Quantifying Sources and Types of Smartwatch Usage Sessions

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ABSTRACT
We seek to quantify smartwatch use, and establish differences and similarities to smartphone use. Our analysis considers use traces from 307 users that include over 2.8 million notifications and 800,000 screen usage events, and we compare our findings to previous work that quantifies smartphone use. The results show that smartwatches are used more briefly and more frequently throughout the day, with half the sessions lasting less than 5 seconds. Interaction with notifications is similar across both types of devices, both in terms of response times and preferred application types. We also analyse the differences between our smartwatch dataset and a dataset aggregated from four previously conducted smartphone studies. The similarities and differences between smartwatch and smartphone use suggest effect on usage that go beyond differences in form factor.

Author Keywords
Smartwatches; smartphones; usage; session; interactions; applications.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
This large-scale longitudinal study focuses on quantifying how smartwatches are used in daily life. The lack of adaption of smartwatches in general population may be due to lack of a "killer app" sufficiently distinguishing the smartwatch from the smartphone [16], the fact that long-term added benefits of using smartwatches are still unclear, or due to (technical) limitations of smartwatches (*i.e.*, network and battery limitations, smaller screen size). Smartwatches need to combine two requirements [16]: provide digital information and functionality of a traditional watch, as well as the ability for personal expression. Wu *et al.* [39] surveyed smartwatch users and concluded that the largest impact users desire from smartwatches are *visible and tangible benefits* when used.

Current smartwatches enable users to synchronise notifications, interact with their smartwatch applications, and display short pieces of information. Min *et al.* [20] report on differences in desired smartwatch functionality between novel users (less than 3 months of experience) vs. experienced users, with novel users prioritising time keeping, while experienced users prioritise notifications in a hypothesised power-saving mode. Overall, notifications are perceived as the main functionality of the smartwatch, with 98% of participants ranking it as the most important feature [20]. Similarly, other studies report the notification functionality [18,40] and the associated ability to access smartphone information using more inconspicuous cues [6,23,25] as equally important, indicating that smartwatches play a different social role when compared to smartphones. Understanding the similarities and differences in smartwatch and smartphone use can inform us about how this technology is appropriated by end-users, and whether current interaction methods are suitable.

We investigate the frequency and context of smartwatch notifications, and their associated usage sessions. We analyse a dataset collected from 307 unique users during the first half of 2016, and perform a quantitative analysis on how and when users interact with their smartwatches. We analyse the dataset in terms of usage session types based on both the source of the device use, and in terms of interaction styles. To the authors' knowledge, this dataset is the largest currently available on smartwatch usage. We also collect smartphone usage data to understand the similarities and differences in smartwatch and smartphone use. These differences can inform us about how this technology is appropriated by end-users, and whether current smartwatch interaction methods are suitable.

RELATED WORK
While early smartwatch models faced significant technical limitations for general adoption (*e.g.*, limited battery life [27]), these problems have since been reduced. Min *et al.*

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[20] studied the recharging habits and battery use of smartwatches, and concluded that a modern smartwatch can easily maintain functionality for a period of at least 24 hours, usually more, depending on the user. The participants were not unanimously satisfied with the battery life of their smartwatches and 53% experienced situations where the smartwatch ran out of battery more than once per week. In this paper we focus on the way smartwatches are used, and not on the technical capabilities of the devices.

Purpose and Usage of Smartwatches

Wu *et al.* [39] conducted a survey of 212 participants, and drew conclusions on the different factors that impact consumer's acceptance of the smartwatch. Neither ease of use nor gender have impact on the acceptance of the technology, as people have already accustomed to handling wristwatches. The key requirement is *result demonstrability* [21,36], indicating that the outcome of smartwatch use should be able to be both communicated and observed. A smartwatch can be used as a simple extension of a smartphone, where the benefits of its use need to be quantifiable, or as a standalone device/platform for an application, where the benefits are implicit as long as the application(s) are useful to the consumer.

Smartwatches also enable inconspicuous use, compared to smartphones, which can release the social tension caused by frequent smartphone use [23,25]. Additionally, the nature of a persistently carried device on one's wrist can reduce the problem of user availability [3,30]. Yalçin [40] reports survey results regarding prioritising notifications on smart devices and notes that, similar to smartphones, users attend to notifications from specific application categories, such as communication or calendar applications, and tend to dismiss notifications from other types of applications, such as games. PrefMiner is an application developed by Mehrotra *et al.* [19] for creating personal notification preferences, but is limited to smartphones. Weber *et al.* [38] studied users' notification preferences in multi-device environments with over 50% of their participants wanting to receive notifications via their smartwatch instead of their larger devices.

Applications of Smartwatches

Wearable devices have become an important tool in solving health problems [22] as they provide various applications for monitoring energy expenditure, hence promoting physical activity amongst users [5]. In particular, the gamification aspect of smartwatch applications encourage improvement or keep up the healthy lifestyle by rewarding the users for achieving the daily steps or exercises goals [16].

Smartwatches may collect biological, environmental, and behavioural information about user's activity due to constant contact with skin [15]. Smartwatches are also likely to be carried in-person throughout the day and do not have the issue of being forgotten somewhere, or being in a state where the user is not necessarily alerted of incoming messages or notifications.

Researchers also studied detection of eating [7,26,33], smoking [31,33], drinking coffee [33], and giving a talk [33]. Findings suggest that being able to detect human activities might help in mitigating bad habits, such as drinking too much coffee, smoking, or skipping a meal [33], and argue that detection of user activities might be useful in determining the optimal time for interrupting the user. For example, the user should not be interrupted while typing or writing, but could be interrupted while drinking coffee or smoking [33].

Micro-usage and Interactions

The literature contains relevant work on user's behaviour on both smartphones and smartwatches. As the smartwatch is often used in conjunction with the smartphone of the user, its usage patterns influence the way smartwatches are used. Smartphone usage can be classified into *glance*, *review*, and *engage* categories [2], ranging from short interactions in which only the lock screen is queried for the latest notifications, to long usage sessions in which multiple applications are used.

