

Situating Wearables: Smartwatch Use in Context

Donald McMillan¹, Barry Brown¹, Airi Lampinen¹,
Moira McGregor¹, Eve Hoggan², Stefania Pizza³

¹Mobile Life Centre
Stockholm University, Sweden
{don, barry, airi, moira}
@mobilelifecentre.org

²Dept. of Computer Science
Aarhus University
Denmark
eve.hoggan@cs.au.dk

³CoRiS
Sapienza University of Rome
Italy
stefania.pizza@uniroma1.it

ABSTRACT

This paper studies how context influences smartwatch use. Drawing on 168 hours of video recordings of smartwatch use, we explore the effects of the presence of others, activity, location and time of day on 1,009 instances of use. Watch interaction is significantly shorter when the user is in conversation, than when alone. Activity also exerts influence—with significantly longer watch use while eating than when socialising or performing domestic tasks. One surprising finding is that length of use is similar at home and work. We note that usage peaks around lunchtime, with an average of 5.3 watch uses per hour throughout a day. We supplement these findings with qualitative analysis of the videos, focusing on how use is modified by the presence of others, and the lack of impact of watch glances on conversation. Watch use is clearly a context-sensitive activity, and in discussion we explore how smartwatches could be designed taking this into consideration.

Author Keywords

Smartwatch; wearable; video analysis;

ACM Classification Keywords

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

INTRODUCTION

Smartwatches are one of the first wearables to reach mainstream prominence, with usage centred around notifications, activity tracking, and timekeeping. Open questions remain, however, about how these devices are used, and in what settings. In this paper, we draw on video data collected from twelve participants, who wore an Apple

smartwatch for one month, with the three last days recorded by cameras worn by the participants. This gives us an exceptionally detailed view on how smartwatches are used; what for, who with, and in what contexts. From 35 days of recording, we have over 168 hours of dual-aspect recording covering 1,009 instances of watch use—around 6 uses per hour, with each use being on average 6.7 seconds long. In our previous paper drawn from this data, *Smartwatch In Vivo* [44], we focused on why and how smartwatches are integrated into the daily routines of our participants. In this paper, we focus on the contexts in which the smartwatch is used. In particular, we look at the use of smartwatches while others are present and how current activity and watch usage are tied together.

A key finding concerns how the presence of others affects watch usage. Watch use when other people are present is shorter, involves less interaction with the watch, and is more focused on basic functionality (notifications and checking the time). This suggests that watch users are sensitive to the presence of others and modulate their watch use in response to their social setting. Second, we look at the role of location and activity in watch use. Dividing usage by situation—work, home, transit and other settings—we can see that watch use varies depending on the location and current activity. After reviewing the quantitative data on the characteristics of watch use, our video corpus lets us dig deeper into individual situations of use to understand more of why particular behaviours were commonplace, and why smartwatches are used in particular ways. To examine the potential for smartwatches to disturb conversation, we analyse cases where the watch leads to a disruption or pause in talk. We find surprisingly few examples: from the 146 instances of watch use in conversation, we identified only 32 cases (22%) with any pause in conversation. When we look in depth at these clips, we find evidence that conversation is remarkably robust to pauses incurred by watch use.

This data, then, provides a unique perspective into watch usage. We approach the materials with a mix of quantitative and qualitative methods to provide an overview of watch use, alongside detailed analyses of specific instances. In discussion, we explore the relationship the smartwatch has to daily interactions in and around technology, focusing on how people use and adapt technology, rather than being distracted and isolated by it. We also discuss how context

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CHI 2017, May 06 - 11, 2017, Denver, CO, USA

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ACM 978-1-4503-4655-9/17/05...\$15.00

DOI: <http://dx.doi.org/10.1145/3025453.3025993>

could be brought into design to better manage the timing and the modality of users' interactions with wearables.

BACKGROUND

Smartwatches have a long history grounded in early digital watches and organisers, such as the Swatch/HP's Webwatch [51], the Microsoft SPOT [35:36–43], and the Fossil PalmOS powered Wrist-PDA. Recently, this form factor has found new life in the Android Wear platform and Apple Watch, both achieving some popularity [47]. In a parallel development, there has been an increase in the amount of wrist-worn activity trackers – primarily aimed at health, fitness, and the quantification of personal action [53].

Wearable devices have been used as sensors to recognise everyday activities [10], and for a variety of biometric inputs [4]. Researchers have also explored wearable activity trackers, noting that their acceptability is a function of their ease of use and their perceived usefulness rather than the intention to do more exercise [52], and that the lifecycle of use presents interaction challenges in initiation, ongoing use, and when disengaging from the devices [32].

A particularly active research area has been the exploration of new input modalities for smartwatches. The mechanics of touch on small devices have been examined in detail [31,42,48,56], as has text entry [13,20,22,33,39,45] and new input modalities, such as tilting and twisting the screen [57], tracing letters on other surfaces with a finger [55], interacting around the device [34,41], interacting with just gaze and attention [2], and even blowing on the watch [9].

However, there has been relatively little study of the use of smartwatches 'in the wild'. Quintana *et al* [46] provided smartwatches to teachers to be used alongside traditional digital classroom tools, noting the teachers' preference of the watch over a smartphone or tablet, as its use was more accountable and less distracting to the students. Lyons [37] looked at traditional watch wearers' practices to learn lessons for the smartwatch. Giang *et al* compared notification distraction between smartwatches and smartphones [18]. Cecchinato *et al* [8], as well as Schirra and Bentley [49], interviewed smartwatch wearers to better understand how and why they used the device. This last paper emphasised the importance of notifications as a watch function, alongside the importance of appearance in choosing a watch.

