Thesis

Exploring User-defined Gestures for Alternate Interaction Space For Smartphones and Smartwatches

Submitted by

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Abstract

Exploring User-defined Gestures for Alternate Interaction Space For Smartphones and Smartwatches

In smartphones and smartwatches, the input space is limited due to their small form factor. Although many studies have highlighted the possibility of expanding the interaction space for these devices, limited work has been conducted on exploring end-user preferences for gestures in the proposed interaction spaces. In this dissertation, I present the results of two elicitation studies that explore end-user preferences for creating gestures in the proposed alternate interaction spaces for smartphones and smartwatches. Using the data collected from the two elicitation studies, I present gestures preferred by end-users for common tasks that can be performed using smartphones and smartwatches. I also present the end-user mental models for interaction in proposed interaction spaces for these devices, and highlight common user motivations and preferences for suggested gestures. Based on the findings, I present design implications for incorporating the proposed alternate interaction spaces for smartphones and smartwatches.

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CHAPTER 1

Introduction

As mobile and wearable devices become cheaper and more versatile, people are becoming more inclined to obtain devices like smartphones and smartwatches for everyday use. Recent advancements in mobile form factor, battery life, sensor capabilities, processing power, and versatility of applications have contributed to the growth of smartphones and smartwatches, which are now mainstream products in the current marketplace [31, 44]. Today, smartphones are used for purposes other than making calls or sending texts, such as, *reading, navigating maps, taking pictures* or *playing games.* Smartwatches are being used for *navigation, health tracking, call/text notifications and voice search.* With this extension of capabilities in these devices, there has been a major technology shift in input techniques where physical keyboards or buttons have disappeared in favor of touch-enabled screens in smartphones and smartwatches.

While touchscreen interaction is a popular input technique for both smartphone and smartwatches, this input method does present specific interaction issues for end-users. For example, many smartphone users prefer using smartphones one-handed [23]. In one-handed smartphone interaction, the thumb of the phone gripping hand becomes the main channel of input, and other auxiliary fingers are seldom used. In this form of interaction, the hand's thumb can not often reach the entirety of the screen. This is known as the *limited thumb reachability* problem [8] in smartphones (Figure 1).

The *limited thumb reachability* problem is specific to one-handed interaction in smartphones. But there are other interaction issues present in both smartphones and smartwatches due to their small screen size. For both devices, users mostly provide input by tapping or

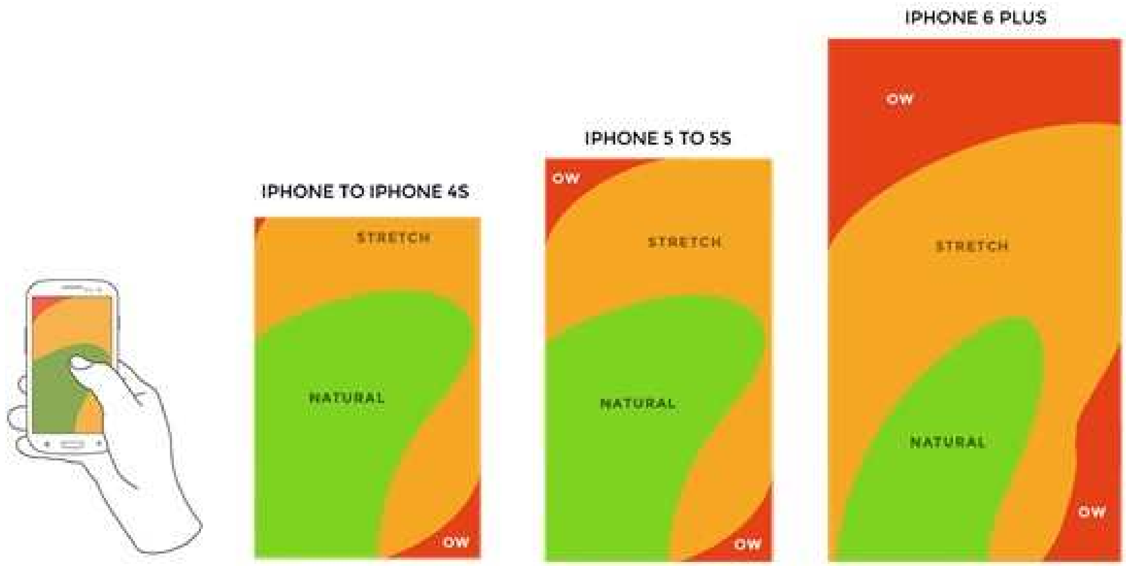

FIGURE 1. Limited Thumb Reachability in Smartphones [19, 20].

swiping the touchscreen. This results in *fat finger* [7] and *occlusion* [67] problems. The *fat finger* problem describes the issue of input errors caused by the relatively large size of a user's finger in contrast to the size of a target on the touchscreen. The *occlusion* problem describes the occlusion of a large portion of viewable screen due to relatively wide finger surface. Both of these problems are more acute in smartwatches than smartphones, as the screen size in the watch is significantly smaller compared to smartphones.

Tackling these issues for smartphones and smartwatches have necessitated further exploration of the input space for both devices. For smartphones, shifting [5] or shrinking the screen [51] to bring difficult to reach areas closer to the user's thumb does address *limited thumb reachability* problem. But this reduces input space for one-handed interaction - increasing both *fat finger* and *occlusion* problem. As such, utilizing the back of device using the otherwise unused fingers of the phone gripping hand have been suggested by many researchers [77, 7, 59, 65, 66, 18, 14, 34, 77, 75, 4, 48] to address all three problems in smartphones.

To reduce both *fat finger* and *occlusion* problems in smartwatches, *voice commands* and *non-touchscreen* based gestures have been proposed as alternate input spaces [44]. Although *voice-command* based interaction with smartwatches is reliable in in-door environments [68], in public space the interaction becomes difficult because of environmental noise. This has inspired researchers to look at non-touchscreen based gestures like *skin-input* [17, 41], *watch-edge* [40] & *watch-band* interaction [2], and air–gestures [25] to extend the present touch-screen input capability for smartwatches.

Prior research has mainly focused on developing alternate interaction technologies for smartphones and smartwatches using designer-defined gesture sets. There has been limited research in exploring end-user's interaction preferences for the back-of-the device gestures in smartphones, and different form of non-touchescreen gestures in smartwatches. Gestures conceived by designers as opposed to end-users can sometimes fail to meet important design criteria like *discoverability*, *ease-of-performance*, *memorability* and *reliability*. According to Morris [37], this can occur as the small group of interaction designers can sometimes fail to represent the larger end-user population.

To address this concern, *elicitation studies* [72] have been suggested by researchers to determine end-user preferences for gestures in proposed interaction spaces while designing new interaction technologies. Studies have shown that end-user defined gestures obtained from elicitation studies are easier to learn and recall [70] , easier to perform [38] and more appropriate [38] than designer–defined gestures.

In this thesis, I explore end-user preference of gestures in proposed alternate interaction spaces of smartphones and smartwatches. I present the results of two studies exploring end-user mental model of designing *back-of-device(BOD) gestures for smartphones* and *non-touchscreen based gestures for smartwatches*. From the results of the studies, I identify a set of user-defined consensus set for *back-of-device(BOD) gestures* in smartphones and *non-touchscreen gestures* in smartwatches for common interaction tasks. I provide insights to users' mental model and their criteria for creating gestures. I also provide some design guidelines for incorporating these alternate interaction spaces for mobile devices . The end goal of my research is to bridge the gap between new interaction technology research and end-user preference for interaction with mobile and wearable devices.

The rest of the thesis is organized as follows. In Chapter 2, I give an overview of related work in *elicitation studies* for designing gestures for new interaction spaces and discuss proposed alternate interaction spaces and techniques for mobile devices. In Chapter 3, the elicitation study for back of device interaction in smartphones - including the data collection methods, elicitation study results and observed trends are discussed. In Chapter 4, the elicitation study for exploring non-touchscreen gestures in smartwatches is discussed. In this chapter, I describe the data collection method, as well as a taxonomy for non-touchscreen gestures, a user-defined gesture set, and common trends observed during gesture creation in smartwatches. In Chapter 5, the implications for designing gestures in proposed alternate interaction space in smartphones and smartwatches are explored with respect to the findings of the two elicitation studies. The dissertation concludes with a discussion of possible future work in Chapter 6.

CHAPTER 2

Related Work

2.1. Elicitation Study in Gesture Design

Elicitation studies are widely used tools in user-centric computing to inform the design of gestures [63]. In an elicitation study, users are given the results/effects of performing a task or action. Participants are asked to come up with and perform gestures that they feel best match those effects. A consensus gesture set from an elicitation study can be defined if there is sufficient consensus among participants' gestures [72]. Wobbrock proposed a quantitative measurement of the gesture consensus called *agreement score* [71] which extracts the degree of consensus among participants for each task according to the following equation:

$$A_t = \sum_{P_i} (\frac{P_i}{P_t})^2 \tag{1}$$

In Equation 1, t is a task in the set of all tasks T, P_t is the set of proposed gestures for task t, and P_i is a subset of identical gestures from P_t. The range for A is $[0, 1]$.

Elicitation studies are particularly appropriate for informing the design of new technology since the methodology does not require that the system be implemented to determine the user's needs and desires [37]. Elicitation studies have been performed to help guide the design of gestures in surface computing [38, 72]. These have also been applied to determine single-handed and bimanual gestures on tabletops [29]; finger, body and remote based gestures to control the TV set [61, 62, 64]; hand gestures for augmented reality [43]; motion gestures [49], and above-the-device gestures [13]. These studies found the gesture sets for various application domains and alternate input spaces for different technologies, as well as qualitative data such as user's evaluation of the ease of execution and the *fit-to-function* of proposed gestures. In addition, they provide insight into users conceptual ideal about how they would interact with a specific technology or device. Lastly, these studies have shown that the preferences of a specific (elicited) gesture for a given task is influenced by technical expertise [11] and culture [13].

2.2. Using Alternate Input Space and Techniques in Smartphones

Limited thumb reachability problem [8] (Figure 1) in smartphones increases with increasing form factors in smartphones. To address this problem recent large screen smartphones are equipped with features that can shift the entire screen [5] or shrink the entire screen to bring difficult to reach areas closer to the user's thumb [51]. Although these solutions address the limited thumb reachability issue, they reduce the input gesture space for the user to enable one-handed operation, thereby increasing both the *fat finger* [7] and *occlusion* [67] as the effective touch-space becomes smaller.

To address these problems, alternate interaction techniques like mid-air interaction [52, 81, 6] and motion gestures [53, 22, 45, 33, 42, 39] have been proposed for smartphones. An issue with proposed mid-air interaction technique is the necessity of the alternate hand to provide gestural input. Naturally, this interaction technique does not support one-handed interaction. This is problematic in scenarios where the end-user uses the alternate hand for doing other tasks, like carrying shopping bags or holding a bus handle [77]. In proposed motion gesture techniques, it is difficult to see the screen while performing the gestures because of the proposed movements of the phone.

Researchers have also looked into utilizing the back of the device for providing inputs to the smartphone to tackle these issues [78]. In back-of-device(BOD) interaction, the unused fingers of the phone gripping hand resting on the back of the device are used to create gesture inputs. This input space supports one-handed interaction as it can be reached using the unused fingers of the phone–gripping hand, and does not have the same visual target acquisition problem associated with motion gestures. Back-of-the-device gestures in smartphones provide an alternative one-handed solution to the limited thumb reachability problem by enabling the user to interact with previously unreachable areas of the screen by using one of two methods:

(1) Directly mapping unreachable areas on the front touchscreen to areas that are reachable using the (longer) index finger on the the back of the device.