Ferreira *et al.* [9] introduced the term *application micro-usage*, describing the brief bursts of application interaction: "*approximately 40% of application launches last less than 15 seconds and happen most frequently when the user is at home and alone*" [9]. Smartphone usage is typically short, with Yan *et al.* [41] finding that 50% of mobile phone engagement lasts less than 30 seconds. Van Berkel *et al.* [35] distinguish between continued and new usage sessions. Their results show that for the majority of cases in which people unlock their phone, they intend to start a new objective as opposed to continuing a previous one. Previous work also briefly looks at the types of sessions and interactions on smartwatches, and both Min *et al.* [20] and Gouveia *et al.* [13] report users habitually engaging in brief usage sessions.

Notifications are a critical component of smartphone interaction, with users receiving an average of 63.5 notifications per day according to study by Pielot *et al.* [24]. Most notifications are checked by the user within a short time interval, with messages and emails generating majority of notifications [24]. New ways in which users will operate their combined smartphone and smartwatch are being actively explored (*e.g.*, a diabetes diary toolset [1]), as well as explorations on which device is more suitable for which interaction (*e.g.*, driver engagement to notifications [12]).

Although notifications are inherently disruptive and distractive [29], users place value on receiving notifications from sources important to them. For instance, Sahami Shirazi *et al.* [29] conducted a large-scale assessment of mobile notifications and report that users value notifications depending on their source: messages and notifications about people and events are more important, in line with the survey results of Yalçin [40].

DATASET

Our smartwatch dataset was collected in-the-wild with an application available on Google Play Store called Insight 4 Wear[1], introduced in [28]. The user accepts the provided end-user license agreement to allow the application to store the information locally and periodically (every three hours), check for Wi-Fi connectivity, and upload the logged data to the server. All data is anonymised to respect the user's privacy and no contact information is stored. The users are all anonymous and only device identification numbers (Android device ID) are stored. Due to the anonymity of our users, we are not able contact them. The demographic distribution of the users (provided by Google Play Store) shows 44.72% of the users are from North America (US and Canada), 26.13% from Central Europe (UK, Germany, Spain, France, Netherlands), 3.02% from Australia, 2.51% from India, and 23.62% from elsewhere. Our analysis considers the following recorded data:

Data	Entries
Notification information Time when the notification was displayed on the device, and what application triggered it.	2,801,082
Screen events When the screen was turned on, when the screen turned off.	800,119
Device ID	307

Table 1. Information about the dataset.

In total, 307 users contributed data. The data was collected between January 1st 2016 and July 15th 2016. 74.6% of the users (N = 229) had the application installed and logging for *less than 30 days* (M = 7.09, median = 4.02), 19.5% of the users (N = 60) for a timespan *between 30 and 90 days* (M = 74.86, median = 64.03), and 5.9% of the users (N = 18) for *more than 90 days* (M = 133.40, median = 135.47). We were able to collect manufacturer and model details from 267 devices (Table 2).

Application Categories

Each notification contains the package name of the triggering application, which is a unique identifier set when the developer uploads the application to Google's Play Store. This package name is stored with each arriving notification. Thus, we were able to infer the applications category of each notification in our dataset by cross-referencing with the Play Store. In addition, we followed the recommendation by Brown *et al.* [4], and further grouped applications into more general categories (Table 3).

Smartwatch Data Pre-processing

Android Wear smartwatches allow interaction through touch or voice commands. The screen can be turned on by touch, by moving one's wrist, or by incoming notifications as long as the smartwatch is already in a specific position (the screen facing upwards) or if the light sensor detects a light source towards the screen. This makes it challenging to programmatically infer intentional interaction. We use similar methodology as Gouveia *et al.* [13] to infer usage sessions where we consider the screen ON and OFF events on the device.

Device Model	Manufacturer	Devices
Moto 360	Motorola	83
HUAWEI WATCH	HUAWEI	49
SmartWatch 3	Sony	39
G Watch R	LG	36
LG Watch Urbane	LG	23
G Watch	LG	12
ASUS ZenWatch 2	ASUS	9
Gear Live	Samsung	9
ASUS ZenWatch	ASUS	5
Samsung Gear 2	Samsung	2
Unknown	Unknown	40

Table 2. Distribution of device models.

General Category	Application Categories [4]
Communication	Communication
Productivity & Admin	Productivity, Tools, Education, Business, Books and Reference, Finance, Personalization
Health	Lifestyle, Health and Fitness, Medical
Internet & Social	Entertainment, News and Magazines, Sports, Social
Maps and Travel	Travel and Local, Weather, Transportation, Shopping
Media	Music and Audio, Photography, Media and Video
Games	All categories of Games
Other	Unspecified or unlisted in the Play Store

Table 3. Application generic categorisation.

To infer interactions and usage sessions from the dataset, we combine screen use data (indicating when the screen was turned on) and notification data (indicating when a new notification has arrived on the smartwatch). We begin by cross-referencing the arrived notifications with the screen use data.

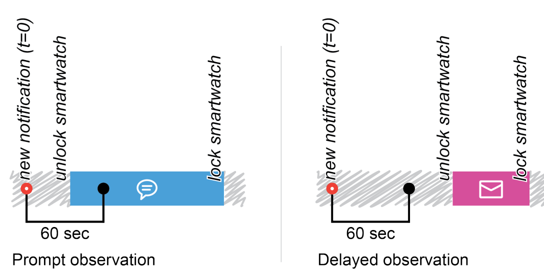

Figure 1. Labelling a notification on how swiftly it is observed.

