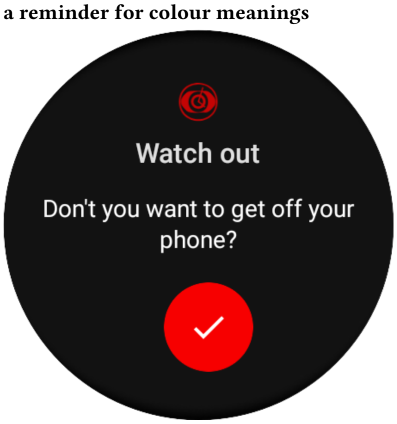
[15]Google Fit, https://www.google.com/fit/–Accessed May 2023

[16]TimescaleDB,https://www.timescale.com/–Accessed May 2023

(a) ***Watchful***'s watch face — similar state as Figure 4a



(b) ***Watchful***'s list activity on the watch - a reminder for colour meanings



(c) ***Watchful***'s test alarm activity on the watch

Figure 7: *Watchful*'s watch application screens.

the application in the foreground was converted from a descriptive representation into time-series data points with one-minute resolution. As depicted in Figure 9, this transformation resulted in six data points for each event, each with a duration value that represents a fraction of the event's duration at the given timestamp of the full minute. Consequently, the process of preparing data for statistical analysis for arbitrary time frames and buckets, with optional gap-filling functionality, was simplified through this transformation. To conduct an initial exploration of the data, which had been consolidated into a unified database, the visualization tool *Grafana*[17] was employed. Custom views were implemented through dashboards, facilitating insightful analysis.

5 RESULTS

Data from 3 of the original 9 participants were excluded due to incomplete and erroneous records, resulting in a remaining group comprised of 5 males and 1 female, with an average age of 23.5 years and standard deviation = 1.70. It should be noted that for metrics related to the physical attributes of participants (such as sleep patterns), baseline data preceding the study commencement was not available. Consequently, any conclusions regarding the impact of the interventions on these physical attributes are outside the scope of the presented user study.

5.1 Impact of the intervention on phone usage

To test for significant changes between baseline and passive/active intervention phases, a Wilcoxon signed-rank test was used due to the small sample size. The key findings from the study on the impact of intervention methods on screen time and app usage include the following key points:

(1) **Screen Time Reduction:** There was a notable decrease in overall screen time during the first week of the study, which was statistically significant ($p = 0.03125$, effect size $e = 0.572$). However, this reduction was less pronounced during the active week, where intervention methods were fully implemented ($p = 0.15625$), as shown in Figure 10.
(2) **App Usage with Defined Limits:** For apps that had usage limits set, there was a consistent decrease in usage across both passive and active weeks. During the passive week, usage dropped by 17% ($p = 0.028839$, effect size $e = 0.3965$), and during the active week, it decreased by 6% ($p = 0.1489$).
(3) **Changes in "Problematic** [18]**" App Usage Patterns:**
   (a) A reduction in usage of "problematic" applications was observed between 19:00 and 07:00 during both passive and active phases, approximately -5% ($p = 0.00049$, $e = 0.33$).
   (b) Conversely, there was an increase in overall usage of these apps during the day (between 07:00 and 19:00) in the active phase.
(4) **Effectiveness of Alarms:** Alarms introduced as part of the intervention did not perform as reliably as expected. The presence of alarms might have nonetheless contributed to the continued reduction in the usage of apps with limits between 19:00 and 07:00. The selection of the time window for daily limits could have been more optimal.

[17] Grafana Labs, https://grafana.com/grafana/–Accessed November 2023
[18] Among the top 5 apps renowned for their "endless scrolling" and binge-use tendencies, with enabled alarm limits.