(2) Remapping unreachable areas on the front touchscreen to reachable areas with other fingers on the back of the device.

Since the effective screen size remains the same, the problems of increasing occlusion and wrong target acquisition, as in in [5] and [51], can be avoided.

Many research studies have been conducted to utilize the back of mobile or handheld devices as a possible input space. Some of the proposed methods of utilizing the back-of-device as input space include:

- Applying additional hardware [34, 77]
- Using the existing rear-facing camera [75, 4]
- Using the existing internal sensors [48]

Noor et al. [34, 35] explores the how back-of-device grips can be used to predict front-screen touches in smartphone. Leiva [32], Catala [9] and De Luca et al. [12] analyzed authentication techniques on smartphones using taps and shape gestures on the back of the smartphone. Baudisch et al. [7] explored using touchpad on the back of device to improve bimanual interaction in smartwatches. Similarly, Stienstra et al. [58] researched on showing contextual information of smartphone apps by interacting with a button on the back of device. *Backpat* [54, 55] uses pats of the index finger, middle finger, or thumb on the back or side of the device to support one-handed operations for tasks like *text selection* and *zooming*. Similar to *Backpat*, *Timetilt* [48] explores the use of tap on the back of device for switching modes in smartphone and *Tapback* [47] explores the use of back-of-device taps for controlling voice servers. Xiao et al. [75] and An et al. [4] take a different approach by using the smartphone camera to recognize the phone-gripping hand's finger movement and postures. Researchers have also looked at the range of motion of unused fingers of the phone gripping hand on the back of device. Hakoda et al. [15] and Yoo et al. [78] provide research data on reachability of fingers on the back of device, and identify usable zones on the back of device for interaction.

Although the potential of using the back-of-device as a alternate input space has been extensively analyzed, most of the existing research focuses on developing interaction techniques with a pre-defined set of gestures suggested by the researchers. Existing literature lacks research on user-preference for different gestures that can be performed on the back of device, as well as the user-preference of mapping between smartphone tasks and possible gestures. Exploring end-user preferences in back-of-device interaction with smartphones can compliment existing research in this area, and help make the proposed alternate input space more usable for end users.

2.3. Using Alternate Input Space and Techniques in Smartwatches

In light of both the fat finger and occlusion problems occurring with small touchscreens, researchers have proposed alternate input techniques for smartwatches that do not involve interacting with the touchscreen. *GestureWatch* [25] and *Hoverflow* [28] use mid-air gestures above smartwatches and other wearable computing devices as input. *Abracadabra* [16] and *zSense* [69] use magnetic sensor-based around-the-device (air) gestures to interact with wearable devices. Xu et al. [76, 82] have explored finger and hand gesture recognition in the watch wearing hand for smartwatches. Kerber et al. [24] proposed several motion-based gestures using the watch wearing hand's wrist to interact with smartwatch.

Xiao et al. [74] developed a watch prototype that supports pan, twist, binary tilt, and click on the watch face of a smartwatch. *Bandsense* [2] combines touchscreen gestures with pressure-sensitive multi-touch gestures on a wristband to enable interaction. *Edgetouch* [40] uses sensor-enabled edges of a smartwatch to recognize touchscreen gestures around the edges of the watch.

Skinput [17] and *Skinwatch* [41] make use of a user's skin to extend the gesture space for smartwatches and other wearable devices. Knibbe et al. [26] proposed using the back of the users watch-wearing hand to enable manual and bimanual gestures for smartwatch interaction. *SkinButtons* [30] is another skin-interface based interaction techniques with smartwatches that projects icons on the smartwatch screen to the user's skin using tiny projectors.

In addition to research that attempts to extend the size of the interface, there is a body of research that explores the use of non-gesture-based interaction. Akkil et al. [3] proposed and studied the use of facial glances and gazes as an alternate way for interacting with smartwatches. Song et al. [57] created and showed that a 2D RGB camera based gesture recognition system for mobile devices can be used for smartwatch interaction. *WatchMe* [60] is another camera-based gesture recognition technique for smartwatches that uses image processing/OCR to recognize input on a drawing canvas composed of everyday objects. *Blowatch* [10] allows users to blow air towards wearable devices to control interaction.

Another body of research has focused on recognizing muscle movements of the watch wearing hand for gesture-based interaction with smartwatches. Rekimoto [46] utilized sensors embedded in a normal wristband to detect forearm movement and wrist-shape changes in the band-wearing hand. Similarly, Morganti et al. [36] showed a prototype muscle-computer interface implemented in the wrist-band of a watch that can recognize objects, grasps, and forearm gestures. *Tomo* [81] allows gross hand gestures and thumb-to-finger pinches to be recognized in a smartwatch. *Wristrotate* [24] can similarly recognize gestures like *push*, *pull*, *curl*, *rotate* and *doubleRotate* on the watch wearing hand.

Similar to back-of-device(BOD) interaction research in smartwatches, existing literature on alternate interaction space research in smartwatch mostly focuses on developing new interaction techniques with pre-defined gestures proposed by the researchers. There has been no formal exploration of user-preference for gestures in these proposed alternate interaction spaces in smartwatches. As such, no research data is available on gesture preferences in these interaction spaces, as well as user-preference for mapping possible smartwatch tasks to different gestures. Researching end-user preferences of gestures in these proposed interaction spaces can compliment existing research in this area, and provide design guidelines to incorporate a combination of these proposed interaction techniques in smartwatches.

CHAPTER 3

Exploring User-Defined Back-Of-Device(BOD) Gestures for Smartphones

We conducted an elicitation study [56] to understand end-user preferences for back-of-device(BOD) interaction in smartphones. We limited our elicitation study to one-handed interaction to simulate *limited thumb reachability* issue alongside *fat finger* and *occlusion* problem in smartphones.

3.1. Method

We elicited user-defined gestures for back-of-device interaction by conducting interactive, one-on-one interviews with 15 participants aged 19-33 (Mean = 23.73, S.D. = 3.95, 6 females, 1 left handed). They were recruited using a departmental email list and compensated with a $10 Amazon gift card. All participants owned smartphones. The study was performed using a LG Nexus 4 smartphone running Android 5.0.1. Custom code was developed in Java using the Android SDK [21] to help present the tasks in the study.

In each interview, we asked the participant to create a one-handed back-of-device gesture, while thinking aloud, for a set of given smartphone tasks. We designed a set of twenty-three tasks by analyzing common operations regularly performed in smartphones. Table 1 shows the complete list of tasks. Each task was accompanied by a visual reference (either an image or a short video) displayed on the phone's screen using custom software that showed the effect of performing the task. Once the participant was satisfied with the elicited gesture, he was instructed to perform the gesture for recording purpose. A video camera was used

Table 1. The List of Tasks Presented to Participants in Back-of-Device(BOD) Smartphone Elicitation Study, Grouped by Category.

Category	**Sub-Category**	**Task Name**
Navigation	System-Phone	Next (Horizontal)
		Previous (Horizontal)
		Go To Home Screen
	Application	Next (Vertical)
		Previous (Vertical)
		Pan Left
		Pan Right
		Pan Up
		Pan Down
		Zoom In
		Zoom Out
Action	System-Phone	Answer Call
		Ignore Call
		Hang-up Call
		Mute Microphone
		Switch to Speakerphone
		Lock Phone
		Act on Selection
	Application	Take Selfie
		Copy
		Cut
		Paste
		Open Context Menu

to record the participant's hand performing gestures on the back of the device. Each session lasted 30-45 minutes in length.

Because the primary aim of our study was the elicitation of user-defined gestures, our focus was not to distract or affect user performance with recognizer or sensor technology. Therefore, we didn't support any gesture recognition during the elicitation study. Instead, the participants were encouraged to focus on gesture design and performance while assuming that the smartphone was acting like a *magic brick* [50] capable of tracking and detecting the gesture they designed. This methodology was adopted in order to reduce the likelihood that participants would limit their proposed gestures based on their understanding of current technology and gesture recognition techniques.

3.2. Results

Our results consist of elicited gestures, agreement scores for given tasks, subjective ratings for each gesture, and qualitative observations. Each observed gesture was coded by two different researchers to ensure consistent labeling. The qualitative observations were extracted from the participants' feedback from the conducted interview sessions.

3.2.1. Agreement Scores. Agreement scores [73] for the task and gesture set developed by our participants are illustrated in Figure 2. We found that only two tasks had significant consensus, garnering agreement scores of 0.76. These elicited gestures were *swipe-left* and *swipe-right*, and corresponded to pulling or pushing the content of the home screen to move it. The consensus gesture set for the tasks are shown in Figure 3.

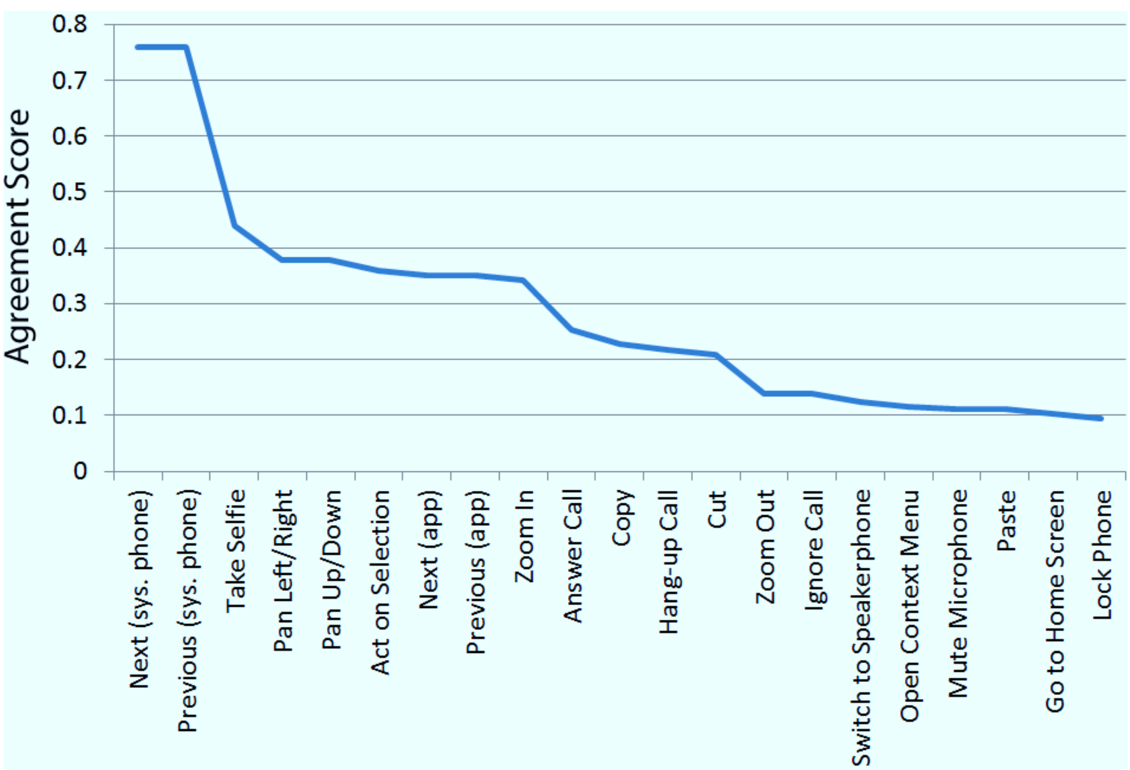

Figure 2. Agreement Scores for Each Task Sorted in Descending Order for BOD Gestures in Smartphones.