[1] http://insight4wear.com

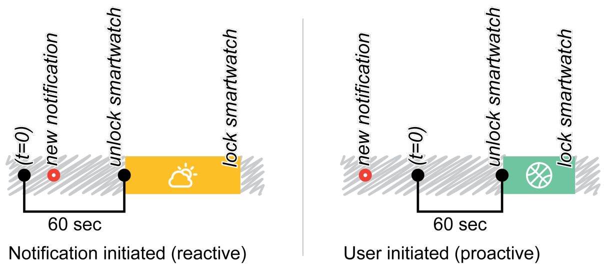

Figure 2. Labelling each session as *notification initiated* or *user initiated*.

Figure 1 illustrates the two different scenarios: a notification is either observed promptly following a specified time window, or the observation is delayed. We apply a 60 sec. window to each notification, after which we do not consider the particular notification in our analysis due to its observation being delayed significantly. The threshold was determined based on previous work [29], that showed that roughly 60% of interactions with notifications occurs in the first 60 seconds, followed by a very long tail for remaining interactions. Ultimately, for each notification we include: user ID, source application, time, label (observed *promptly* or with *delay*), and session length (if available).

Next we analyse each of the logged usage sessions using a 60 sec. window (Figure 2) to determine if a usage session was *notification initiated* (reactive) or *user initiated* (proactive). For each usage session we include: user ID, start time, duration, usage label (user vs. notification initiated), and source application of the notification (if available).

The dataset contains some known outliers. For example, usage session where the screen is turned on for a long period of time are instance where the devices are likely to be charging. To prevent these erroneous entries from skewing the data, we apply a low-pass filter of 5 minutes. A total of 1696 (0.2%) sessions were removed due to the filter. We base the threshold on two earlier studies [8,41] on smartphone session lengths, where the session length ranges from ten seconds to four minutes. We argue that removing the entries over this threshold discards sessions where the user was not aware of the device's screen being on, or sessions where the user did not interact with the device regardless of the screen being on. Additionally, the sessions analysed by past literature (for smartphones) report *continuous* usage sessions, consisting of several *individual sessions*, tend to not exceed five minutes on average [34,35].

Observing the distribution of usage session length (where the notification was not ignored or missed, N = 328,587), we noted that the median session length is exactly 5 seconds and that 22.1% of all the sessions have this exact length (N = 72,786, M = 8.63). These values are also visible in Figure 10. This is a hardcoded delay when the screen turns on and off without any further user interaction. Therefore, we label all sessions lasting five seconds or less as "*peek*", and those lasting longer than five seconds as "*interaction*".

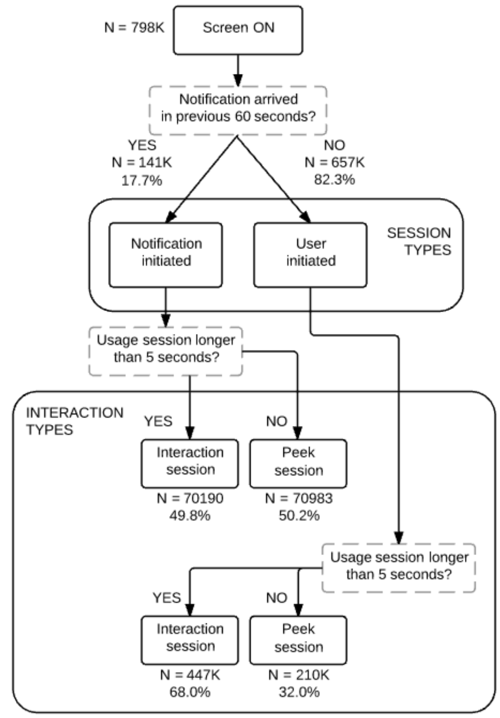

Figure 3. The categorisation of usage sessions.

Because the preferred smartwatch features broadly fall under "functionality" and "notifications" [16,20], we divide usage sessions into a) *proactive* sessions (where the smartwatch was used to glance at screen for time unprompted), and b) *reactive* sessions (sessions where the device use was due to an arriving notification).

Our pre-processing gives rise to two datasets. Firstly, a dataset of 798,423 usage sessions labelled by *session type* (peek vs. interaction) and *session initiator* (notification vs. user). The distribution of usage sessions to these categories is shown in Figure 3.

Secondly, a dataset of 2,801,082 entries containing the notifications that arrived on the smartwatch, shown in Figure 4, and labelled according to: the users' response - observation is either prompt or delayed, the length of the resulting usage session, and the delay between the notification arriving and the beginning of the session.

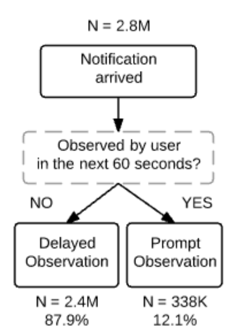

Figure 4. The categorisation of arriving notifications.

Both smartwatch datasets contain further data on user, time, application, and application category.

Comparison to Smartphone Dataset

From four previously published studies [10,14,35,37], we aggregate a dataset of 347,576 smartphone screen entries, from 445 unique users between February 2014 and May 2016, which we then transform into 120277 unique usage sessions. Each session has an associated session length (M = 229.34 seconds), and the daily session count (M = 60.08) for that user on that particular day. This dataset is used to draw quantified comparisons between usage sessions on smartwatches and smartphones. There was no information in these datasets regarding the arrival of notifications or used applications so analysis on these aspects was not performed.

ANALYSIS AND RESULTS

We refer to *usage session* or *session* to describe instances where the smartwatch was used (the screen was turned on). We identify two **interaction types**:

- **Peek**, a brief usage session where the device is used for five seconds or less. (N = 517,989).
- **Interaction**, a longer usage session lasting for more than five seconds. (N = 280,434).

And two **session types**:

- **User-initiated (proactive):** A usage session that does not follow a notification arriving on the device, indicating that the user chose to interact without being prompted. (N = 657,250).
- **Notification-initiated (reactive):** A usage session that follows a notification arriving on the device within the previous 60 seconds, indicating that the user was prompted to use the device due to the notification. (N = 141,173).