Contrasting this with the smartphone, researchers have considered similar topics, such as notifications, distraction, and connection with desktop computing [11,29,54]. In particular, Ferreira *et al* [16] combined quantitative logging of use with surveys to explore the contextual factors in user initiated vs system initiated usage. Pielot *et al* [43] found that over 60 notifications a day was usual, while Leiva *et al* [36] looked at the effect of task interruption caused by incoming phone calls.

The role of *context* in technology use has been an ongoing concern particularly with mobile devices. In ubiquitous computing, there have been longstanding efforts to make devices more context sensitive, and to study the impact of context on mobile device use (mainly smartphones). For example, Do *et al* [12] document how the presence of others (signalled by the presence of Bluetooth devices) influences which smartphone apps are used. Research using tracking of mobile device use has grown as devices have become a broader part of everyday lives [5–7,28,38] and while there have been a few different largescale studies of smartphone usage (with thousands of users each), they tend to rely solely upon what can be logged on the device (e.g. [30]). This dependence on on-device logging results in large volumes of data collection, but little detail on the sites of use. This can be contrasted with work that uses video to study smaller groups of users, such as our previous "in vivo" work on smartphone use [5].

METHODS

For this study, we wanted to record and understand smartwatch use, but also unpack some of the context in which devices are used. Accordingly, we adopted methods similar to our earlier studies of mobile phone use [5], where participants were equipped with wearable cameras to record the moment-by-moment details of how they use a device, and the environment where usage takes place [38]. We made a small 'sensor bag' which contained two cameras with long-life batteries that allowed them to record for eight hours each. One of the cameras was directed to record the scene around the participant (pointing forward). The second recording came from a small 'stalk' camera that was mounted on the shoulder of the participant (looking downwards), so as to capture the participant's body and wrist. This angle captured interactions with the watch.

We recruited our participants using social media and advertising on local activity websites (Couchsurfing and a student group on Facebook). Our sample was somewhat skewed in terms of age (between 23 and 36, median age 30), and gender (7 female and 5 men). Five of the twelve participants were students. Other participants' occupations included management consultant, entrepreneur, accounts clerk, medical researcher, and fraud analyst. All participants regularly used an iPhone, and had not previously owned a smartwatch. We adopted this as a filtering method to exclude 'early adopters', in part as smartwatch users are still a relatively small group.

Participants were given an Apple Watch, with a choice of a small (38mm) or large (42mm) model. Our participants used the watches for at least 28 days prior to recording their final three days of use with the wearable cameras. This, we feel, is an adequate length of time for a consumer device to be learned and integrated, to some extent, into everyday practice. Indeed, this is considerably longer than most studies involving hardware deployment in HCI and several participants remarked on changes to their routines from the

use of the watch—from more active lifestyles to simply being more timely. On the day the recording started, participants were given the wearable cameras and asked to record the rest of their day, with a researcher meeting with them the next day to collect the recordings and to address any problems or concerns. On the third day, the cameras and the smartwatch were collected and, for most participants, an interview was carried out there and then. The interviews lasted between 45 minutes and 1 hour, with questions covering their experiences of the watch and the recording procedure.

As with any wearable camera study, there were some issues concerning when cameras could be worn, and how to manage permission from those caught on camera but not part of the research. Therefore, we asked our participants to turn the cameras off when inappropriate, and allowed them to choose which days were recorded. For practical reasons, two participants only recorded on two days, and one on four days, making for a total of 35 days of recording—24 workdays, 11 weekend days. This resulted in over 168 hours of dual-aspect recording covering 1,009 instances of watch use.

Analysis

To analyse the data, we used a mix of both quantitative and qualitative methods. To gain an overview of the data, we started by watching the video and extracting clips where there was any interaction around or with the watch. For nearly all the video, the watch was visible, or if the watch itself was obscured (such as when it was under a coat sleeve), then the arm was at least captured such that the time of interactions with the watch would be visible (if not the actual interaction). For timing, we counted from illumination of the screen to either the hand moving back to its original position or the screen turning off.

For each video clip of usage, we coded each watch use instance. The coding categories were decided by 4 authors collaboratively watching a subset of 20 clips and noting details that could be extracted. The resulting array of information coded for each clip included the length of interaction, the instigator of use, the presence of others, the location, apps used, notification sources, etc. Two researchers then worked on the coding, assessing each clip in terms of each category. An initial 5% was coded collaboratively to set a benchmark, with a further 5% of the independently coded data processed by both coders, and then compared to calibrate the coding procedure partway. This resulted in a table of all instances of watch use, as well as data on the features of that use. The statistical analyses presented in this paper were carried out on a smaller data set from which we had removed all instances where the watch screen was not visible. While more accurate (and potentially longer term) data could be retrieved from automatic logging techniques, having access to the video data allowed us to record details concerning the context

which would not have been available to a device-only logging study.