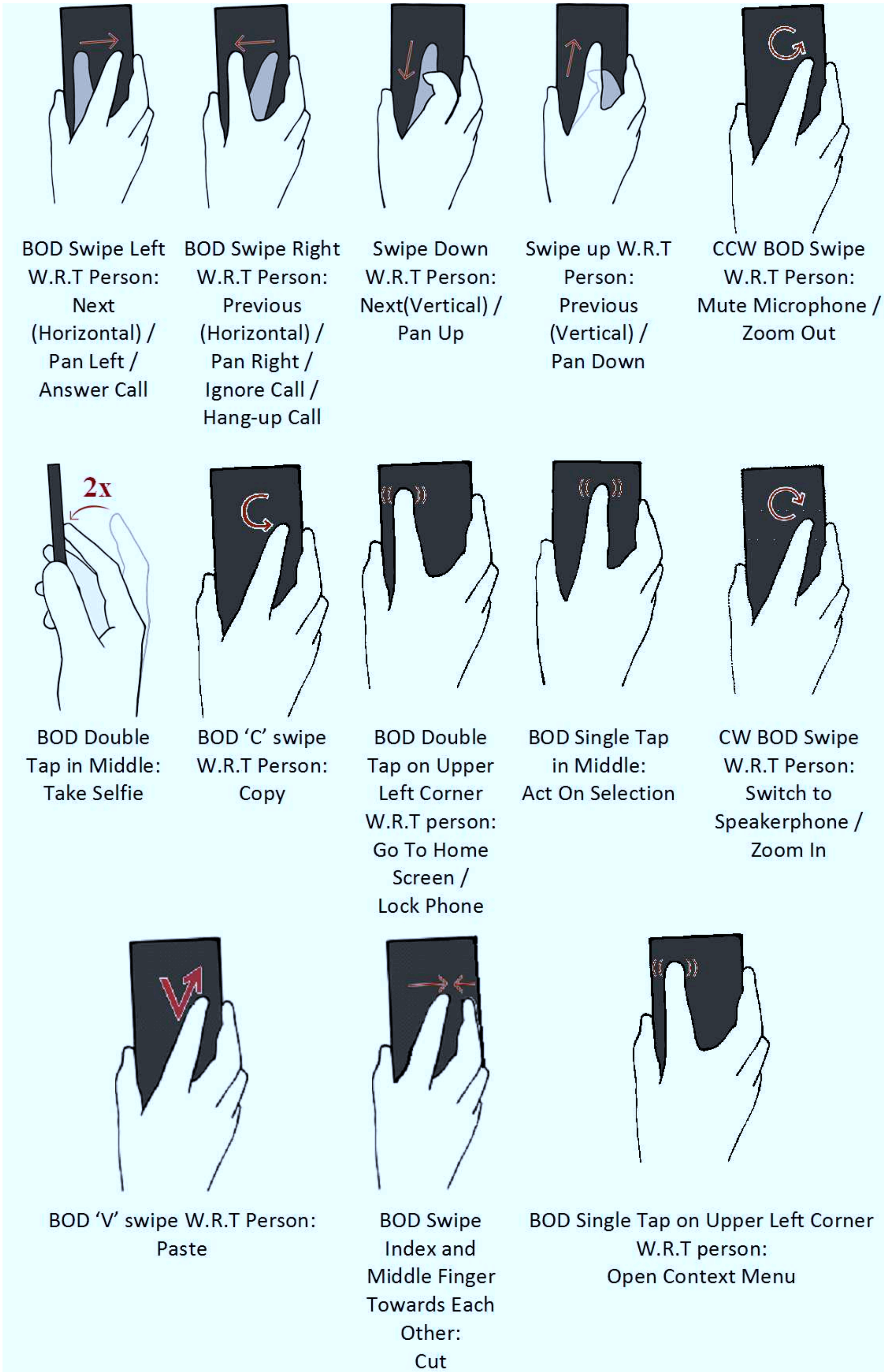

FIGURE 3. Consensus Gesture Set for BOD Interaction in Smartphone

3.2.2. Subjective Ratings for Gestures. When rating how appropriate their gesture was for the given task, participants thought the consensus gestures were a good match (M: 5.87, SD: 1.32). Figure 4 shows a per-task summary of the responses. All tasks receive a match rating of at least a 5, with the lowest being 5.07 for *Mute phone*. Similarly, participants thought their gestures were easy to perform(easiness) (M: 5.97, SD: 1.42) with the lowest rated task, Go to home, still receiving a 5.27 (Figure 5). Finally, participants were more varied in their likelihood to use their consensus gestures, but were still positively inclined (M: 5.15, SD: 1.91. *Mute* and *Go to home* garnered the lowest ratings of 4.6 and 4.4 respectively (Figure 6).

3.3. Qualitative Observations

While designing the gestures, the participants were heavily influenced by *legacy bias*, *concern for accidental input*, and *ease of performance*. We observed that participants were