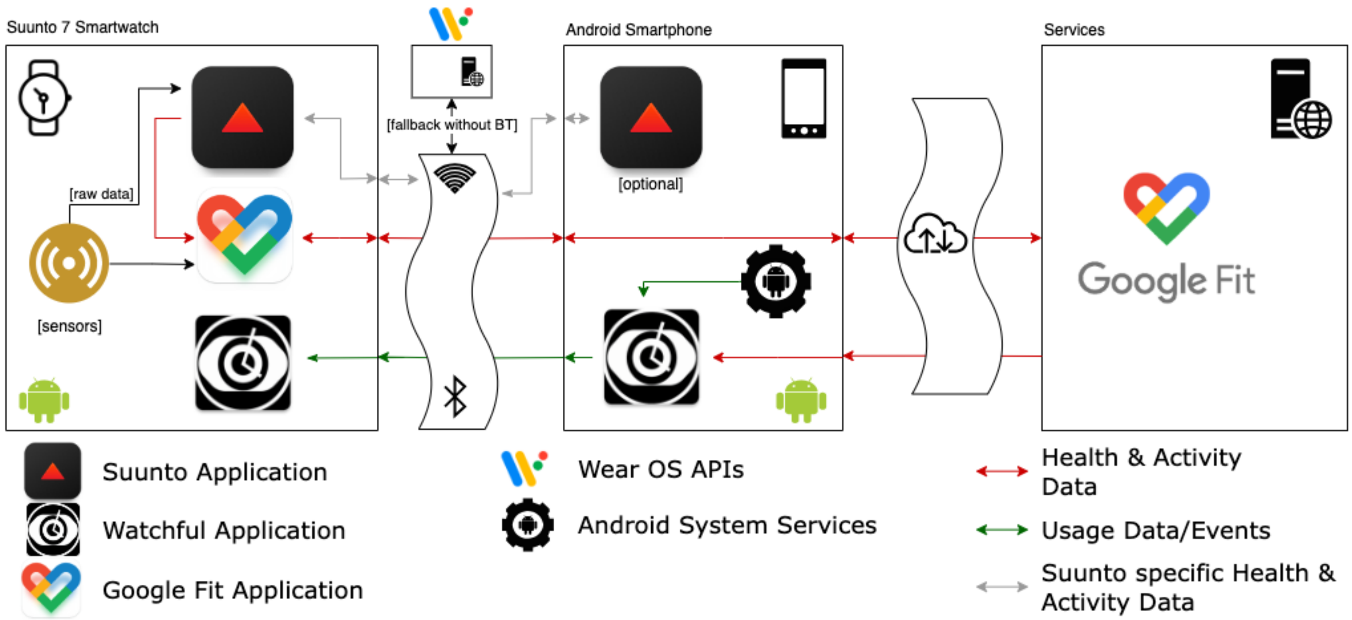


Figure 8: Data flow between all components.