Beyond this generated quantitative data, we also have access to videos of each watch use instance. This allows for a rich contextual analysis, leading to a deeper understanding of not only what the user did when interacting with the watch, but insights into why they did so. For this analysis, we collectively watched all the clips, around 8 hours of video in total. We then selected clips for closer analysis using an ethnomethodological approach: *“It is necessary to understand the sorts of activities in which people engage, the events with which they deal, and the sorts of tools and technologies they rely upon”* [24, p115]. All those present had experience using with the Apple watch prior to this session. Using our understanding of the social, physical, and technological issues with interactions, we selected clips that were particularly revealing of smartwatch use—either due to interaction with another person around the watch, or action involving the use of the watch.

This smaller corpus of 110 clips was used for a lengthier analysis of the interaction around the watch to examine the talk, device use, and bodily interaction. We drew on interactional analysis and the broader body of work in HCI that looks closely at the moment-by-moment interaction with technology [6,17,25–27]. Accordingly, our analysis took the form not of the repetition of a formal method, but a much more crafted set of analysis sessions and informed inspection of clips. Each extract was thus looked at as an individual, unique instance of use—but also inspected for examples that we can extrapolate to be present in other situations, too.

RESULTS: PATTERNS OF USE

Our 12 participants recorded 168 hours and 21 minutes of video, from 35 days. Each participant recorded on average just over 14 hours of video (with a min of 5hrs 29 min and a max of 22hrs 15 min). The videos contained 1,009 instances of watch use. Of these, there were 69 clips where the watch was obscured by clothing, the angle of the camera, or some other issue. Removing these clips leaves us with the 940 instances of watch use upon which our analyses were conducted. Watch use ranged from 1.5 instances per hour to 8.6 per hour, with a mean of 5.3 per hour. Watch uses were on average 6.9 seconds long (max=205s, min=0.2s, median=2s). This is very clearly different from the 38 second median for smartphones [6].

We have previously discussed findings from this material in [44] – in contrast to the broad overview provided in that paper, we focus here in detail on the context of watch use and watch usage during conversation. We start by presenting a statistical overview of our results, drawing out some relationships around context and watch use. The paper, then, covers the time of use and its impact on how the watch is used. From there, we discuss the social context of use—whether the watch wearer is alone or with others,

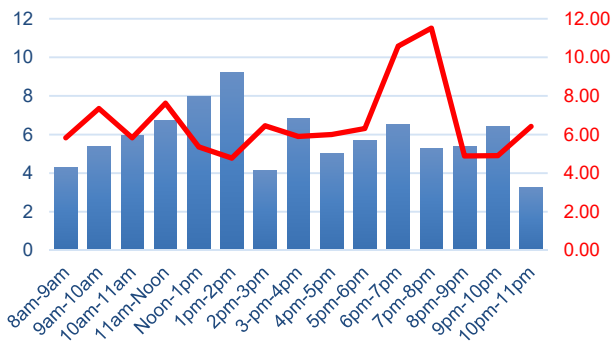


Figure 1: Frequency of watch uses (average by hour) and (red) mean seconds of watch use (8am-11pm)

and whether they are in conversation or not. This lets us analyse how users calibrate their usage depending on social situations. Following this, we look at watch use in particular task-contexts—what the wearer is doing when watch use takes place. Lastly, we look at where watches are used. All three of these variables (social context, current activity, location), as well as time of day, are interdependent parts of what constitutes the context for watch use. After these statistical analyses of the effect of context on usage, we revisit these aspects with the help of qualitative video analysis. This offers a more in-depth look at how participants used the watch in a social context.

Time

The initial variable that we looked at to understand use was time of day. Our video recordings come from user selected sections of their day, with breaks chosen to protect privacy. With our 35 total participant-days we can look collectively at the use of the watch by time of day. For each hour of the day between 8am and 11pm we collected an average of 10 recordings. As we only have one recording between 11pm-midnight, we dropped this hour from consideration. Figure 1 shows the total number of watch use events caught on video for each hour of the day. We normalised the data by the number of participants who had their cameras recording in that hour. This gives us a mean of 5.3 watch uses per hour from 8am-11pm, with peaks in usage around 1pm, 6pm and 9pm. This data shows some similarity with time usage data of mobile phones [6].

If we look in turn at the mean length of watch interactions (the red line in Figure 1), we can see that there is a peak in length of interaction in the early evening where the length of the average watch interaction spikes up to 11.5 seconds. As we discuss later, the length of watch interactions is heavily dependent on the social context, and participants were more likely to be alone in these early evening hours.

Social

“Swiping around on the smartphone may start out as harmless distraction, a mere diversion from pauses in the flow of conversation, but it may end up subverting the intimacy and emotional connectivity one finds between people that are engaged in conversation.” [1, p. 230]

	Touch	No Touch	All
Alone	35% (234)	65% (434)	71% (668)
	15.36 (sd=15.19)	2.00 (sd=1.60)	6.68 (sd=11.09)
W/other	25% (32)	75% (94)	13% (126)
	19.90 (sd=24.99)	2.10 (sd=1.36)	6.62 (sd=14.73)
Talking	27% (40)	73% (106)	15% (146)
	12.43 (sd=16.29)	2.22 (sd=1.82)	5.01 (sd=9.73)
	33% (306)	67% (634)	100% (940)
	15.45 (sd=16.64)	2.05 (sd=1.61)	6.41 (sd=11.45)

Figure 2: Social context of watch use vs proportion of touch/non-touch use and length of use

In research into the use of mobile devices, a longstanding concern has been how mobile devices might disrupt face to face interaction, through notifications or distraction. One potential concern with smartwatches, then, is that they may make this problem worse. Accordingly, one important contextual feature that we wanted to study was the role that the presence of others has on watch use.