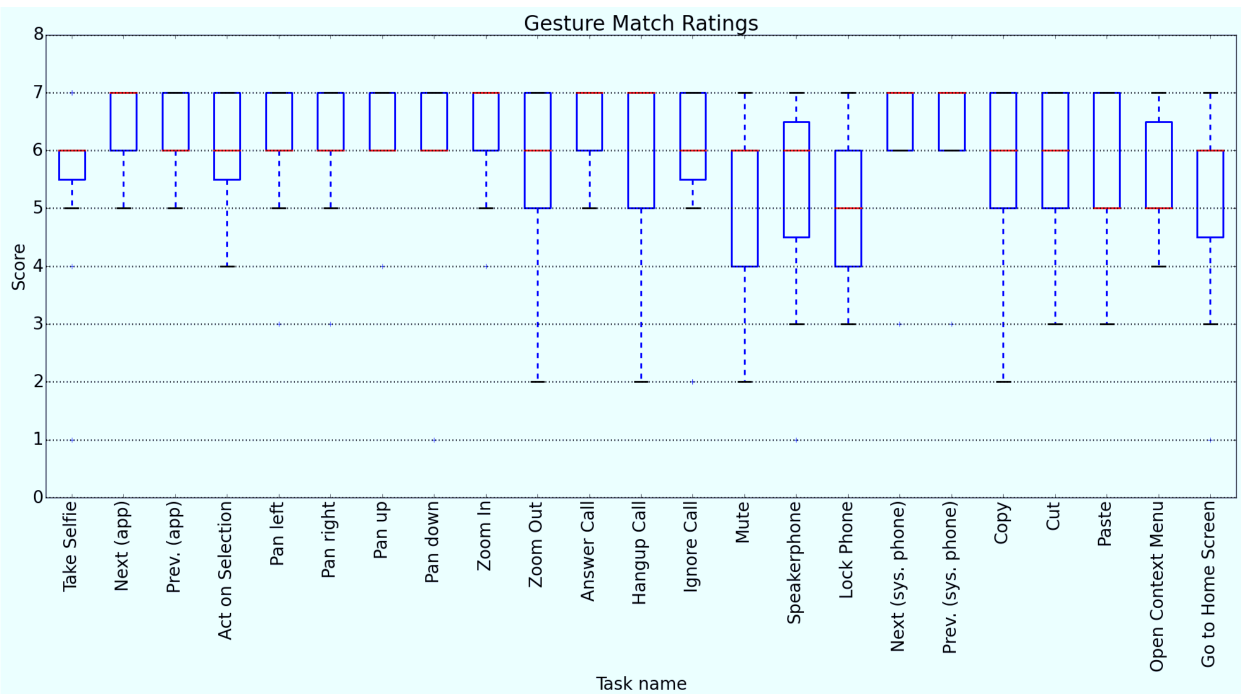

Figure 4. Gesture Match Ratings for BOD Interaction in Smartphone

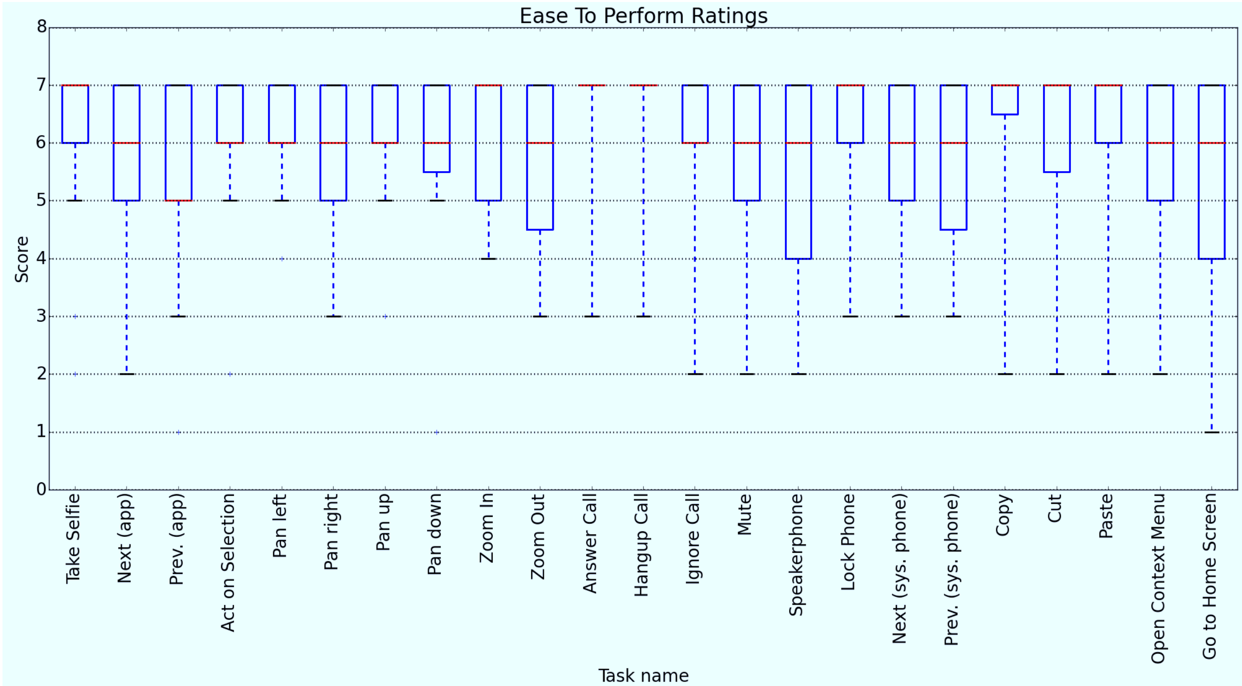

FIGURE 5. Easiness Ratings for BOD Interaction in Smartphone

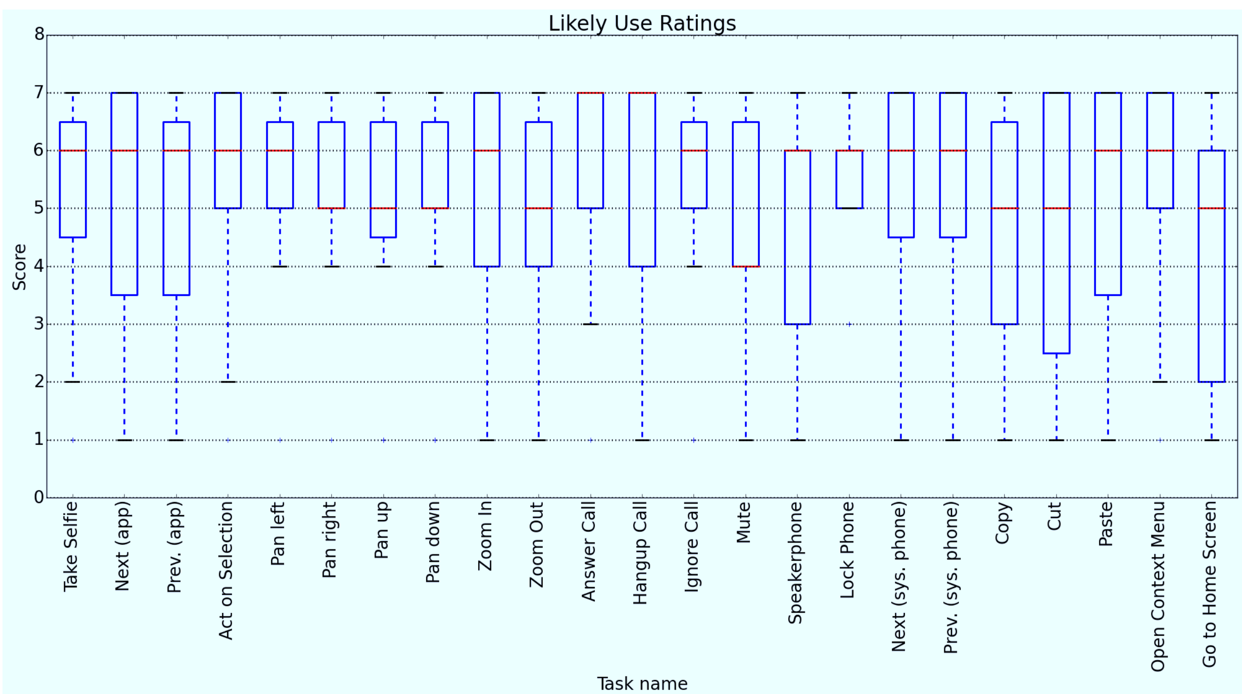

FIGURE 6. Frequency of Use Ratings for BOD Interaction in Smartphone

divided in deciding between moving content over moving viewport while doing scrolling/map panning tasks. In this section, we discuss these qualitative observations.

3.3.1. Legacy Bias. In an elicitation study, the participant's gesture proposal is often biased by their experience with prior interfaces and technologies. In HCI terminology, this is defined as *legacy bias*. During our elicitation study, we observed that the participants were noticeably influenced by previous interaction experiences with WIMP(windows, icons, menu and pointing) interfaces. For example, for map navigation tasks including *Pan(left/right/up/down)* and *Zoom(in/out)*, most users mimicked the gestures they were already applying on the front touchscreen of smartphones/tablets. The participant identified those gestures as more appropriate and natural. One participant said the following:

> *"To pan the map down, I'd like to slide my finger from down to up because this is the same gesture when I'm doing map navigation in front screen. [P8]."*

Some participants mimicked keyboard shortcut key patterns by creating 'C' and 'V' gestures for *Copy* and *Paste*, influenced by traditional PC use. Additionally, some participants created gestures that were influenced by popular applications. For example, some gestures created for *Answer/Hang-up/Ignore Call* were inspired by front-screen interaction with phone, where swiping in one direction or the other is synonymous with acceptance or rejection.

3.3.2. Concern for Accidental Input. Some of the participants designed gestures to be resistant to accidental triggering. For instance, users suggested double tap or rhythmic taps on the back of the device for some selection/action tasks. These participants indicated a concern that normal phone handling like grasping or holding, or bumping the phone while in a pocket would be misread by the phone as a back-of device gestures. The participants believed that while a single tap can sometimes occur by accident, actions like double tap or rhythmic taps were perceived less likely to be performed accidentally.

3.3.3. Concern for Easiness. We observed that participants carefully considered simplicity and easiness when designing gestures. As a result, many elicited gestures were short, memorable, and easy, such as *tap*, *double tap*, and *swipe*. Some of these gestures were location specific. For example, participant P1 used the gesture of one tap in the middle of the back of the device to mimic the action of taking a selfie, whereas he tapped once on the upper left corner to open an application. We observed that most of these simple gestures could be completed quickly.

3.3.4. Natural and Consistent Mappings of Gestures. In general, analysis of the user-designed gestures showed that for the navigational tasks (e.g. *next item, previous item, up, down, left, right*), participants tended to apply gestures that were similar to their front touchscreen counterparts. Furthermore, for the tasks that are equivalent but opposite of each other, participants frequently designed similar gestures in opposite directions/orientations. For example, participants that chose *swiping right*(Figure 3) for viewing the previous screen chose swiping in the opposite direction for navigating to the next screen.

Similarly, some participants employed circular gestures in opposite directions for mimicking the opposite actions of *Mute* and *Switch to Speakerphone* (Figure 7). For muting the microphone, these participants preferred anti-clockwise circular gesture using index finger resting on the back-of-device. Once the device is muted, they suggested making clockwise circular gesture using index finger to unmute. The same circular gesture (in clockwise direction) was suggested during normal operation of phone to turn on the speaker. Once the speaker was turned on - another anti-clockwise circular gesture was suggested as the preferred gesture to turn it off. Participants who suggested these gestures for mute and speaker actions viewed these as simple and consistent mapping - as muting-unmuting and turning on/off speakerphone was viewed as toggling actions.

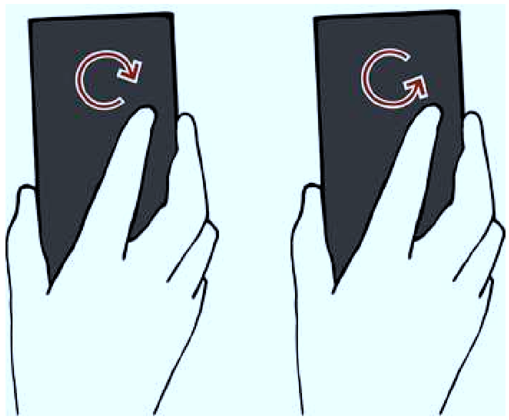

FIGURE 7. Clockwise and Counterclockwise Swipe for Muting/Unmuting and Turning On/Off the Speaker-phone

3.3.5. MOVING CONTENT VS. MOVING VIEWPORT. One reason for generally low agreement scores was a conflict between two approaches to movement (e.g., navigating a map) on a mobile phone. Roughly half of the participants chose to move the content, as if they were pulling or pushing the content with their finger, while the other half performed inverted gestures that moved the viewport instead. This conflict is likely due to participants' differing prior experiences with movement types across devices.

3.3.6. PHONE ORIENTED AND LOCALIZED GESTURES. The vast majority of elicited gestures were phone-orientated, meaning swipes were made along the vertical and horizontal axes of the mobile phone. Although we observed that this appeared to result in slightly more awkward finger movement for the participants, participants remarked that these gestures were easy to use. We also observed that participants performed the same gestures, such as tap, on different places or in different orientations to perform different tasks. For example, for taking a picture with a front camera participant P1 created a tap on middle in the back of phone. Whereas for opening an app, P1 used a tap on the upper left corner (Figure 8).

3.4. Challenges of New Tasks

Although most of the tasks considered in our study already had popular mappings to front screen gestures in smartphones, some common tasks did not have prominent corresponding gestures. For example, while editing selected text by *Copying*, *Cutting*, or *Pasting* is commonly done using a mobile device, there are no surface gestures mapped to these tasks. For these sets of tasks, participants usually had difficulty designing a back-of-device gesture. This caused the agreement scores to be low in comparison to the other tasks. However, participants frequently tried to create simple actions similar to those used with other computing devices, such as, using a finger to draw a 'C' or 'V' on the back of the phone for doing copy or paste(Figure 9), which conforms to the "*ctrl*+C" and "*ctrl*+V" keyboard shortcuts.

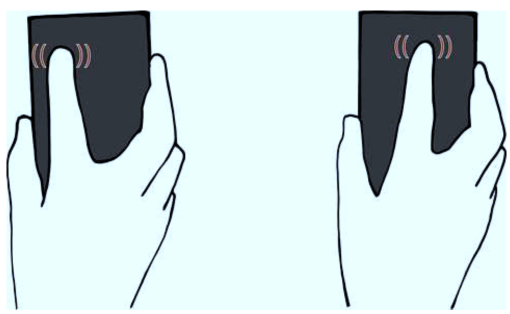

Figure 8. Upper Left and Middle Tap on Back of the Phone by P1

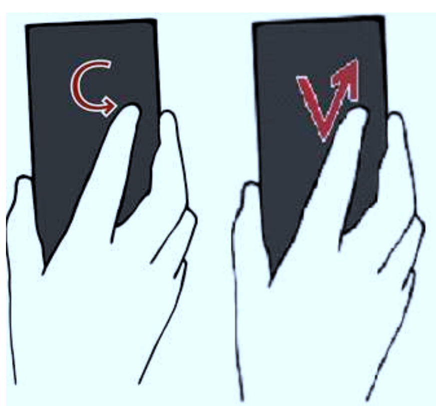

Figure 9. Drawing a 'C' on Back of Device to Copy a Piece of Text, and then Drawing a 'V' on Back of Device to Paste the Copied Piece of Text

CHAPTER 4

Exploring Non-touchscreen Gestures for Smartwatches

To solve both the *fat finger* and *occlusion* problem in smartwatches, a number of alternate input techniques have been proposed. However, similar to alternate input space research in smartphones, these researches on alternate input space in smartwatches have focused heavily on interaction technology design with designer-defined gesture set. To incorporate end-user preference with this existing line of research in smartwatch interaction, we conducted an elicitation study to explore non-touchscreen gestures for smartwatches suggested by the users.

4.1. Method

4.1.1. Participants.

Twenty-five(25) volunteers, ten female, recruited from a local university (12/25) and community (13/25) participated in our study. Participants were aged between 20-42 (Mean = 24.76, SD = 6.06) and all but three wore a watch on their left wrist. All participants owned a smartphone, but none of the participants had any prior smartwatch experience. The participants were compensated with a $20 Amazon gift card.

4.1.2. Selection of Tasks.

One of our specific aim is to understand user's mental model of interaction with a smartwatch for different tasks. In addition, our study answers the following questions:

- Does orientation of tasks have influence on gestures people perform?
- How do users interact with tasks with similar but opposite effects?

- Do the users prefer symbolic gestures over simple tap and swipe gestures?
- Do the users repeat the same gestures based on context?

To understand users' mental model of interaction with smartwatches, we decided to test for the most common tasks that can be performed on different smartwatches. The tasks were chosen by analyzing functionalities of different smartwatches currently on the market. Similar to the grouping of tasks in smartphone BOD elicitation study (Section 3.1), the tasks were grouped into two categories: *action* and *navigation*–based tasks. Within these categories, we created two sub-categories based on task target. Tasks that are specific to smartwatch system (e.g., viewing or setting time, navigating *horizontal* or *vertical* lists) were included into the *System/Smartwatch* category, and tasks that are specific to a particular application (e.g. Google maps) in a smartwatch are included under *Application* sub-category.

After grouping the tasks into these sub-categories, a scenario representing each task was chosen for inclusion in the study. This method allowed us to create tasks that would be representative of the tasks used on a smartwatch but minimize task duplication. In total, Thirty-one (31) tasks were presented to the participants during the study (Table 2). In the list of tasks, we included tasks related to call functionality because a number of smartwatches act as an extensions for the user's smartphone [44] and support call/text notifications and call control functionalities.

4.1.3. PROCEDURE. The study began with the researcher explaining the study and providing the participant with a Moto 360 smartwatch to wear during the study. The purpose of the watch was to strictly act as a reference and did not provide any visual elements specific to tasks. In our study, we were careful not to constrain the users' behavior by the limitations of current gesture recognition technology. Instead, we sought to remove the gulf of execution

TABLE 2. The List of Tasks Presented to Participants in Smartwatch Elicitation Study, Grouped by Category.