We use a Chi-Square test to analyse how usage sessions and notifications are divided throughout the day. Unsurprisingly, the results show that both sessions ($\chi^2 = 254{,}280$, $p < 0.05$) and notifications ($\chi^2 = 452{,}700$, $p < 0.05$) are unevenly spread across the hours, mostly focused during 8am-10pm. Users who had logged data from at least seven days had an average of 142.1 usage sessions (5,107 days, 725,548 sessions) per day. The usage sessions from smartwatch and smartphone datasets are divided across day according to Figure 6. The increased use of the smartwatch during daytime (8am to 8pm) is clearly visible in the distribution of the usage sessions. Next we describe the results of our analysis on the different interaction and session types in terms of hourly frequency during a day, followed by other conditions, such as application category.

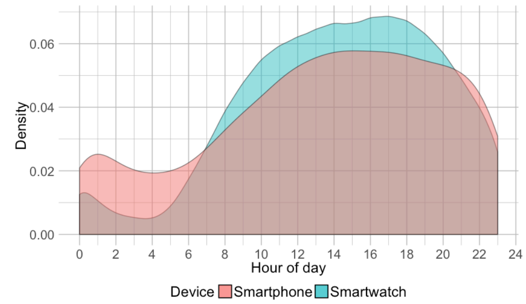

Figure 6. Distribution of sessions throughout the day.

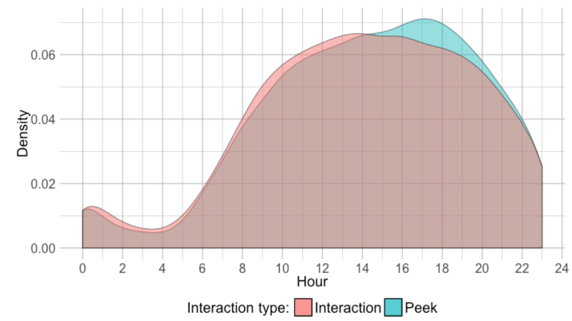

Figure 7. Session density on smartwatch throughout the day according to *interaction type*.

Usage Sessions on Smartwatches

We analyse the frequency of sessions by comparing the "peek" (N = 517,989) and "interaction" (N = 280,434) categories using a Chi-Square test for both hourly granularity, and for period of the day (divided into night, morning, afternoon, and evening). Both tests are significant ($p < 0.05$) for the two different categories, hour of day (χ^2(hour) = 1192.9) and period of day (χ^2(period) = 611.9), indicating that the time and period of the day result in different type of device usage. In the later hours of the day (from 2pm to 10pm), users are more likely to engage in brief *peek* sessions, rather than in a longer *interaction* session (Figure 7).

We analyse the frequency of sessions according to whether they were *user initiated* (N = 657,250) or *notification initiated* (N = 141,173). Two Chi-Square tests considering hour of day and period of the day gave significant results ($p < 0.05$); χ^2(hour) = 203,820 and χ^2(period) = 164,940 for user initiated sessions; χ^2(hour) = 51,605 and χ^2(period) = 41,313 for notification initiated sessions.

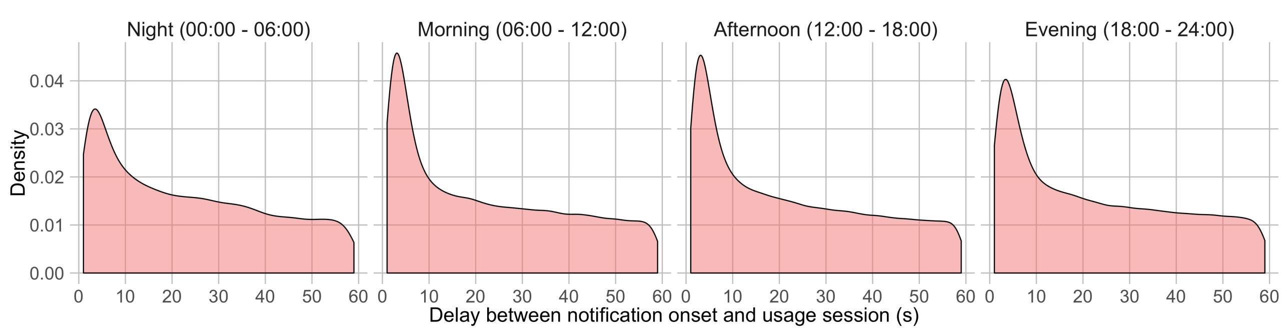

Figure 5. Delay between an arriving notification and the following usage session according to the period of day.

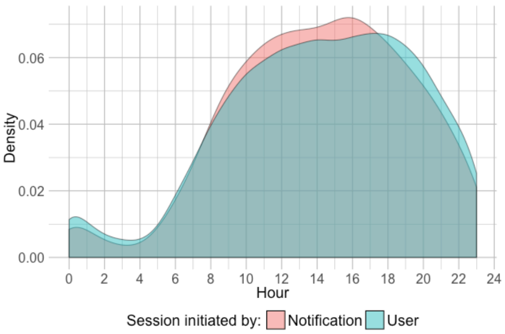

Figure 8. Smartwatch session density throughout the day according to *session type*.

Finally, a Chi-Square test between the two conditions (user initiated and notification initiated) across the hours of the day was significant ($\chi^2 = 898.09$, $p < 0.05$).

These results indicate that the two types of sessions vary significantly during the day (Figure 8), and across each other. Specifically, we observe that during the morning and afternoon (between 8am and 5pm) a device use is more likely to be initiated by an arriving notification than by the user's own volition.

Next we consider how session *duration* varies throughout the day. A two-way ANOVA shows that the interaction effect of how a session is initiated (user vs. notification) and hour of the day significantly affect session duration ($F = 25.56$, $p < 0.05$), as well as both the main effects (F(hour) = 161.66, F(session type) = 4419.77, $p < 0.05$).