We broke social presence down into three categories: being in conversation, being in the presence of others but not in conversation, and lastly being alone. We defined presence of others as those you know, so we did not include crowd situations (similar to notions of ‘incipient talk’ [3]). The nature of our data means that we cannot say how much time our participants actually spent in each of these categories overall—we did not sample the video when there was no watch use. Moreover, participants at times turned the cameras off based on social considerations. However, we can look at the characteristics of watch use within the watch cases we analysed, and thus consider the effect that the presence of others has on the length of watch use.

Figure 2 gives an overview of this, listing how the social context of use affects whether a watch was interacted with using the touchscreen. The results of a repeated measures logistic regression indicate that there is a significant main effect for touch (Wald Chi-Square = 12.3, $p < 0.001$) and for social context (Wald Chi-Square = 11.3, $p < 0.001$). The interaction between social context and touch is also significant (Wald Chi-Square = 33, $p < 0.001$).

The presence of others appears to have some effect on whether watch use involves a touch interaction. Post-hoc tests, with Bonferroni correction, show that when participants use the watch while with others or talking to someone, they touch the watch significantly less often than when they are on their own ($p < 0.001$).

If we look at the length of interaction, then clearly touch interactions are much longer than no-touch interactions. A repeated measures ANOVA showed a significant main effect for touch ($F(1, 752) = 10.2$, $p = 0.001$), social context ($F(2, 208) = 4.68$, $p = 0.01$), and a significant interaction for touch and social context ($F(2, 748) = 8.09$, $p = 0.13$).

As we move from being alone, to being with others and then to being in conversation, the average length of interaction falls from 6.68 seconds (alone) to 6.62 (with others), to 5.01 (in conversation). Touch interactions do seem to change in length, however—when participants were alone their touch interactions with the watch were 15.36 seconds long, 19.90 when with someone and not talking (although the standard deviation here is quite large), and 12.43 when with someone and in conversation. This data, therefore, suggests that when alone, there is a significantly higher proportion of usage that involves touching the watch, and that watch interactions are significantly shorter when in conversation.

Figure 2 essentially summarises the intersection between social context and watch use across our whole corpus, making a powerful argument for the context dependent nature of watch use. Simply put, watch users are sensitive to the presence of others.

When we break down the applications used alone and with others, shown in Figure 3, we see a clear distinction in which app is used. There is a large diversity of applications used on the watch, although usage is dominated by the watch face, notifications, and workouts. We, therefore, simplified the application being used by dividing it into five categories. Workout is the workout timer, notification is an incoming notification, clock is the Apple watch face. NotMsgManagement (**Notification/Message Management**) covers reading old notifications and managing or deleting notifications, and includes looking at or managing emails in the mail app, too. The other category covers all other app use on the watch (including the countdown timer, Siri, and third party applications).

The results of the repeated measures ANOVA show a significant main effect for applications on the length of interaction with the watch ($F(4, 748) = 31.4, p < 0.001$) and a significant interaction between social context and application ($F(8, 737) = 11.8, p < 0.001$).

In terms of the proportions of use, the repeated measures logistic regression shows a significant main effect for application (Wald Chi-Square = 9.6, $p < 0.05$) and again, a significant effect for application and social context (Wald Chi-Square = 16.04, $p < 0.05$). Post-hoc tests with the Bonferroni correction show that when with others and when talking there are differences in the apps being used.

If we look at the data overall, we can see that the clock dominates usage, at least by count (53% of all use, $p = 0.02$). It is important to note, though, that these uses are very short (averaging 1.93 seconds long). Checking the time becomes a larger part of usage, and as a shorter mode of use, this suggests that there is some adjustment in orienting watch use for others around us. This is particularly the case when in conversation, where time checking accounts for 65% of use. There is a pattern of applications that can be used more quickly and less intensively when with others. Notifications

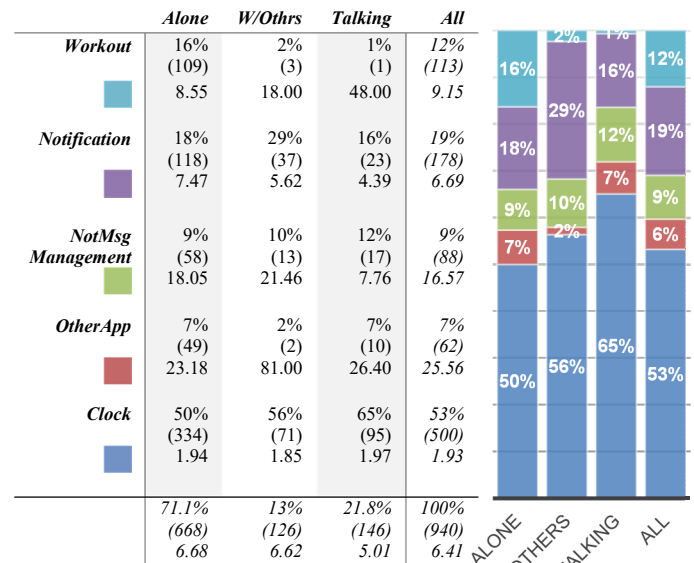


Figure 3: App use by social context, % of times watch used by application, and median length of use

take up more of use when with others, but not when talking to others. This suggests that perhaps notifications are being ignored when talking with others (although we have no direct data to assess this). The increase in notifications when with others may simply be an effect of users receiving notifications while at work (and with others). Lastly, the use of the workout app is essentially a solo activity—with a very small number of uses when with others or when talking with others.