Category	**Sub-Category**	**Tasks**
Navigation	System/Smartwatch	Previous (Vertical)
		Next (Vertical)
		Previous (Horizontal)
		Next (Horizontal)
		Go To Home Screen
	Application	Pan Left
		Pan Right
		Pan Up
		Pan Down
		Zoom In
		Zoom Out
Action	System/Smartwatch	Set Hr/Min/AM-PM
		Switch Between Hr/Min/AM/PM
		Confirm Time
		Start Stopwatch
		Stop Stopwatch
		View Time
		Act on Selection
	Application	Answer Call
		Hang up Call
		Ignore Call
		Mute Microphone (Call)
		Unmute Microphone (Call)
		Turn on Speaker (Call)
		Turn off Speaker (Call)
		Open Context Menu
		Switch Application
		Lock Screen
		Copy
		Cut
		Paste

[19] between end users' psychological goal and physical action. The participants were encouraged to focus on gesture design and assume all conceived gestures would be recognized by the smartwatch. Furthermore, they were not constrained to inventing a unique gesture for each of the given tasks, and therefore, could repeat their gesture for different tasks if they chose to do so. The only constraint we imposed upon the participants was that they could not touch the screen of the smartwatch while performing their gestures.

We presented the list of tasks in Table 2 by breaking it up into 6 different groups based on the function of the task. We verbally described the action performed by the device and asked the user to create an input gesture that would activate the device action. We instructed participants to think aloud while making the gesture and to repeat their gesture one additional time. Next, the participants were asked some exploratory questions about the posture of the gesture. For example, the required duration of a finger press, or the number of fingers required to perform a zoom gesture. All verbal responses and gestures created by the participants were recorded using a video camera. For each participant, a transcript of the recorded video was created to extract individual quotes as well as classify and label each gesture designed by the participant. The quotes were then clustered to identify common themes using a bottom-up, inductive analysis approach.

After the participants proposed a gesture that was appropriate for the intended task, the participants were asked to rate the gesture using an 11-point Likert scale (Appendix A) on each of the following statements:

- The gesture I picked is a good match for its intended use.
- The gesture I picked is easy to perform.
- The gesture I picked is easy to remember.

We were also interested in exploring whether social context had any effect on the gesture preference. In order to accomplish this, participants were asked to rate their comfort level with regards to performing their gesture in different environments and social contexts (shown in Table 3) on an 11-point Likert scale.

4.1.4. Data Analysis and Coding. Two researchers coded gestures independently using synchronized audio and video. This classified body part(s) used and their motion

Table 3. The List of Environments and Social Context Used to Explore Social Acceptability.

Environment	**Social Context**
Home	Alone
	With Family
Work	Alone
	Among Colleagues
Public	Among Friends
	Among Strangers

characteristics. Transcripts of the sessions were analyzed using grounded theory and an affinity diagram to discover themes.

4.2. Results

During our study, the data we collected included transcripts, video recordings, non-touchscreen gestures designed by users, and user ratings of gestures. From this data, we present themes emerging from our interviews, taxonomy for non-touchscreen smartwatch gestures, and a user-defined consensus gesture set for smartwatch interaction.

4.2.1. Gesture Taxonomy. We constructed taxonomy for non-touchscreen gestures using the gestures collected from our elicitation study. Similar to Ruiz et al. [49], our taxonomy consists of two main taxonomy dimensions,*gesture mapping* and *physical characteristics*. *Gesture mapping* describes how gestures are mapped to different tasks by the participants. These include the *nature*, *context*, and *temporal* dimensions of the gesture. *Physical characteristics* describe the gesture characteristics themselves and include the duration, size, complexity, and modality dimensions of the gesture. The full gesture taxonomy is listed in Table 4.

4.2.1.1. *Gesture Mapping.* The *nature* dimension of *Gesture Mapping* defines the mapping of the gesture to physical objects. This dimension can be viewed in the following ways:

Table 4. Taxonomy of Non-touchscreen Gestures for Smartwatch Interaction Based on Collected Gestures

Gesture Mapping		
Nature	Metaphor	Gesture is a metaphor of another physical object
	Physical	Gesture acts physically on object
	Symbolic	Gesture visually depicts a symbol
	Abstract	Gesture mapping is arbitrary
Context	In-context	Gesture requires specific context
	No-context	Gesture does not require specific context
Temporal	Discrete	Action occurs after completion of the gesture
	Continuous	Action occurs during the gesture
Physical Characteristics		
Duration	Short	Duration of the gesture is less than 0.5s
	Medium	Duration of the gesture is between 0.5 and 1.5s
	Long	Duration of the gesture is longer than 1.5s
Size	Small	Gesture can be performed in less than $439cm^3$ of physical space
	Medium	Performing gesture requires between $439cm^3$ and $1467cm^3$ of physical space
	Large	Performing gesture requires over $1467cm^3$ of physical space
Complexity	Simple	Gesture consist of a single gesture
	Compound	Gestures can be decomposed into simple gestures
Location	Rim	Gestures performed on the rim of the watch
	Band	Gestures performed on the watch band
	Skin	Gestures performed on the user's skin
	Mid-Air	Gestures performed in mid-air
	Multiple	Gestures that are performed in multiple locations

- *Metaphoric gestures:* The gesture is a metaphor of another physical object. For example, to cut a piece of text on screen, the user makes a two finger scissor gesture above the smartwatch.
- *Physical gestures:* The gesture directly acts on screen content (i.e., direct manipulation).
- *Symbolic gestures:* The gesture depicts a symbol. For example, drawing a '3' in air above smartwatch.

- *Abstract gestures:* The gesture mapping is arbitrary.

The *context* dimension describes whether a gesture requires a specific context or is performed independently. For example, the *swipe right* mid-air gesture is context specific (in-context). If performed while viewing a list, the content will scroll right, whereas, performing the gesture while the phone is ringing will answer the phone. In contrast, hovering the hand over the watch for a period of 2 seconds will lock the screen regardless of context, and therefore, is context independent.

Lastly, the *temporal* dimension describes if an action on an object occurs while or after making a gesture. In a *discrete* gesture, the action occurs after the gesture has been made, and in a *continuous* gesture, the action occurs before a gesture input ends. For example, for *act on selection* task, the action occurs after the user completes a doubletap in air above smartwatch. This is a discrete gesture. A good example of a continuous gesture is the use of swiping above smartwatch for map panning. In this gesture, the map pans simultaneously with hand movement, instead of discrete movement of map in the direction of swipe after a swipe is complete.

4.2.1.2. *Physical Characteristics.* The *physical characteristics* dimension of our taxonomy captures the characteristics related to a gesture's *duration*, *size*, *complexity*, and *location*.

The *gesture duration* dimension describes the temporal requirements of performing a gesture and is divided into 3 categories: *short* (gestures taking less than 0.5 seconds), *medium* (gestures taking between 0.5 and 1.5 seconds), and *long* (gestures taking longer than 1.5 seconds). For example, short gestures include single taps and swipes on the rim of the watch. Double/triple taps and swipes above the device takes longer than 0.5 seconds, but are usually finished within 1.5 seconds. As such, these gestures are categorized as *medium* in duration. Lastly, an example of a gesture with a *long* duration would be hovering the hand over the watch face for more than 1.5 seconds.

The *size* dimension of our taxonomy describes the physical space required to perform the gesture, and is divided into the following categories:

- *Small:* The gesture movement can be performed in a region constrained by a 7.6cm cube (i.e., 439cm^3 space) identified by the blue border shown in Figure 10. These gestures involve extremely little physical movement of a small body part - like making a tap or scroll on rim/watch band, on-air tap with a single finger while keeping hand still.
- *Medium:* The gesture movement can be performed in a region constrained 12.7cm x 15.2cm x 7.6cm rectangular space (space equal to 1467cm^3). Examples include a single twist (rotation) of arm away from body, or making in-air swipes above the smartwatch in the space marked by the red box in Figure 10.
- *Large:* All gestures requiring 3D space larger than 1467cm^3 are considered as large size gestures. These gestures include rotational motions along multiple body joints.

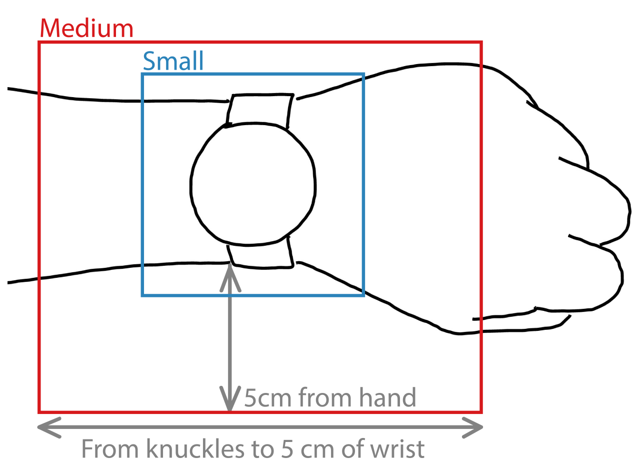

Figure 10. Illustration of the *Small* and *Medium Size* Dimensions of Gesture Taxonomy for Smartwatches

The *complexity* dimension of a gesture describes whether the proposed gesture can be decomposed into constituent gestures or not. A pinching and pulling gesture used for map panning operations is an example of a *compound* gesture where the gesture can be divided into two spatial discontinuities: a *pinch* and a *pull*.

Lastly, the *location* dimension captures where, in relation to the user's body, a gesture is performed. Categories in the location dimension include: *rim, band, skin, mid-air, and multiple locations*. *Multiple location* gestures are mostly *compound* gestures that are performed using a combination of *rim, band, skin, mid-air* gestures, for example, an index finger tapping on watch band and then make a mid-air pull gesture using alternate non-watch wearing hand.

Figure 11 illustrates the breakdown of the 775 gestures collected during the study using our taxonomy. As shown in the figure, gestures tended to be *simple continuous mid-air gestures* with *medium* duration.

4.2.2. User-defined Gesture Set for Smartwatch Interaction. A user-defined gesture set for our specific tasks was generated using the set of all 775 elicited gestures collected from our participants. For each task, identical gestures were grouped together, and the group with the largest consensus was chosen to be the representative gesture for the task. Ties in group size were broken by using the subjective ratings. We refer to this gesture set as both our *consensus set* and our *user-defined gesture set*. The user-defined gesture set is shown in Figure 12.