The findings show that the length of the smartwatch session fluctuates during the day, and sessions tend to be longer during the night (1am to 5am) (Figure 9). The smartphone sessions show less fluctuations, average session length being 3 minutes 52 seconds, and the mid-day sessions being the shortest (M = 3 minutes 35 seconds). Also, smartwatch sessions initiated by notifications are longer: the mean length for notification-initiated sessions is 10.67 seconds, and 7.94 seconds for user-initiated (Figure 9 and Figure 10). The mean differences are significant, tested using two sample t-test ($t = 55$, $p < .05$), and Kolmogorov-Smirnov test shows the differences between the two distributions ($D = .176$, $p < 0.05$). The differences of the session length distributions between the two smartwatch conditions are clear, as user initiated use is often shorter than, or exactly five seconds, indicating brief glances at the device. It can also be considered likely that when user is presented with a notification, consuming this information will take time and the following interaction with the device is longer than for the user initiated sessions. Note that sessions less than five seconds in length indicate the user interacting with the device followed by actively turning off the screen, which also happens more frequently for user-initiated sessions. Additionally, when comparing the session lengths between the two devices, smartphone sessions are clearly longer duration.

Next, we consider the hourly frequency of users observing notifications promptly (notification followed by device use), or with a significant delay (no device use after an arriving notification). A Chi-Square test was statistically significant ($\chi^2 = 31.801$, $p < 0.05$) indicating that users are more likely to observe the arrival of a notification during different times of day. Specifically, users are more vigilant in the late afternoon (4pm to 6pm) and less vigilant early in the morning or late in the evening. The hourly trend of promptly observed notifications is very similar to the general trend of arriving notifications with a significant correlation between the two distributions ($t = 17.248$, $p < 0.05$, $r = 0.97$). The distribution of notifications across the day is shown in Figure 11.

Finally, following the recommendations by Van Berkel *et al.* [35] and Soikkeli *et al.* [34], we verify the existence of *continuous* sessions consisting of multiple *individual* sessions within a certain time threshold (T = 45 seconds, as per [35]). This may represent cases where a user quickly and repeatedly uses their smartwatch, with short breaks in between, to complete a larger objective. For each session we look for a subsequent *user initiated* session within this time threshold recursively. We found that 81.1% of usage sessions do not satisfy this requirement, while 10.9% of cases consist of two consecutive sessions, and 9% consist of three or more (Figure 12). These results show the scattered nature of smartwatch use, and also show that with more frequent use – continuous sessions with more than two individual sessions – the average length of the interaction in each individual session decreases.

Notifications and Application Categories

In the collected dataset, most notifications are from five application categories: 38.5% from "Tools", 21.9% from "Travel and Local", 11.6% from "Other", 9% from "Communication", and 6% from "Health and Fitness". Only 9.4% of all notifications result in potential interaction sessions (*peek* or *interaction* sessions), and 19.7% of the notifications arrive when the device is already in use, or while charging.

The mean delay for the notification initiated usage sessions is 23 seconds (median = 20 seconds), and the mean *interaction session* length is 17.89 seconds. Figure 8 offers further understanding of how swiftly arriving notifications are responded to. The delay between the notification arriving and the start of a usage session was significantly different

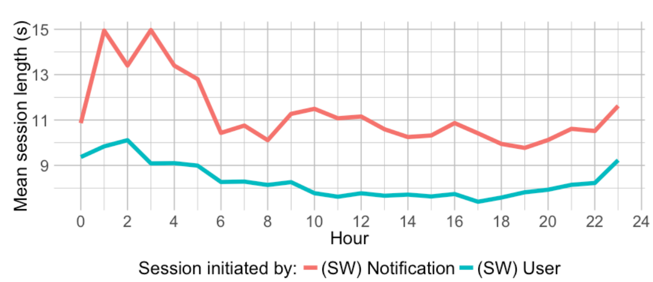

Figure 9. Mean session lengths throughout the day according to the smartwatch (SW) session type.

($F(3, 338{,}132) = 43.83$, $p < 0.05$) across the different periods of the day. We chose not to test the difference in delay per application category, because the user has no way of knowing which application was responsible for the notification prior to observing the notification and starting new usage session. Users observe arriving notifications faster during daytime (6am to 6pm) than during the evening and the night.

Of the notification-initiated sessions, 50.4% lasted equal or less than 5 seconds and are considered *peek* instances, while the remaining 49.6% were longer *interaction* instances.

To analyse the impact of application categories on *session types*, we ran a Chi-Square test over the two variables *session type* (interaction vs. peek) and *application category*. The results were significant ($\chi^2 = 7{,}124.9$, $p < 0.05$) and can be seen in Figure 13. These results indicate that application category of an arriving notification has a significant impact on the resulting device use, in terms leading to interaction or being peeked at. Users are more likely to start an interaction session when the arriving notification is from e.g. "Communication" category, and more likely to peek (and not interact) when the notification is triggered by an application from "Maps and Travel" or "Health" category.

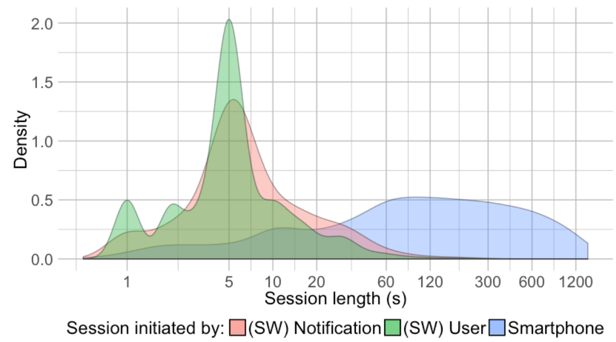

Figure 10. Overall density of session length distribution for both smartwatch (SW) session type (red, green) and device type (Smartphone = blue).