To summarise Figure 3, participants narrow their watch use when they are in talk, with a move towards more basic watch functions, namely checking the time, and their checking of notifications seems both less frequent and shorter.

Activity

A second way of looking at the data is in terms of the activities of our participants as they used the watch. We categorised watch use by the ‘primary activity’—this is, what a participant was doing before and after watch use, or simultaneously with watch use. As has been discussed in earlier research [44], the smartwatch use does not monopolise the activity of users, with users able to do some activities simultaneously (such as walking, talking, eating).

We started by coding all watch events using a broad 155 category coding of activity, borrowing categories from the US Bureau of Labor’s Time Use survey Activity Coding Lexicons [50]. We simplified this by recoding to seven core categories. Five were taken from the 18 top-level BLS codes (work task, travelling, food consumption & preparation, domestic duties). While some categories such as volunteering and government service were not relevant to our data, we also split the “Socialising, relaxing and leisure” into two categories—“Socialising”, and “Relaxing”, and added “Exercise” as its own category. Socialising

	<i>Domestic</i>	<i>Food</i>	<i>Relax</i>	<i>Social</i>	<i>Travel</i>	<i>Work</i>	<i>Exercise</i>
<i>Alone</i>	6.34	11.93	6.73	n/a	6.58	6.03	4.7
<i>W/Others</i>	5.17	6.48	6.49	2.00	8.00	8.6	2.00
<i>Talking</i>	n/a	7.9	3.04	2.75	11.4	4.98	n/a
<i>All</i>	6.23	9.93	5.93	2.46	6.96	5.93	4.68

Figure 4: Mean seconds of use by Activity / Social Context

refers to leisure activity when the main activity is meeting with others for conversation (such as a drink in a pub) and relaxing refers to leisure activity when on one's own, or with others when the main attention is not on the other people (such as watching television with a partner). The count of watch uses while in each activity was Work 161 (17%), Travelling 283 (30%), Food 83 (9%), Socializing 145 (15%), Domestic 58 (6%), Relaxing 96 (10%), and Exercise 114 (12%). Again, however, we cannot directly analyse the prevalence of these different activities, as our data is only a sample of the times that the watch is used (so any times the watch is not used are absent from our data). We focus on the length of watch use, and how use changes between different activities. The results of the repeated measures ANOVA show a significant main effect for activities on the length of interaction with the watch ($F(6, 235) = 3.56, p < 0.005$) and a significant interaction for social context and activity ($F(7, 594) = 2.6, p < 0.005$).

Figure 4 shows the mean length by each activity, and then breaks this down by being alone, being with others, and being in conversation. The mean length across different activities is broadly similar. Interestingly, there is not much difference between domestic/relaxing and work tasks.

There is a significant difference between socialising and all other tasks (post-hoc tests with Bonferroni correction, $p < 0.05$). Socialising always happens in the presence of others—and, as our analysis above illustrated, this is reflected as shorter watch interactions. Activities coded as 'work tasks' (e.g. working at a computer and taking part in meetings) produced watch interactions which were mostly unaffected by the presence of others. One explanation would be that the tasks themselves are engaging to an extent more influential on the use of the smartwatch than social context. Another possible explanation would be that while most of our participants worked in the presence of others, this relationship enforced different behavioural norms due to the working environment.

A significant difference can be seen between eating alone and with others (post-hoc tests with Bonferroni correct, $p < 0.05$). The three longest interactions with the watch (3m 24s, 1m46s, and 1m43s) were of participants eating alone in public. The same pattern can be seen when watch wearers were relaxing (such as watching television, listening to music, or reading a book), in that the average length of interaction with the watch drops when others are present.

	<i>Home</i>	<i>Other</i>	<i>Outdoor</i>	<i>Transit</i>	<i>Work</i>	<i>Restrnt</i>
<i>Alone</i>	7.43	7.58	4.89	8.60	7.00	14.00
<i>W/Other</i>	6.61	3.05	7.31	6.00	9.00	8.46
<i>Talking</i>	3.79	2.75	7.27	22.00	4.98	9.85
<i>All</i>	7.03	5.09	5.31	8.82	6.36	10.06

Figure 5: Mean seconds of use by Location / Social Context

Travelling (which includes activities such as taking the bus, walking, and waiting at the station) shows the length of interaction as longer when with people than when alone. Looking more closely at the data, and as can be inferred from the confidence interval bar on the graph, a number of long watch interactions take place amongst a majority of shorter interactions. All the interactions above 2 standard deviations from the mean length follow a pattern of watch use during a period of movement in silent companionship. These include examples of jogging with a partner and adjusting the activity tracking application, walking through an office while replying to messages on the watch, and walking with someone else while attempting to use Siri to place a phone call.

Location

Another important aspect of the context of use is the location the user is in. Figure 5 breaks down the average length of interactions with the watch by location. For the location categorization, we drew on our observations of the video recordings—broadly categorizing settings in terms of home, work, transit, outdoor, restaurant, and other.