We used the agreement score standard [63] by Wobbrock and Vatuvu to extract the consensus among participants for each task (Figure 13). Similar to other elicitation studies [49, 56, 72], agreement scores range between 0.4 and 0.1. The overall agreement score

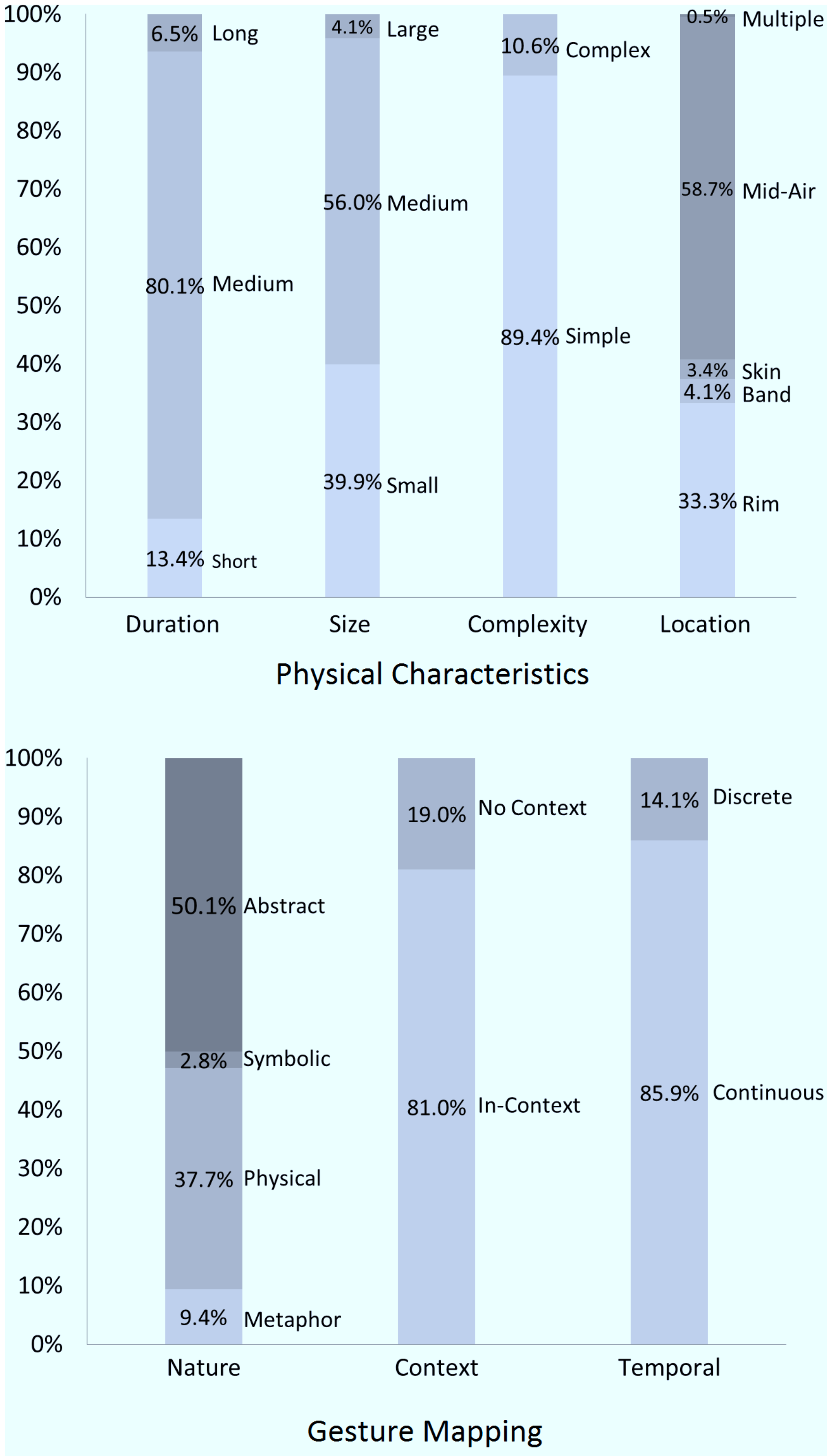

FIGURE 11. Percentage of Gestures in Each Taxonomy Category for Smartwatch Gestures.

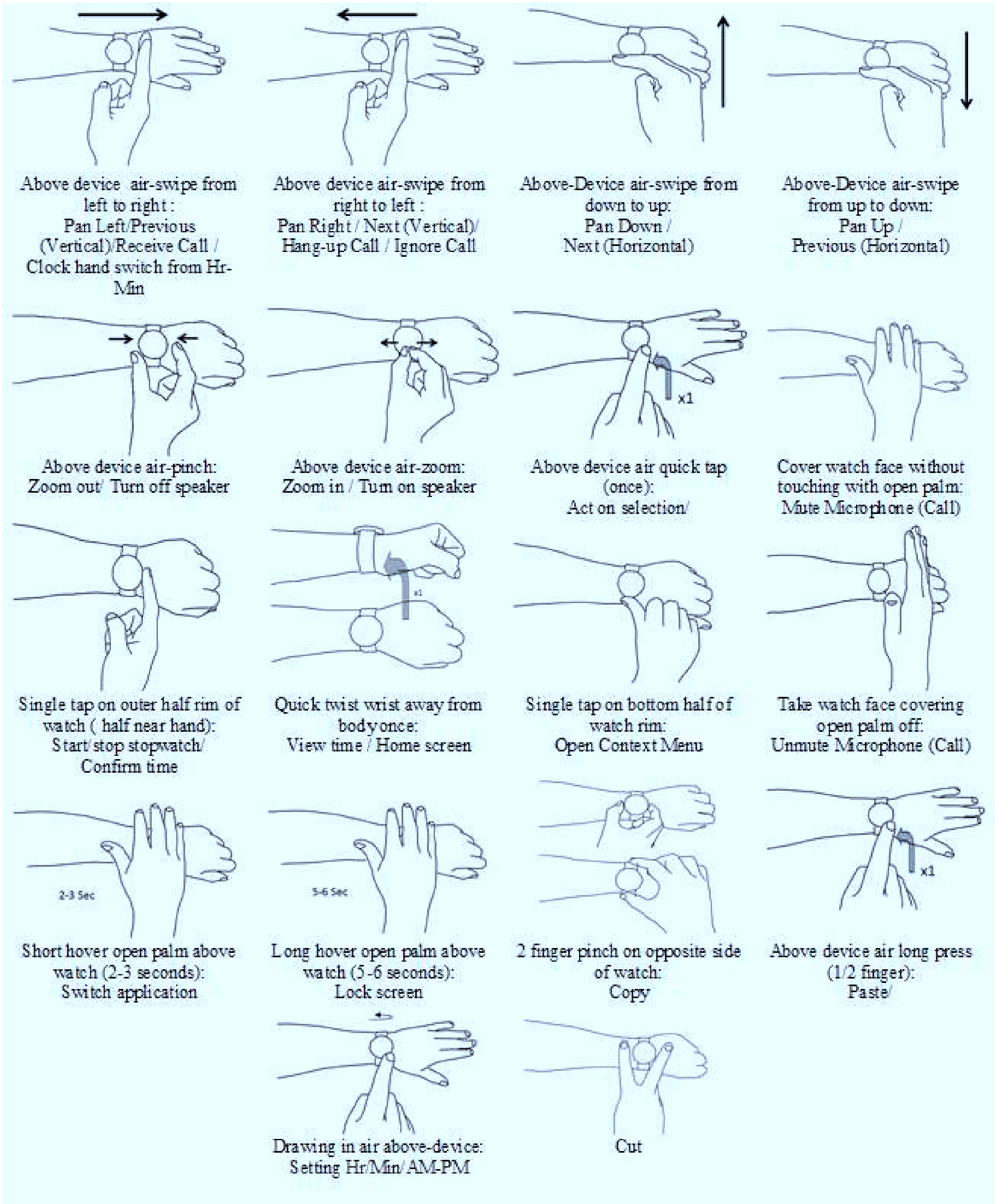

FIGURE 12. User-defined Non-touchscreen Gestures for Smartwatch Interaction Obtained from the Participants.

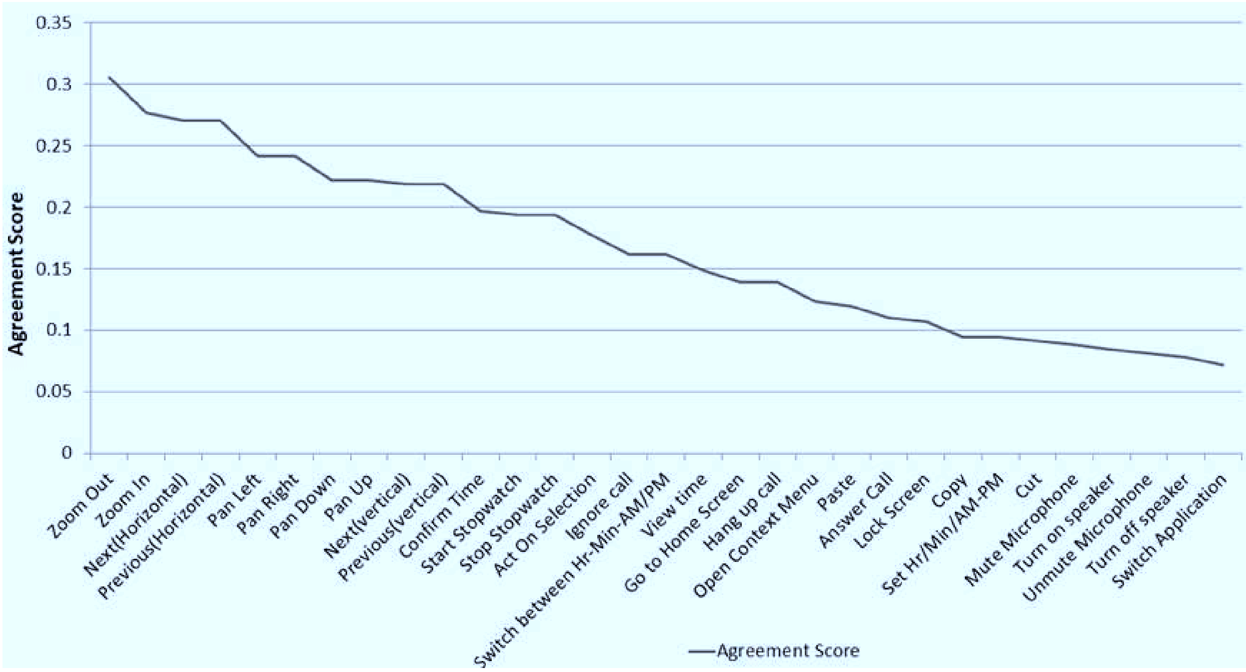

FIGURE 13. Agreement Scores for Tasks in Non-touchscreen Gesture Elicitation Study

(A) is 0.16. Similarly to Wobbrock et al. [73], we rated each task's conceptual complexity independently. Referent's conceptual complexities correlated significantly and inversely with the agreement scores (r = -0.743, $F_{1,29}$ = 35.684, p <0.01). In general, we found that as conceptual complexity of the task increased, participant agreement decreased.

4.2.3. Social Acceptability. Analysis of the collected social acceptability ratings for the elicited gestures revealed several findings. Alternate hand gestures that continued and went beyond the enclosed spaces illustrated in Figure 10, were considered to attract more public attention and were rated to be less socially acceptable. Hence, the participants did not feel comfortable performing such gestures in public and office environments. Physical touch gestures, like touches on the watch rim and band received high social acceptability ratings. All users felt comfortable performing such gestures in populated social contexts.

Moreover, small and medium sized gestures received nearly perfect social acceptability rating in all cases. The results of these ratings showed that participants were comfortable making small and medium gestures in public and office settings, and large gestures were only deemed comfortable in non-public settings (e.g., being alone or being among family). All participants echoed the sentiment of participant P10, who said the following:

"I don't want to attract too much attention to myself."[P10]

This was re-iterated by participant P15:

"When I am among people, I don't prefer making gestures that attract attention from people and makes [sic] me look crazy." [P15]

Our findings support prior work exploring the social acceptability of gestures [14,18,24]. Gestures that can be performed without drawing a lot of attention or cannot easily be interpreted by bystanders are considered socially appropriate. In our case, gestures that can be performed in the interaction volume described by Figure 10 are considered socially appropriate gestures for our context.

4.3. Discussion

In this section, we discuss the qualitative observations and implications of our results to designing for non-touchscreen based gestural interaction on a smartwatch.