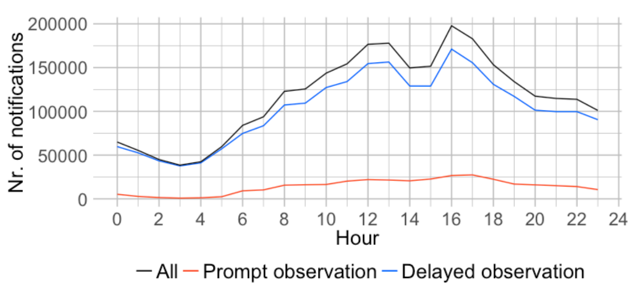

Figure 11. Notification distribution of all (black), promptly observed (red), and delayed observation (blue).

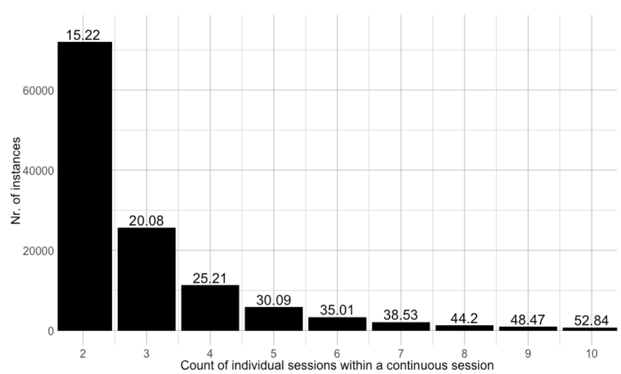

Figure 12. Multiple individual sessions make up a continuous session. Number above bar represents the mean duration (sec) of the continuous sessions (excluding breaks between use).

Next we look at the relationship between session length and application categories. We compare session length across both the general categories and the individual application categories (see Table 3). A statistically significant difference (one-way ANOVA) was found between session length and both the general category level ($F(7, 141165) = 133$, $p < 0.05$) and application category level, ($F(36, 141136) = 67.86$, $p < 0.05$) respectively. Sessions initiated by "Communication" or "Other" notifications lead to longer session lengths than from e.g. "Maps and Travel". The results are visualised for the general categories in Figure 14.

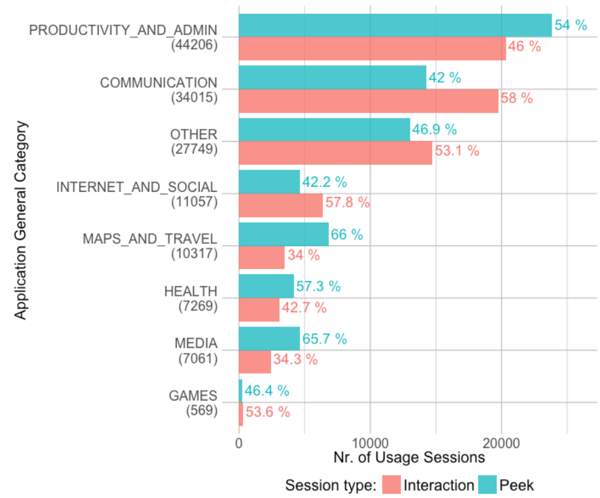

Figure 13. Interaction type per general application category.

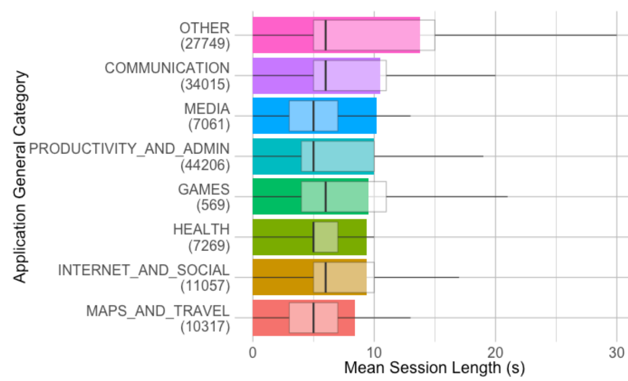

Figure 14. Mean (bar) and distribution (box) of session lengths for different general application categories.

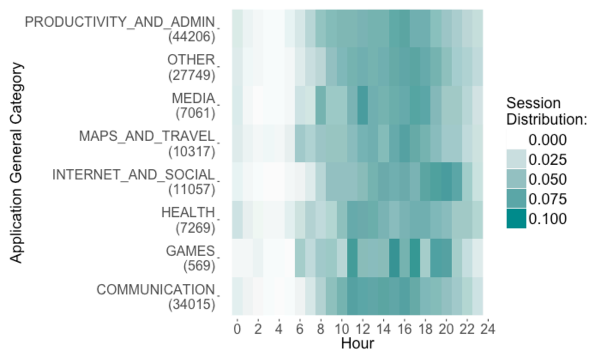

Figure 15: Notification initiated sessions according to the source (general category) of the arriving notification.

Lastly, we analyse the distribution of *usage sessions* initiated by an arriving notification over the course of the day using both the general application categories and individual application categories. The results were significant for both general ($\chi^2 = 3{,}360.4$, $p < 0.05$) and individual ($\chi^2 = 9{,}795.6$, $p < 0.05$) application categories, indicating that time of day has an impact on the frequency of notification-initiated usage sessions from different application categories, as visualised in Figure 15. The distributions are normalised for each category (horizontally), so the visualisation shows that users prefer notification initiated use from "Communication" applications during the daytime (from 8am to 4pm) over other periods and from "Internet and Social" applications during the evening (6pm to 10pm).

In conclusion, our results show that the nature of smartwatches leads to different type of use than with smartphones. The results of session lengths and daily counts between our smartwatch and smartphone datasets are visualised in Figure 16. The trend of shorter and more frequent sessions on smartwatches is clearly visible.

DISCUSSION

Given our analysis of a large-scale smartwatch usage dataset, we are now able to draw comparisons to previous findings on smartphone usage found in literature. To the authors' knowledge, our work is the first to report a large-scale quantitative investigation of smartwatch use in-the-wild. In addition, we consider how both internal factors (notifications) and external factors (time of day) affect use.