Each of these location categories collected together a reasonable number of instances of watch use across our data. Home included 410 instances (44%), Work 131 (14%), Outdoors 272 (29%), Public Transit 47 (5%), Restaurant 32 (4%) and Other 48 (5%). The results of the repeated measures ANOVA show no significant effect for location on the length of interaction with the watch ($F(5, 175) = 1.3, p = 0.25$). While there are more home instances than work, this was perhaps due to the nature of the daily routines of our participants (two of whom worked at home), as well as some participants recording while they were at home (such as on weekends) rather than during work days. We would not take from these numbers, then, that smartwatches are used any more at home than work. Outdoors is slightly lower—suggesting perhaps distraction while walking, transit is slightly longer, again suggesting the opportunity that transit provides for longer usage.

Lastly, restaurant shows the longest use, with a high standard deviation. On looking at the data, here, there are a number of very long instances amongst solo diners, contrasted with shorter watch use instances when in the company of others.



Are you going to eat lunch here Fredrik? Now I can leave soon.

[looks at watch *1*]

We have a meeting at 1pm.

Figure 6: Checking the time before lunch.

RESULTS: SMARTWATCH USE IN CONTEXT

The quantitative results thus far give us a general idea of the ways that watch use is context dependent. Analysing the video extracts in more depth lets us unpack further what is going on with and around the watch in different contexts. Here we turn to examine individual instances of use, and the context of smartwatch use, in more detail.

Time

Figure 6¹ gives a flavour of our data—a simple example where the watch is used to check the time. Clearly there is a role for the smartwatch as a timepiece used for coordination. While this may seem to focus on the obvious, co-ordinating activity is one of the major uses of the watch. We have a number of clips where the watch is checked ‘visibly’, followed by talk about and activity such as lunch (‘shall we go’), or alternatively part of discussing that an activity (such as a meeting) was over and that, for example, the group needed to begin to orient towards their next task. For example, in Figure 8, a participant looks at their watch before lunch, and mentions the upcoming break along with a meeting that they need to take after lunch.

The watch, here, has something of a dual purpose—partly checking the time (how long do we have for lunch before the meeting) but also showing to others an orientation to time. From analysing the videos, we are able to add some deeper understanding to the 53% (500) clock use instances recorded from their surrounding context.

“I know some people would get irritated or think that I was in a hurry if I were to check my watch because they maybe didn’t know or even if they knew I had the Apple watch, they didn’t really think about that I was just checking a notification or something.” - A

As this quote from participant A describes, there is an

¹ All the transcripts here they have been translated to English, with some extra notation added – (numbers in brackets are pause with length in seconds), [square brackets contain overlapping talk], is:: for elongated speech, hhh for laughter and *number* for where images are taken.

interesting ambiguity caused by the added functionality of the smartwatch over a regular wristwatch. In raising one’s hand to look at the watch, the wearer can be seen as topicalising the time [14], but since the watch face also displays the details of appointments it could be used as a reference to the up and coming meeting, as well—and, indeed, in this case the watch is lifted just before mentioning the meeting. At the end of lunch, the participant makes another similar exaggerated check of the watch to emphasise that they are late for their meeting.

Sociality

To explore the way in which *social* context influenced usage, we selected from our corpus examples where the watch use had relevance to an ongoing social interaction.

Pauses and disruption

One possibility we wanted to investigate was that of disruption. One useful resource is the work of Newman, Button and Cairns [40]. They examine pauses in doctor–patient interactions while doctors consult computer or paper medical records (drawing on related work by Heath [23] and Greatbatch *et al* [21]). They coded pauses in interaction, where doctors checked records, as to whether topic was ‘retained without restatement’ or was ‘changed/restated’ after the pause. This provides a useful empirical definition of disruption. Coding their examples, the authors found that as long as a pause is less than 5 seconds, in 90% of their cases there was no topic change or restatement. This suggests that conversation is usually robust enough to weather pauses of 5 seconds or less.

Turning to our data, we can see that notifications appear on the watch (and are checked) in conversation, and at times this can lead to pauses in participants’ speech. There were 146 clips in our collection where participants were talking while they used their watch. Out of these, 32 instances (23%) have some sort of pause in the talk or social interaction—two with the other conversationalist pausing, and 30 with the speaker pausing. Yet, in only *two* of these clips is there a change in topic or restatement. This suggests a strong robustness in talk to watch usage. Indeed, in the majority of watch usage during talk there is no detectable impact, in part because watch use is quite short (a mean of 5.02 seconds) so that even when pauses do happen, topic change/restatement is very rare.

Going further, we took the pauses that did occur and examined them to see if there were any notable interactional patterns. Figure 7 and Figure 8 give us two examples of talk pausing while the watch user checks their watch. In both cases an incoming notification (from an email in the first example case, and Messenger in the second) arrives, resulting in a recognisable short pause in talk.