4.3.1. Legacy bias. Participants in our study had no prior experience with using a smartwatch. However, participants showed a considerable amount of legacy bias from using touchscreen devices and traditional PCs. For many tasks (e.g., scrolling and zooming), the participants designed gestures that mimicked touchscreen gestures. Participants who mimicked a touch screen gesture often perceived their gesture as well-suited to the task, easier to perform, and easier to remember.

For scrolling and panning gesture, 70% of the conceived gestures were some form of swipes and scrolls mimicking touchscreen gestures. Some participants used above-device swipes for map panning and touch-based scrolls for moving to next and previous items. One of the participants who did this said he preferred making panning gestures in 2D plane, and said the following:

> *"For scrolling, you go up-down or left-right... for panning, you can pan in x-y axis."[P9]*

Non-touch gestures for map panning and zoom were almost always made directly above the watch. When asked about potential occlusion on screen, one participant said:

> *"There is a gap between the hand and watch - I can see more than touching..."[P6]*

A common theme observed during the mapping of the zoom operations was the association of finger spreading and pinching gestures - which was a legacy bias from using touchscreen devices. When the participants were asked for their reasoning behind their chosen gesture, most of them often made comments describing it as the *"most natural"*.

> *"To zoom in, the first gesture that comes to my mind is using my thumb and my index and pull them apart it is what I do on the screen of my phone and tablet."[P7]*

Most participants preferred to use alternate non-watch wearing hand to create finger spread/pinch gesture around the smartwatch, compared to unimanual finger spread/pinch gesture using the watch wearing hand. When the preference of *number of fingers* was explored, most participants (57%) preferred using two fingers (index and thumb) for finger pinch/spread compared to five-finger gestures and echoed the sentiment of P6 who said the following:

> *"Using two fingers(of alternate hand) for zooming above the watch creates less occlusion of the screen compared to using five fingers. It is also faster."[P6]*

The directionality of touchscreen gestures was also mimicked when it was applicable. For example, 88.7% of the gestures conceived for previous and next scrolling mimicked the respective directionality of the corresponding touchscreen gesture. A participant's writing hand or watch-wearing hand had no effect on directionality of the gesture.

> *"To move to the next item in horizontal list, I prefer dragging one finger from right to left when I am touching the screen, I scroll to the left."[P19]*

4.3.2. Influence of analog watch use. We observed that some of the elicited gestures are influenced by participant's previous interaction with different kind of analog watches like wristwatches and stopwatches. For example, some of the participants came up with a *two finger pinch and winding* gesture to set the time or scrolling through vertical lists. For moving through horizontal list, or changing from hours to minutes these participants made a *two finger pinch and pull/push* gesture. These participants said that these gestures were being influenced by the use of notch on analog wristwatches.

We also observed some form of two finger pinches on opposite sides of rim for different tasks, like *starting/stopping a stopwatch.* This was influenced by participants prior interaction with analog stopwatches.

4.3.3. Natural and Consistent Mapping of Gestures. Two noticeable patterns were observed from the gestures that were elicited for tasks that have similar or opposite effects. For unary transition tasks (tasks that cannot be performed before a task with the opposite effect is performed, e.g., starting or stopping a stopwatch), the participants selected one of two strategies. The first strategy was to perform the same gesture twice (for both opposing tasks). For example, for muting and unmuting a microphone, some participants performed the same gesture of a two finger pinch with index and thumb on watch rim (Figure 14). The second strategy was to perform the same gesture in the opposite direction. Continuing with our muting example, some participants performed gestures with opposite effect (covering the watch face with their opposite hand for muting and uncovering it for unmuting). Overall, 57% of the participants envisioned the unary task pair shown in Table 5 as toggling a switch and repeated the same gesture.

Binary transition tasks are tasks that can be performed a consecutive number of times before performing a task with the opposite effect (e.g., pan left and right). For this type of gesture, participants always suggested similar gestures but in the opposite direction. For example, a horizontal swipe to the left was the most common gesture for the next task, and a horizontal swipe to the right was the most common gesture for the previous task.

Current touchscreen interfaces in mobile devices commonly require the user to move the content while the viewpoint remains static. We wanted to determine if users would continue to follow this paradigm. Results from our study showed that when the use of alternate

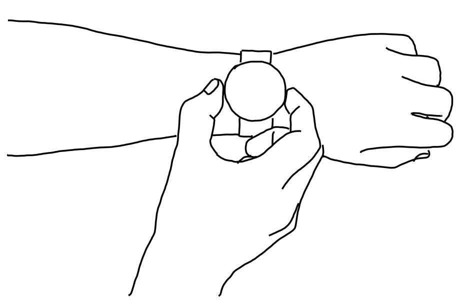

Figure 14. Two Finger Pinch with Index and Thumb on Watch Rim Proposed by Some Participants for Muting and Unmuting the Microphone

Table 5. List of *Unary* and *binary* transition task pairs.

Unary Transition Task Pairs	**Binary Transition Task Pairs**
Mute Microphone - Unmute Microphone	Pan Left - Pan Right
Turn on Speaker - Turn off speaker	Pan Up - Pan Down
Start Stopwatch - Stop Stopwatch	Zoom In - Zoom Out
Answer Call Hang up Call	Next (Vertical) - Previous (Vertical)
	Next (Horizontal) - Previous (Horizontal)

hand is allowed, the participants preferred moving the content rather than moving the viewpoint. Users stated that this was a result from them being more comfortable mimicking the touchscreen gestures of other technologies.

In addition, we wanted to understand if task orientation or content layout had any effect on the gestures participants proposed. Therefore, we presented two lists in both a horizontal and vertical layout. Our results demonstrated that the orientation almost always affected the participants' choice in gesture, with gesture direction being consistent with the orientation of the task.

4.3.4. Concern for Accidental Triggering. Users were concerned about accidental touches, taps and swipes on or around the smartwatch, and subsequent accidental action triggering. Participants showed a conflict between designing simple gestures and gestures that were more deliberate and less prone to accidental triggering. For example, for the *act on selection* task, a number of participants made a double *air-tap* gesture above the screen, considering a double tap gesture more distinct and less likely to be accidental.

A recurring theme among the participants were the preference of having the gesture recognizer in the watch be triggered and turned off in specific body postures. 72% participants said that they preferred having the non-touchscreen gesture feature activated when they have made a specific posture to look at the watch (Figure 15). They preferred this feature to be activated until the arm is moved back and slid parallel to body. During our discussion, the participants said the possibility of accidental touch/tap/swipes on or above the device is lower when someone is actively looking at his/her watch. But when the arm is slid parallel to body - the chances of accidental brushes or touches on band/rim are much larger because of natural body movement.

Participants also said that due to natural body movements during tasks like walking, scrolling/panning gestures created with motion of *alternate* or *watch wearing* hand can be accidentally triggered. For gestures that involved hand/arm motion (i.e., *above device swipe using alternate hand* , *twist/shake/tilt/movement using watch wearing arm*), participants preferred to use another triggering mechanism or hand posture to provide another level of confirmation for gesture recognition. A common theme in the observed hand/arm motion gestures was the observation of specific hand postures using the watch wearing hand, like *making a fist* or *spreading all fingers of hand except for thumb*. Among these secondary 'triggers' observed in this category, "*closing the fist* of watch wearing hand" during hand/arm motion gesture was the most common observed posture (Figure 16). In general, participants preferred to make a fist on watch wearing hand while using the other hand to create scrolling/panning gestures around the smartwatch.

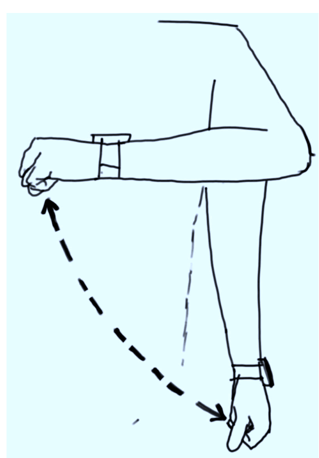

FIGURE 15. Posture of Looking at the Watch, and Then Moving Arm Back and Sliding it Parallel to Body

4.3.5. Preference of Different Physical Touch Gestures. For physical touch-based gestures, users showed significant preference for touching the watch rim over touching the band or skin. The rim was used for gestures in both vertical (scrolling/panning up and down) and horizontal (scrolling/panning side to side) directions, whereas the band was used only in scrolling up and down.

One notable pattern was the preference for using the "outer" half of the rim located towards the hand for vertical swiping and tapping gestures, and the "bottom" half of rim located closer to thumb for horizontal swiping. A participant who wore the target watch on his left hand said the following for next/previous item scrolling in vertical direction:

> *"I am swiping on the left half because the right half contains the watch notch. If the watch notch was not there, I would prefer swiping on the right side."[P22]*

For touch based tapping gestures, most taps tended to occur on the outer half of the watch (near three o'clock) and mostly with the index finger. The second largest number of physical taps occurred on the bottom half of the rim near 6 o'clock, mostly with the thumb. Users were asked about their preferences for different physical tap gestures. Most

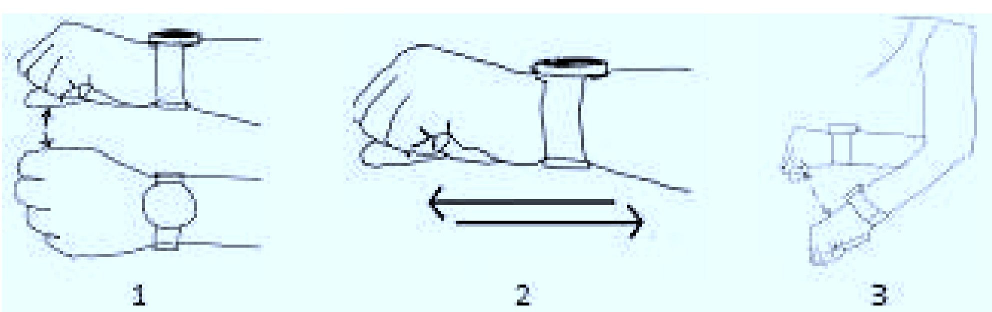

Figure 16. Some Observed Gestures Using Only Watch Wearing Hand Involving a)Tilting b)Twisting and c)Moving Watch Wearing Arm in a 2D Plane Horizontal to Ground. Notice the Fist of Watch Wearing Hand

participants stated that they prefer single finger taps, adding that the finger preferred for performing taps depends on the location of the gesture.

Several types of physical 2–finger pinch gestures were observed during the study. The most common place to perform a 2-finger pinch was on the watch rim. Two finger presses almost always tended to be on opposite halves of the rim - mostly along the arm axis. 76% of 2-finger pinch observed on the watch rim was along the arm axis.

4.3.6. Preference of Feedback for Non-Touchscreen Gestures. There was a strong feeling among the participants that feedback accompanying the gesture is important. While they expected visual feedback to be displayed on the screen, participants also stated a preference for additional feedback through vibration and/or sound. Vibration feedback was preferred over sound by the participants. A majority of participants gave similar opinion to P6 who said:

> *"I prefer vibration to sounds coming from [the] watch ... I may not hear the sound when I am in public but I can definitely feel the watch vibrating." [P6]*

In addition, feedback was deemed to be more important in some tasks than others, with there being a significant consensus among participants to receive feedback for hang-up call, ignore call, act on selection, and confirm time.

> *"For every air-scroll to move to the next or previous item, a vibration is unnecessary and irritating. But when I am terminating a call, a vibration feedback is useful - this lets me know if I accidentally terminated the call." [P12]*

4.3.7. Preference of Using Alternate Hand Over Watch Wearing Hand for Creating Gestures. During our study, we did not put any constraints on the users on the use of alternate non-watch wearing hand. The participants were free to use the alternate hand to make gestures on or around the smartwatch while not touching the screen. Among the collected gestures, only 8.6% of the collected gestures involved the use of only the watch wearing hand. Participants generally preferred to use alternate hand to make physical gestures while making posture similar to Figure 15. In our user-defined consensus set for non–touchscreen gestures (Figure 12), only one of the gestures involved using only watch wearing hand.