External factors in particular enable us to begin articulating the daily habits and activities of the users. Conversely, internal factors reveal *interaction requests* from the device in the form of arriving notifications. The combination of these two factors captures some of the underlying reason for smartwatch usage sessions, and offers some insight about the purpose of these devices, and their relationship to smartphones.

Session Types

We identify two session types, *user initiated* (proactive use) and *notification initiated* (reactive use) and show how the internal factor of requested attention impacts the frequency of the two different types (Figure 8).

The majority of sessions (80.0%) are initiated by the user, with these user initiated sessions being on average shorter (mean of 7.94 seconds) than notification initiated sessions (mean of 10.67 seconds) (see Figure 9 and Figure 10), while sessions on smartphones are longer - Soikkeli *et al.* [34] report 4 minutes and 23 seconds on average and data from our aggregated datasets reports 3 minutes and 49 seconds.

Since the smartwatch also serves as a device used for timekeeping, a large portion of usage is expected to be *peeks*. Our results in Figure 3 show that about more than half the sessions (65.2%) are *peeks*, for example to check for arriving notifications or new messages, even when no cue is presented to signal the arrival of a notification or a new message.

These results suggest that the habit of quick unprompted *peeks* (and micro-usage [9]) seems to carry from smartphones to smartwatches, and longer unprompted interaction sessions are less frequent. For smartphones, Banovic *et al.* [2] classify a median of 46.6% smartphone usage sessions as a glance session, which is their shortest classification on usage duration. We argue that for smartwatches, ease of access results in an increase in peeks, since the user does not need to go through the physical procedure of digging his or her pocket or bag for the device.

This ease of access is further highlighted by the fact that our smartwatch users had on average 142.1 sessions per day. The amount of daily sessions is higher than the previously reported values by Gouveia *et al.* (107 sessions per day) and

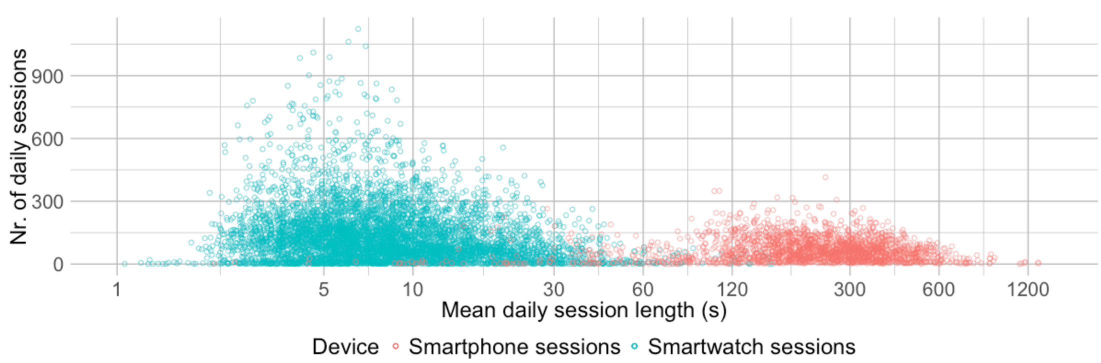

Figure 16. Distribution of daily usage sessions between smartwatches (blue) and smartphones (red).

Min *et al.* (95.6). This is an order of magnitude bigger than the respective values for smartphone use, as in our aggregated smartphone dataset we identified an average of 60.1 sessions per day. Van Berkel *et al.* [35] report differences in the total session lengths when taking into consideration *continuous* sessions consisting of multiple *individual* sessions, but for our smartwatch dataset the session lengths of the continuous sessions follow a different trend. When repeatedly initiating new usage sessions close to each other, the average length of each individual session is progressively reduced, indicating less interaction with the device and type of use that can even further be more associated to the (habits) of brief glances.

Multiple elements are likely to contribute to the differences in smartwatch and smartphone use. First, smartwatches are limited in their input capabilities, making these devices more suitable for consuming content rather than generating new content. Second, the typical placement of the smartwatch (on the wrist of the user) allows for quick interaction, explaining the higher number of daily interactions. Third, the smartwatch is likely to be used as a timekeeping device, adding to the number of (short) interactions. Last, the current user base of smartwatch users is most likely to be self-selected technology enthusiasts, therefore also explaining the high number of daily usage sessions.

User expectations with regards to notifications are different for different form factors, as was shown by Sahami Shirazi *et al.* [32]: calendar, VOIP, and messenger notifications rated as most important for smartwatch users. Figure 13 shows that the application categories of “Productivity and Admin” and “Communication” make up for the most number of usage sessions. This indicates that not only do users believe notifications from these applications are most important, but these applications actually occupy most of their smartwatch usage time.

Impact of Application Types

Next, we analyse the associations between different application types and smartwatch use in more detail. We found that both the frequency and length of a session are impacted by the application type, as shown in Figure 14 and Figure 15. The visualised data consists solely of sessions following a notification. This indicates that when a user’s attention is requested, the source of request significantly impacts the resulting interaction. Similar to results reported by Sahami Shirazi *et al.* [29] - users are slower to respond and more likely to dismiss notifications from sources they do not deem important - the source of the notification on smartwatches also impact the resulting interaction. Notifications generated by different application types are more likely to prompt interaction sessions at different times of the day (Figure 15), result in interactions of different length (Figure 14), and also impact the session type (Figure 13).

This behaviour of selective use based on the source of the notification is similar to that observed on smartphones, with similarities reflect even the level of application category. Users are more likely to *interact* (usage of longer than five seconds) with the smartwatch when prompted by an application from “Communication”, “Internet and Social”, or “Other” general categories, and more likely to *peek* the smartwatch when prompted by an application in the “Productivity and Admin”, “Maps and Travel”, “Media”, and “Health” categories. These results match the survey results of previous work of Yalçin [40].