In Figure 7, two colleagues are talking about a particular problem with a project. A mail notification comes to our participant’s watch while the other speaker is talking. As



B: lots of colour (2.3)
 A: y[ye]
 B: [You] can say its not easy (*)
((A turns wrist and looks at new notification on watch))
 B: but I really like it anyway hehhhhh
((A stops looking at watch as B ends turn and looks at laptop))
 A: (.4) t:t (1.0)
((A moves gaze from laptop to other speaker))
 A: They were actually a bit sensitive in the focus group, but kind of messy. Quite lucky and interesting

Figure 7: Watch user pauses

the speaker approaches the end of his turn, the wearer lifts her hand to read the notification. After three seconds, she puts her hand back down, timed just as the previous speaker finishes speaking. The participant then glances at her laptop, and after a short utterance, and 1.4 seconds after the turn transition point, she starts speaking, making eye contact with her colleague as she starts. This clip seems to suggest a momentary distraction by the watch owner, although it is very brief and does not result in any topical disruption, or restatement. Moreover, the pause happens after the watch has been put down, with a short utterance to ‘hold’ the turn.

In the contrasting example, in Figure 8, we can see an incoming notification delaying the talk of the conversational partner of the wearer. Here, the watch owner is talking and as they finish their turn, they receive (and read) a Facebook message notification. They stop talking, but keep looking at the message, and it is not until they turn away from their watch that the next speaker starts. One possibility here is that the watch wearer is interpreted as being ‘away’ from the interaction while they read their message, and the next speaker does not take their turn until they have their attention. Goodwin’s discussion of aspects of gaze management during talk [19], seems relevant here—in particular his argument that speakers locate their addressee while talking (particularly at the beginning of turns), and that gaze should normally be returned by the recipient. As the watch owner looks, instead, at their watch,



A: If it can relate to the purpose it will be interesting. If it was (*)
((A lifts watch))
 A: just the second time (3.7s)
((watch goes down))
 B: =never mind it is just that we need something

Figure 8: Co-conversationalist pauses

this is not possible until they turn away from the watch, allowing the re-establishment of gaze and the co-conversationalist to start a properly addressed turn. It is worth emphasising that the disruptions here are short (pauses of 4 seconds or so). As discussed above, nearly all of our watch interactions led to no disruption to the talk.

While Newman, Button and Cairnes [40] looked at medical doctor consultations, our data is much more varied. Even if a doctor turns their attention from the patient to their records, the doctor is still engaged in providing care for the patient. Watch use is not, in most situations, a demonstrable part of the ongoing social interaction. There is, therefore, the possibility that these watch-induced pauses would annoy the conversational partners of watch wearers, even if the conversation itself would seemingly continue to flow with minimal disruption.

“If something blinks in my bag now, and I take my phone, you know what happens. I got a message. But people don’t know if people look at their watch for long... I had one situation. It was quite fun. I talked to [colleague] about something, and it vibrates - I think I got a message or something - and I looked at it and I read it, and she was suddenly asking me, “Oh. Are you in a hurry? Do you have to go?” “No. I just got a message.” Oops [...] Because of this situation if I look long at my watch usually I calculate how much time I have.” - J

As participant J reports, there is still the possibility for annoyance or frustration through watch use, and this is something that our participants learned to manage in the same way users learn to manage the impact of other interactive devices on their social interactions.



Figure 9: Waiting at the door to use the watch

We can compare this to clips in which an absence of others seems to relax any interactional requirements for minimising usage time. For example, in one clip a participant is walking home after work and as they reach the end of their journey, they prepare to enter their busy family home by first taking the keys out of their bag, next—with keys in hand—they use the watch to switch off a fitness tracker, and finally, they take the opportunity to review and dismiss various notifications during an interaction lasting 23 seconds (Figure 9). In a similar clip, another participant waits for friends and uses the watch to check Instagram for just over a minute. While this would represent a short usage on a mobile phone, for the watch it is relatively long—in the top 1% of usage by length in our corpus.

Activity

We now move on to discuss the role of activity in how the watch is used. Some activities require users' physical and mental concentration; others are such that they offer natural breaks or are relatively undemanding. Cooking and exercise were two notable examples, in that they make demands on your hands but still allow for some watch interaction alongside the main task involvement. As shown above, watch use while exercising has the second lowest mean length of use.

The ability to use the watch while hands are engaged in activity was one aspect of activity that we were interested in. There are a number of instances in the corpus which highlight this sort of 'no handed' use. In one clip a participant is cycling to meet friends and needs to check the prearranged time. They are able to quickly bring up the relevant message without having to dismount and retrieve their phone from their bag. Another common location for using the watch over the phone was in the kitchen:

"Whatever you do with it, you could do it with the phone too but it would slightly more awkward with the phone sometimes. I mean the cooking example, I think is very good where if I'm holding the phone and the spatula and there's three stoves on and whatever. I like that I don't have to take the phone out and drop it in the pan..." - V

Activities themselves could at times occasion the use of the watch. In one clip, a participant is putting a load of washing in a communal washing room. They use Siri (the watch's voice recognition agent) to set a timer. Earlier work on mobile phone interaction has discussed how use can be



Figure 10: Using the watch to read messages while the phone is occupied by an outgoing phone call.

'occasioned' by another activity [6]. In this case, the need to set a timer arises from the washing machine displaying its own countdown as it begins its cycle.

Second screening

As noted above, the position of the wearable on the wrist allows for hands free interaction but this doesn't tell the whole story. This positioning also sets the watch up as an easily accessible second screen. 14% of our captured interactions with the watch showed a participant oriented towards another screen at some point during, just before, or just after their watch interaction. This is perhaps not that surprising—we live in a world of screens, with heavy usage of mobile phones, and smartwatches are specifically designed to fit with that world.