4.3.8. Preference of Non-touchscreen Gestures over Touchscreen Gestures. Participants were asked when they would prefer using gestures over touching the screen. They stated that they would employ a combination of touch and non–touch gestures, depending on the context of use. Some of the scenarios in which participants stated non–touchscreen gestures would be more appropriate than other interaction methods included performing tasks where fingers are dirty or interacting with the screen would soil the smartwatch (e.g., while cooking or cleaning); situations where on screen items are difficult to acquire or interacting with the screen would cause occlusion (e.g., users specified that using gestures to scroll a list to find an item is easier and more efficient than using the touchscreen); and when gestures provide a "shortcut" to actions that are not readily available on the touchscreen (e.g., muting the microphone or turning on/off the speaker).

4.4. Summary Findings

The takeaway from our taxonomy, consensus gesture set and qualitative observations are the following:

- People tend to reuse gestures based on context.
- Elicited non-touchscreen gestures are influenced by legacy bias and prior interaction with analog wristwatch and stopwatch.
- For similar tasks with opposing effects, participants prefer to use the same gesture, or similar gesture in opposing direction depending on task-pair grouping.
- Moving screen content is preferred over moving viewport.
- Orientation of tasks effect gesture orientation.
- When both hands are free, participants prefer using the alternate non-watch wearing hand to create gesture above or around the smartwatch.
- Participants prefer specific postures for activating gesture recognition feature in watch to mitigate accidental gesture triggering.
- Non-visual feedback in form of vibration is preferred for specific tasks.
- For physical touches, specific regions on watch band and rim is preferred for different tasks.

4.5. Comparison to Prior Proposed Non-touchscreen Gestures in Smartwatches

As stated in the related work section, researchers have proposed several non-touchscreen gesture sets motivated by preventing users from occluding the screen. Statements by our participants supported the need for interaction techniques that did not obstruct view of the screen (i.e., non-touchscreen gestures). However, very few participants suggested the previously proposed gestures for the same tasks. We attribute this to the fact that most prior work focused on a specific type of non-touchscreen gestures (e.g., the band [2], watch face [74], mid-air [16], or hand [17]), whereas, we were more open-ended about the types of gestures that participants could perform. The small number of times where our participants mimicked prior designer based gestures occurred when that gesture could be seen as having high legacy bias. For example, Bandsense [2] suggested a tap on the band and Knibbe et al. [26] a single tap on the back of the watch. Some of our participants proposed similar gestures, with the majority of the users proposing mid-air tap above the watch face. All of which can easily be attributed to the legacy bias associated with interacting with touchscreens.

CHAPTER 5

Design Implications for Proposed Alternate Interaction Spaces in Smartphones and Smartwatches

5.1. Design Implications for Implementing Back–of–Device(BOD) Interaction on Smartphones

The research findings for back–of–device interaction [56] on smartphones can extend the findings of Yoo et al. [78]'s BOD Interaction on Smartphones. Yoo's study defines the *comfortable zone* and *extended zone* for back-of device interaction. Both of these zones are located on the upper-half of the back-of device. Results from our elicitation study [56] show that participants prefer creating gestures in this defined region. However, Yoo's research does not give any idea about what kind of gestures people perform in this defined region. The back–of–device interaction elicitation study results for smartphone fills in this gap by giving a direction about different gesture preferences on the back of device, as well as a possible gesture-task mapping for regular tasks.

During the BOD elicitation study, participants showed a valid concern for accidental inputs if the entire back-of device is made sensitive to inputs. Instead of making the entire back surface touch-sensitive– like employing a secondary touch-screen similar to [79], only the region specified by [78] should be made touch-sensitive. Keeping the accidental input concern in mind, the touch input activation on the back and on the front should be synchronized. For example, pressing a hard button on the edge of phone activates both the touchscreen and the touch interface in the back.

From the observed gestures, most of the gestures are limited to different swipes and taps in the specified region defined in [78]. For tapping gestures - we observed that tapping on the upper-left corner on the back of the device (defined as *comfortable zone* in [78]) is used for performing different tasks when compared to tapping on the middle of the back of device. This indicates that for tapping gesture recognition - recognizing the location of the tap on back–of–device is necessary with recognizing the tapping gesture. For swiping in different directions or creating swipe patterns (e.g. creating a 'c' on the back of device), users did not differentiate between middle and upper-left corner in the back, which indicated that location recognition is not necessary when swipe patterns/directions are being detected on the back of device.

5.2. Design Implications for Implementing Non–touchscreen Interaction on Smartwatches

Similar to other elicitation studies, we did not consider how to track gestures in smartwatches. The goal of our study was to understand user's mental models regardless of technology. However, results from our work present several implications regarding what technology would be needed to recognize the gestures in our user-defined gesture set. More specifically, our results show that users prefer gestures that can be finished between 0.5-1.5 seconds, and can be constrained by the $1467cm^3$ region defined in Figure 10. This suggests that very little hardware may be required to enable this type of interaction on smartwatches, and that approaches such as using infrared hardware similar to Hoverflow [28] may be more appropriate than those that use complex depth cameras (e.g., that of Air+Touch [11]).

Similar to our research findings for Back–of–Device Interaction [56] in smartphones, the users were mostly concerned with accidental gesture inputs for smart-watches. From our discussion with the participants, we were able to identify several useful hand and arm postures (discussed in Section 4.3.4) on the watch wearing hand that can help mitigate the accidental input possibilities. These can be recognized using muscle-interface techniques similar to [80]. Activating the gesture recognizer feature of the watch on the arm posture shown in Figure 15, along with a secondary watch-wearing hand posture (e.g. closed fist/open palm with thumb tucked under palm) in user interfaces where horizontal/vertical/2D scrolling is involved will help reduce accidental scrolling gesture input triggering.

CHAPTER 6

Conclusion and Future Work

To counter the existing issues with input spaces in smartphones and smartwatches, I explored the possible use of proposed alternate interaction spaces in smartphones and smartwatches. The focus of traditional research in this area has been the possible implementation of gesture recognition technology, at the cost of overlooking end-user preference for possible interaction in the proposed spaces. As such, I focus on the exploration of end-user preferences in the proposed interaction spaces in smartphones and smartwatches. From the elicitation studies, I present the elicited gestures for common tasks that can be performed in smartphones and smartwatches, and provide insight into end-user mental model of designing gestures in the proposed spaces for these devices. Comparing my results with related work, I describe some design implications for incorporating the proposed spaces in smartphone and smartwatch interaction. Elicited gestures and common themes identified in this research can compliment existing research in alternate input spaces in smartphones and smartwatches, and help create gestural interfaces in these devices with high end-user usability.

Two common themes that were observed during the elicitation studies in this dissertation were end-user concern for triggering accidental inputs, and gestures being influenced by legacy bias. While legacy bias hinders discovering new gestures, Kopsel et al. [27] argue legacy bias eases the transition of interacting with new gesture paradigms.

The research was limited by the cultural and social demographics, as most participants were educated adults who lived in a western culture. The cultural and social norms observed by the participants were more likely to be homogeneous, and it could not ascertained that these same gestures would have the same acceptance in a different culture. For example, the "scissor" gesture elicited by the participants for *text cutting* task in both smartphone and smartwatch can have different acceptance in different cultures. For example, in western culture this posture can be used to symbolize a victory sign or the number '2' , but mean *"go to hell"* in greek culture [1]. As such, one important extension of this work will be the continuation of these elicitation studies accross different cultures with the help of online tools, and determine a user-defined gesture set that is appropriate for other cultures as well.

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APPENDIX A

Likert Scale

For each of the task, we recorded the ratings of each participants using the three statements in Figure 17. A 11-point likert scale was used.

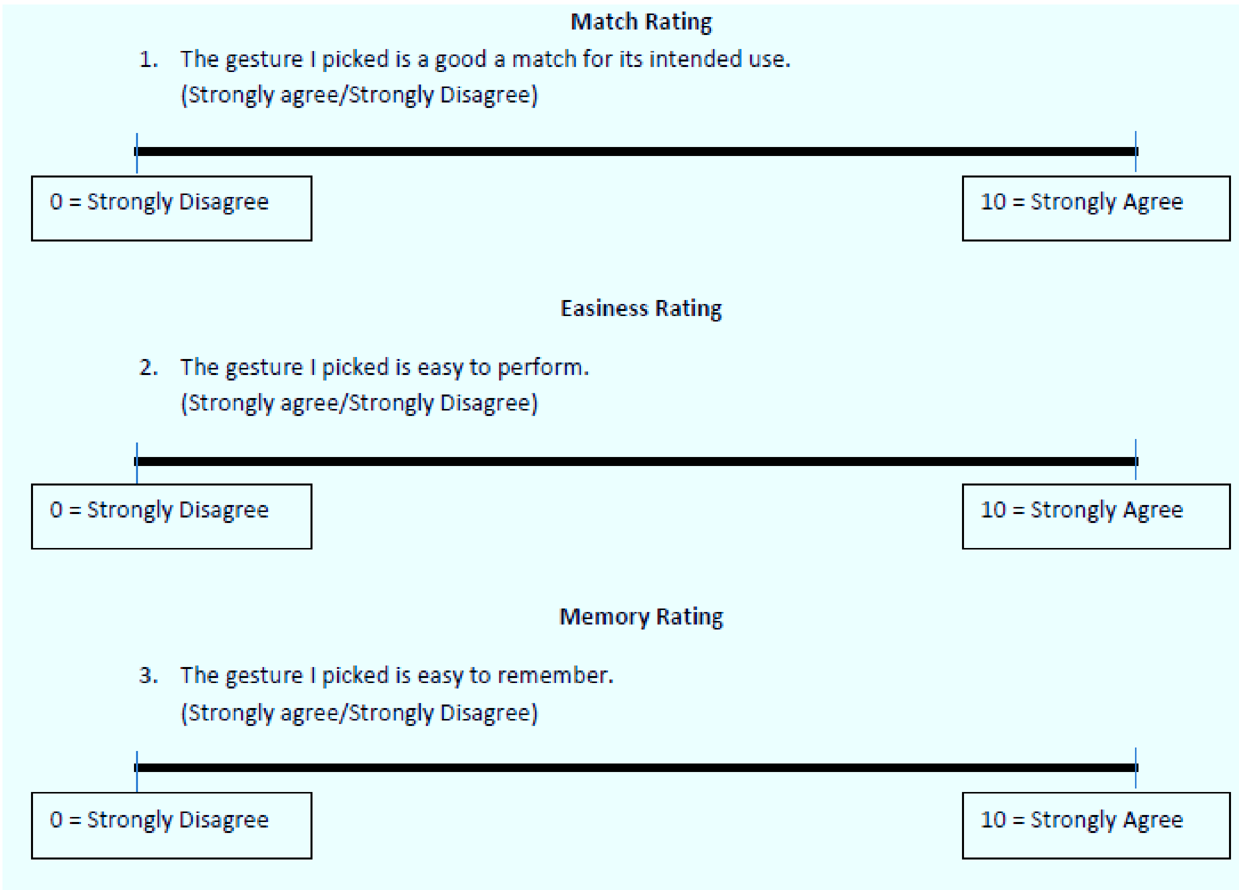

FIGURE 17. Likert Scale Used in Smartwatch Study