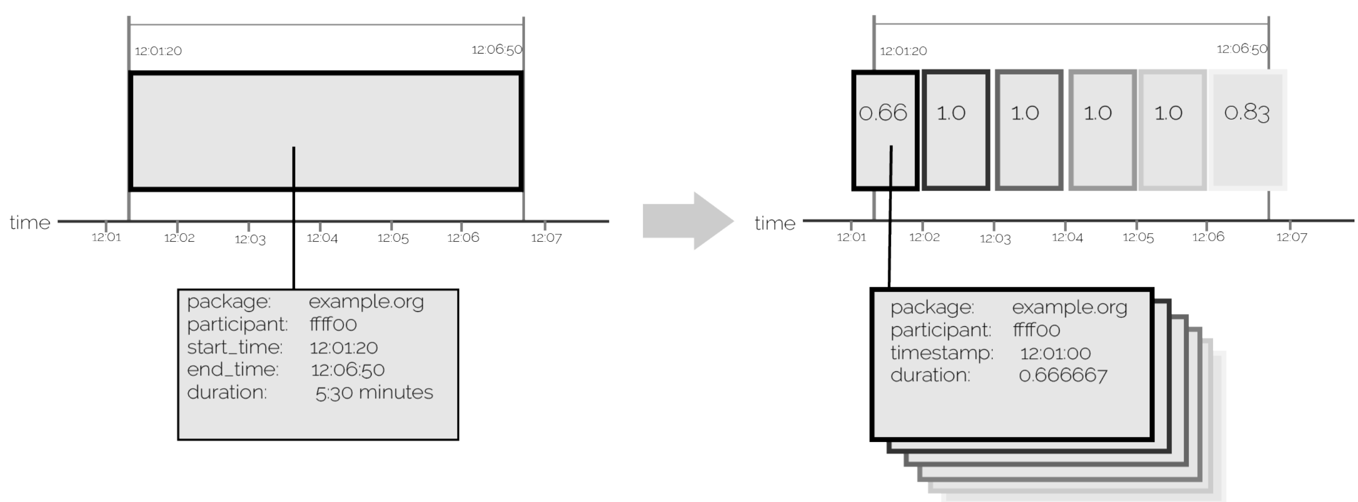
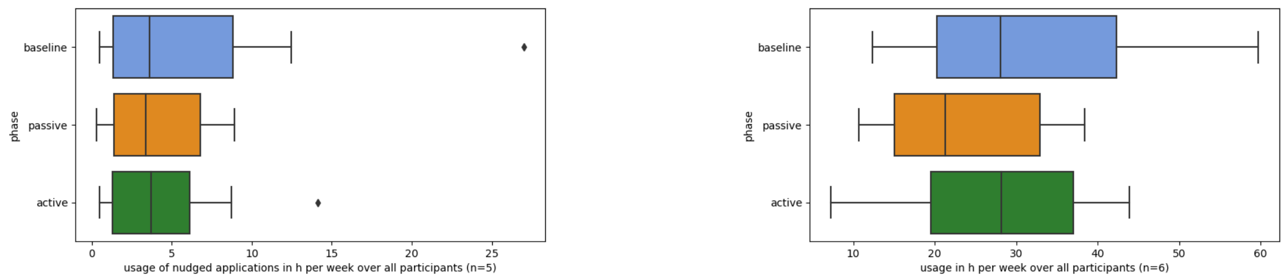


Figure 9: Transforming descriptive event data to data points for easier analysis.

5.2 Findings from survey and interview data

After the first week, participants completed a survey to share initial impressions and feedback, the survey hinted at user experience trends. However, more in-depth insights emerged from semi-structured interviews, with questions emphasizing on personal experiences with the prototype's features, the perceived reduction of screen-time, likes and dislikes and suggestions for future development. Analysis of these interviews, facilitated by a Miro dashboard, and performed by two researchers, identified the following key findings:

(1) **Watch Interface and User Experience**: The watch interface received favorable feedback from participants, although some found wearing the watch to be cumbersome. As Participant 2 described *I used my phone a lot more before that.[. . .] I wasn't used to wearing a watch. And so it was kind of like you have something that always reminds you why you're wearing this [watch] [. . .] I don't really like the watch, as my wrists are too small for the watch.* Participant 4 said *[. . .] Maybe just like being shown how much you use your phone on a daily basis, which the watch facilitates– you're consciously thinking about it. But after a while, it just gets thrown into your subconscious again. So you don't really think about it [=your usage] [any longer].*



(a) Weekly time on apps with limits by phases.

(b) Weekly overall phone usage by phases.

Figure 10: Analysis of weekly usage and changes for both overall and application-specific screen time.

(2) **Alarm Feature Feedback**: Although expressing annoyance with the alarm's vibration feature, participants provided overall positive feedback. Participant 1 shared *I limited my notifications to the watch just because it gets annoying, especially if you're in huge group chats or something. It vibrates all the time, which is really off-putting. [. . .] But you can customise it [=the notifications]. So that's fine.* Participant 6 said *Most useful was the vibration on the watch when I overused too much. Because it was really, you know, it made me kind of angry with the watch. But that was the point. [. . .] every time it vibrated, I didn't want it to repeat, so I didn't even use the app at all. So I just forgot about it. Yeah. So I think that's a good sign.*

(3) **Reduced Phone Interactions**: Participants observed that the watch potentially decreased their phone interactions by enabling them to read notifications directly on the watch. Participant 1 said *I would say that people tend to unlock their phone less if they have a watch just because you get notifications and you can check the time using the watch. Like I think most people they use, they're — even if they just want to check the time or they're bored, they will look at their phone and then say, Oh, I got a new notification. Then they unlock it. So, especially with certain apps that like get push notifications, they give push notifications, so you do engage. So yeah, I think the watch can curb that if that's what you want to do.*