It appears there is still space for the watch, however, even when a phone or other device is being used. We observed a sort of 'second screening', where participants would make use of the properties of the watch to read messages or check information, while their 'main' device was busy on some other task. For example, in Figure 10, our participant has initiated a phone call and while waiting for the call to connect, swaps the phone to his non-dominant hand making the watch available for interaction. The position of the watch on the wrist allows the user to (perhaps somewhat awkwardly) interact simultaneously with two devices. While the physical contortions necessary to do this are not the most ergonomic the fact that the user is able to reorder his devices quickly to enable dual use shows that this is something that is not particularly difficult.

DISCUSSION

Our two results sections have analysed smartwatch use in considerable depth. We began by looking broadly at smartwatch use, analysing how the context of use had an impact on usage in terms of applications, as well as length and style of interaction. This makes the argument that smartwatch use is context sensitive, with participants adapting and tailoring their use to the situations that they find themselves in. In turn, our more detailed analysis of the video data, with support from our participant interviews, dug into similar questions of disruption—looking at how smartwatch use influences talk. We concluded that there was evidence that disruptions to talk are quite rare, a finding already suggested by the short uses of the smartwatch when users are in conversation.

In the discussion, we first review the impact of context on smartwatch use, and second, engage with some design implications of our analysis.

Importance of Context in Everyday Smartwatch Use

We have described how users modulate their usage based on the context. In our videos, we saw little disruption of interpersonal communications resultant from the use of the smartwatch. This leads us to believe that, as users of technology and skilled practitioners of social interaction, we are able to manipulate our technology and our interpersonal communications to take advantage of wearables rather than be overwhelmed by them. In relation to mobile phone usage, Brown *et al* [5] stated: *“Device use is dependent upon and threaded into what goes on around us. It may be that rather than pushing us away from the world, our mobile devices are instead just another thread in the complex tapestry of everyday interaction.”*

However, looking at the progression from the reported social transgressions in the interviews to these skilful interweavings of smartwatch functionality into social situations, we can deduce that this is a learned skill. Our video examples of the smartwatch being allowed to influence an ongoing conversation by the wearer are examples of this—with messages or notifications being used as topical resources, or the watch being used as a prop to communicatively gesture with regards to time or the contents of a message. While with this data we have no way to quantify or examine the cases where the watch is silent, and haptic feedback indicating an incoming message is ignored in favour of the ongoing activity, our quantitative data shows that the watch was attended to less frequently when in the presence of others, and 76% of interactions where the watch was touched happened when alone.

Designing Context Sensitive Smartwatches

We have emphasised the role that context plays on smartwatch use, but not its impact on the functionality of the watch. Context has been a longstanding topic of interest in technology use—most notably in ubiquitous computing. Efforts to make devices context sensitive have produced helpful advances but have proven to be challenging as a broader way of automating device use. Following up on this observation, we suggest using context initially as a way to provide more nuanced notification timing to the user. One of the simplest ways this could be done would be in monitoring the participation of a user in conversation—whether they are talking, or whether others are talking. Offering a ‘stand up’ notification as a user is talking might not be the best timing—it would be relatively straightforward to detect talk and delay the notification for a minute or two. Alternatively, during times of quiet and relaxation, less urgent notifications (such as news or weather) could be delivered. A watch might even ‘invite’ applications to provide extra notifications at particular times, or to suspend notifications at other times (such as when giving a presentation or during extended talk).

More broadly, by detecting whether a notification is read, or discarded as soon as the source is ascertained, a notification management algorithm might better train itself to judge the urgency of notifications, and to decide whether to hide, delay, or show. This could build on work that has explored similar mechanisms for place and smartphone notifications [15], although extended with the broader notion of context that we engage with here. Notifications from certain applications or senders could be delayed in contexts where the user has regularly dismissed them without a glance.

This said, it is important that the relationship between context and activity is not seen as a deterministic one. As has been discussed with respect to mobile phone use, while use can be patterned and occasioned with respect to activity, it is always open to the individual how a device is used. This suggests that key design interventions around context should consider using context while trying to keep users involved in decision making, rather than ‘automating’ excessively. Perhaps rather than suppressing or delaying notifications, wearables such as the smartwatch could take advantage of their place on the body, against the skin, to provide more information in the initial interaction. In the case of the watches studied here, this could be as simple as reducing the force of the haptic feedback for notifications deemed a lower priority.

CONCLUSION

In this paper, we have given an overview of different aspects of smartwatch use. Using a video method, we have analysed smartwatch use across 12 participants, all of them having used the Apple Watch for a month. Recording the participants’ watch use gave us a unique viewpoint, allowing for a close focus on the different ways in which the smartwatch is made part of the world that users find themselves in.

Our video data provides access to more detail on the types of contexts and their impact on usage—such as by differentiating between being in the presence of others versus being in active conversation. It also allowed us to expose the details of use rather than reported preference. An example can be seen in the contrast between the results presented here and survey-based work such as reported in [4]. We can see that use in places such as a restaurant or while watching TV paints a different picture than the reported desire for incoming messages, and show that splitting location context and social context is an important step in understanding, supporting, and predicting use.

ACKNOWLEDGEMENTS

This research was made possible by a grant from the Swedish Governmental Agency for Innovation Systems (VINNOVA) to the Mobile Life VINN Excellence Centre. We would like to thank Laia Turmo Vidal as well as our participants.

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