Our results also indicate the user can benefit from the ease of access provided by the wrist-worn smartwatch:

- As a tool for communication and social interaction, as indicated by the finding that users are more likely to interact when prompted by an application in the “Communication” or “Internet and Social”.
- As a tool for navigation, quickly glancing for guidance or instructions, as indicated by fact that users are likely to spend less than five seconds using the smartwatch when prompted by a “Maps and Travel” application. Another corollary can be that these prompts are dismissed by the user.

The inherent nature of the same notifications being presented to both the user’s smartwatch and smartphone prompts a similar style of interaction on both devices. This is reflected by the fact that the impact of notification source on smartwatch interaction is similar to that observed in the smartphone. Our results might give precedence to the idea that notifications that require interaction can be pushed to the smartwatch only if they are likely to be relevant for interaction methods available on the smartwatch. Applications that are more preferably handled on the bigger smartphone could be delivered there.

Temporal Context

The smartwatch also features some unique interaction possibilities. Smartphones have been criticized for their disruptive nature in social context, with users admitting they disapprove of mobile usage behaviour they display themselves [25]. Here, the smartwatch could potentially offer a more inconspicuous way of fulfilling these information needs. We measured the external factor of time and its impact on the types of usage sessions. For most of the day, except afternoon hours, the frequency of *peek* and *interaction* sessions are similar, as visualised in Figure 7. The main differences between the conditions occur during the afternoon hours. It is also shown that most notifications are *promptly observed* by the user during noon (lunch hours) and late afternoon (around 4). However, considering that overall distribution of promptly observed notifications and distribution of notifications over the day (Figure 11) correlate strongly, indicating that the time of the day itself has no significant impact on the likelihood of a notification going unnoticed, as more notifications also arrive during these time periods.

The low impact of time on the ratio of promptly observed notifications is an indicator of one of the benefits of the smartwatch, as the user's availability is not hindered at different periods of the day, as it occasionally is when using solely a smartphone [3,30]. Further, the user is as likely to be reached by a notification when time is sparse as he is in a more tranquil period of the day. This is also in line with the nature of the smartwatch, as the device itself is commonly present for the user.

Smartphones on the other hand can be located in a pocket or on a table, outside of reach for the user and with the screen not always visible. Even the physical cues such as sound or vibration generated by the smartphone are not always noticed by the user. On the smartwatch, as long as worn by the user, these problems are less likely to occur and the cues are more likely to be observed.

The smartwatch as a covert device offering information to the user also deals with some of the social issues brought up by previous work [23,25] regarding frequent smartphone usage. The results in Figure 5 and the median delay (20.0 seconds) of all notifications show that users interact with notifications on smartwatches faster than with smartphones, as per Sahami Shirazi *et al.* [29] where the overall median was not reported, but where 50% of the notifications were interacted with within 30 seconds. Figure 5 also shows that most notifications lead to usage sessions swiftly (in less than 10 seconds) and the delay is even shorter during morning and afternoon hours. These results indicate that when used in tandem with a smartphone, a smartwatch offers the same functionalities for *receiving* information, in a quicker and more convenient way. This quantified result is in tandem with the user preferences reported by Weber *et al.* [38].

Figure 16 summarises our overall findings. Analysing smartwatch use over a period of six months and comparing it to a dataset of smartphone use gathered during two years, the differences in usage between these two device types become evident.

Limitations
During the analysis, we identified potential outliers that were erroneous as the result of the data collection tool. We use screen ON data to infer smartwatch usage (*e.g.*, charging, user moving arm in a certain position), and therefore some false positives may have been included in the dataset, regardless of our attempts to discard such outliers. Given the size of dataset that was analysed, we are confident that these outliers did not systematically bias our results. Furthermore, our dataset consists only of Android Wear smartwatches. Hence, further research that investigate smartwatch usage with other operating systems is needed.

CONCLUSION
Our analysis looks at a large sample of logged smartwatch use from the first half of 2016 and an aggregated dataset of smartphone use between 2014 and 2016. The aim of the analysis is to increase our understanding of how smartwatches are used in-the-wild, and particularly compare it to smartphone usage.

Our results indicate that the behaviour of smartwatch usage bears resemblance to regular wristwatch usage. Brief and frequent usage sessions are preferred, with the user most likely switching to their smartphone for longer sessions involving the creation of new content as opposed to the consumption of content. We introduce a new term to describe these short usage sessions, *peeks*, in which the smartwatch is used for only five seconds or less.

We found that different application categories result in different types of usage. Similarly, the source of interaction changes depending on the time of day, suggesting a relationship to users' availability.

In an attempt to answer our earlier question – *Should we be designing smartwatches or smartphone extensions?* – we observe that the industry is taking steps towards the former. Companies such as LG and Samsung have recently aimed to release more powerful smartwatches aimed for standalone use [11,17]. These new and more powerful models do benefit from the point of increased availability. We expect that increased network and cellular availability and battery life will make the user less reliant on their smartphone.

Ultimately, our analysis shows that current smartwatches are used more frequently than smartphones, and that smartwatches are used in ways that have not been observed in the analysis of smartphone usage. These results are based on comparing datasets collected both on smartwatches and smartphones. Therefore, it can be argued that standalone smartwatches could build on these unique aspects. Furthermore, we find that user behaviour with regards to notification and application content is similar across both types of devices. We interpret this to indicate that users still prioritise the same type of content, while the method of interaction is adjusted to the unique characteristics of the smartwatch.

Based on our findings, we argue that there is room for smartwatches to be extended by creating novel *interaction* methods, something for example explored in [18]. However, we note that the type of content and applications that users will want to access is likely to remain the same, and users are likely to react similarly to notifications on their smartwatches. Hence, designing applications that leverage the simple interactions available on the smartwatch instead of relying on more complex input methods can significantly extend the benefits of using smartwatch in tandem with the smartphones, or as standalone devices.

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