(4) **Health Data Integration and Sleep Tracking**: While the integration of health and usage data was met with skepticism, the sleep-tracking capabilities of the watch were well-received. Participant 3 mentioned *I like, for example, that I could see how my heart rate changed during the usage of an app. So I could see the excitement that caused the item — the appeal of the app to use it, for example. And I also like that I could see my overall health a bit better. So I like to know when I'm stressed or how I could sleep, for example. [. . .] I think that I've improved my sleep a bit using this app or the watch overall.* Participant 5 said *I think — the most used features where the heart rate sensor and the sleep tracker [on the watch trough the Suunto app]. Because it was like, okay. And now we have a goal to live up to.*

(5) **Enhancing Alarms for Better Accountability**: There is a need to enhance the alarms with greater transparency and accountability. For instance, Participant 4 said *Like, if you set up a threshold for an app. I don't know if you could, like, maybe colour code how far away you are from that threshold.* Participant 6 explained *Like, I want to use the phone for 3 hours a day, and that's it and maybe you just get every hour [a] notification: You've used it for one hour — for 2 hours — as it gets closer to the 3 hours [limit].*

(6) **Structured Guidance and Goal Setting** :A desire for more structured guidance and recognition was expressed by participants, indicating a need for improvement in support. Participant 3 said *Something like an app-specific graph. Like, if you want to use, for example, Facebook a bit less than it would be useful if the app had some summary of only the usage of, for example, Facebook. And then you could set some goals for the week or so maybe or get some notifications that you did better this week and use it less or something like that.* Participant 4 mentioned *You could do something like where you see the — where you put in pre-configured alarms for the most used apps of that person. So the first week, you analyse usage using the watch, and the second [week], you say, "Okay, these are your top three apps. Would you like to set up an alarm for these apps"?*

6 DISCUSSION

Reducing screen time on phones and specific apps proved effective for most participants. The study heightened participants' awareness regarding their app usage patterns. Equipped with the prototype application and the smartwatch, they gained easy access to their usage statistics. This visibility enabled them to make more informed choices about their smartphone interactions, fostering a more mindful approach to app usage. For some participants, wearing a smartwatch was a new experience, acting as a constant reminder of their participation in the study and its objectives. Although this novelty effect tended to diminish over time, in some instances, had a more substantial impact on reducing app usage than initially expected. This was particularly true for those who found the watch's size and weight to be intrusive. We observed instances where nudged applications had set limits that were either close to or beneath the users' average daily usage from previous weeks. In these cases, the alarm feature effectively curtailed the usage of certain apps beyond their preset limits, presumably aiding in the reduction of overall daily screen time for these selected apps. Drawing parallels to the alarm design used by Okeke et al. [33], we infer that the alarm mechanism in our proposed design might not facilitate the development of lasting, sustainable habits over time. In many instances, participants nearly unanimously characterized the alarms as exceedingly irritating and overly aggressive. One participant even went so far as to say that the initial shock of the alarm was so jarring, that they made it their mission to avoid triggering it for the duration of the study. This reaction was not the desired outcome of implementing alarm nudges. Nevertheless, such responses offer valuable insights, highlighting the importance of careful nudge design, as advocated in the concept of "nudge for good" [57]. This behavior is anticipated to be a short-lived reaction, possibly resulting in the eventual discontinuation of the use of such interventions. This aligns with findings from Okeke et al. [33], who noted similar challenges regarding the long-term efficacy and sustainability of their interventions. The smartwatch, by offering timekeeping and notification forwarding features, potentially reduced the frequency of phone interactions for its wearers. By centralizing access to time and notifications, the watch could diminish the temptation to 'wander off' into other phone applications, thus lowering the likelihood of prolonged screen engagement. This concept echoes findings by Oulasvirta et al. [34], who suggested that the habit of checking one's phone can often lead to unintended usage of additional apps, thereby increasing overall screen time. However, the cognitive load associated with receiving notifications on a smartwatch might not be significantly less than that of notifications appearing on a smartphone. This similarity in "attention cost" between device notifications [22, 23, 54] indicates that the selection of which applications are allowed to push notifications to the watch should be made with careful consideration, aiming to balance convenience and potential distractions. The observed reduction in screen time cannot be attributed entirely to the smartwatch app. The mere presence of the smartwatch was found to be sufficient to prompt and remind participants to engage in a detoxification process. The evidence suggests that interventions targeting not only smartphones but also the wider ecosystem, including wearable devices such as smartwatches, have a significant impact on phone usage and result in a notable reduction in screen time. Also, external factors, such as increased workloads, social engagements, or travel, could beneficially influence screen time reduction by naturally limiting free time or altering daily routines. With all participants being students experiencing the busy end of the semester, their phone usage might have been affected. Although these potential influences weren't reported as significant or memorable by the participants during the interview and debriefing, they could have nonetheless played a role in changing their screen time behaviors.

Changing ingrained habits requires time and patience, often more than three months, for sustainable results, with setbacks and motivation lapses being part of the process [18]. Given this, the short-term nature of a two-week intervention is unlikely to yield lasting changes in phone usage habits, with initial reductions in usage typically not sustained over time. This was observed during the study, where usage decreased more significantly in the first week than in the second, indicating a possible decline in commitment to reducing screen time. Participant behaviors, such as disabling features critical for intervention effectiveness, with Participant 2, who disabled Bluetooth during the second week of the study, effectively killing alarm and watch-face data updates, highlight the challenges of maintaining reduced usage. Additionally, the discomfort reported by some participants wearing the prototype watch suggests that while it served as a reminder of their goals, the novelty and its effectiveness faded over time, leading to a probable return to undesired behaviors. This aligns with other studies questioning the long-term viability of digital detox interventions and the observation that even with access to digital well-being tools, many users remain only casually engaged, finding the data interesting but not motivating enough to spur behavioral change [12, 15, 27, 33]. During the study's active phase, participants were asked to set limits on apps they found problematic. One participant didn't set limits, leading to a decrease in overall screen time without significant changes in usage of the most-used apps. The prototype's design unintentionally kept the alarm feature inactive until the second week, a decision that, in retrospect, might have provided clearer insights if implemented differently. Some participants set their usage limits higher than their average, aiming to prevent binge usage rather than consistently reducing screen time. Automating limit settings based on past usage or guiding participants to set more realistic limits could enhance the effectiveness of usage reduction. However, the initial week didn't significantly improve usage awareness, preventing participants from setting impactful limits. Altering alarm settings due to annoyance led to less stringent limits, suggesting that allowing participants to set and adjust their own limits may reduce the alarm feature's effectiveness. Contrarily, fixed limits based on past usage, as seen in other studies [33, 52], could more clearly demonstrate intervention efficacy. Yet, overly strict limits risk intervention abandonment [12, 15]. Lyngs et al. [20] highlighted the infrequent implementation of expectancy components in digital interventions, pointing out the potential of exploring user confidence in reaching goals.

The sleep data from the study indicates most participants go to bed well past midnight. The prototype's definition of a "daily" timeframe as 00:00:00 to 23:59:59 may have led to discrepancies in app usage tracking, where resetting the app screen time at midnight allowed for usage without triggering alarms. This setup potentially reduced the timing effectiveness of alarms but not necessarily their overall effectiveness since usage was tracked. This scenario mirrors findings by Kim et al. [15], where users would wait for usage restrictions to reset at midnight to continue app use. Considering the importance of reducing screen time before sleep [24], it's noteworthy that app usage deemed alarm-worthy tended to spike between 22:00 and 01:00. In hindsight, resetting usage limits right before bedtime was counterproductive. This situation highlights the need for the application's concept of "daily" to align with the users' perceptions and lifestyles, ensuring that interventions like alarms are effective and timely.

6.1 Summary and recommendations

Addressing RQ 1, the alarms did not maintain the initial week's reduction in screen time for various reasons, including their possibly overly forceful nature. Yet, participants found them helpful for cutting down on specific apps, indicating a positive but not generalizable impact due to the study's small scale and brief duration. Future designs might benefit from incorporating positive reinforcements and more refined nudging strategies to effectively encourage screen time modification. The watch face's real-time feedback on phone usage was well-received, providing an easier and more accessible way to monitor screen time than using phone apps or settings. The physical presence of the watch served as a constant reminder to limit phone use, although its novelty and impact faded over time. The notification relay feature of the smartwatch, as noted by one participant, suggested the potential for reducing phone interactions, echoing Pizza et al. [38] discussions on smartwatches' roles in managing phone use. Overall, for RQ 1, smartwatches show promise in supporting digital detox efforts, yet the study only revealed limited short-term effects on screen time reduction. Regarding health data RQ 2, only sleep data provided usable insights, indicating a negative correlation between phone use and sleep quality. The inability to analyze heart rate and step data due to incompleteness accentuates the need for more robust data collection methods in future studies. Finally, answering RQ 3 requires reflecting on the intervention design and prototype issues. Participants' suggestions for improvements, such as alarm snoozing and greater transparency, highlight areas for enhancing user experience and intervention effectiveness. Adapting interventions based on goal-setting literature and user feedback could lead to more effective digital detox strategies.

7 CONCLUSION

This research introduces a novel method aimed at aiding individuals in their digital detox efforts, leveraging a smartwatch-smartphone ecosystem to implement an intervention based on negative reinforcements. Even though the the growing interest in digital well-being, the utilization of wearable technology in facilitating digital detox remains relatively unexplored both in academic literature and practical applications. The designed system features a mobile app that monitors and reports phone usage data, enabling users to set daily screen time limits for specific apps. Exceeding these limits triggers a vibration alert on the connected smartwatch, encouraging users to reduce their usage of the particular app. The system also integrates with Google Fit to provide a comprehensive view of the user's physical health metrics alongside their device usage data, offering a holistic approach to managing screen time and well-being. A preliminary study involving six participants provided insights into the effectiveness of this approach, revealing a significant reduction in screen time during the initial week of usage. However, the efficacy of the alarm feature in the second week was inconclusive, with participants either setting lenient limits or adjusting them to avoid triggering alarms, suggesting difficulties in establishing realistic self-regulation goals or resistance to the intervention's intrusiveness. Smartwatches exhibit potential as tools for enhancing digital detox initiatives, as evidenced by participants' increased awareness of their screen habits and a reduction in phone interactions, facilitated by the watch face's easy access to usage stats and health data. Yet, the study's limitations, including its brief duration and small sample size, temper the conclusiveness of these findings. Participants' mixed feedback about the alarm's effectiveness and their appreciation for the watch face's simplicity indicate areas for further development, emphasizing the need for a more user-friendly and adaptive intervention design. Future directions should explore the integration of smartwatches with emerging health data standards like *Health Connect*[19], expanding compatibility and potentially increasing user adoption. Additionally, adopting a more nuanced approach to tracking and intervening in phone usage—possibly through innovative metrics and personalized feedback—could enhance the efficacy and user acceptance of digital detox solutions. A key area for further research is the psychological impact of reducing screen time. Future research should aim to provide a more comprehensive assessment of the psychological indicators of well-being, encompassing positive and negative affect, anxiety, and other measures of psychological well-being. This focus is essential in order to determine the efficacy of reducing screen time and its ultimate utility in enhancing overall mental health, thereby addressing whether such reductions are genuinely beneficial in the long term.

Limitation. The study has a few constraints that impact the scope of its findings. The small number of participants and technical issues could have influenced the limited data collected. The study's short duration of two weeks likely captured only the immediate effects of the intervention, with the intensive alarm feature possibly leading to longer-term disengagement. The intervention design, while adaptable to a smartwatch interface, deviates from established best practices and lacks personalized feedback, suggesting room for improvement. Participant diversity is limited, as all are university students from similar backgrounds. Additionally, the user interface's reliance on color coding poses accessibility issues for individuals with color vision deficiencies, indicating a need for more inclusive design considerations.

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