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Doctoral Thesis

Designing Intra-Hand Input for Wearable Devices

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Designing Intra-Hand Input for Wearable Devices

A dissertation submitted to
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DoYoung Lee

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Approved by

Advisor
Ian Oakley

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Designing Intra-Hand Input for Wearable Devices

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This certifies that the thesis/dissertation of DoYoung Lee is approved.

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Abstract

Current trends toward the miniaturization of digital technology have enabled the development of versatile smart wearable devices. Powered by capable processors and equipped with advanced sensors, this novel device category can substantially impact application areas as diverse as education, health care, and entertainment. However, despite their increasing sophistication and potential, input techniques for wearable devices are still relatively immature and often fail to reflect key practical constraints in this design space. For example, on-device touch surfaces, such as the temple touchpad of Google Glass, are typically small and out-of-sight, thus limiting their expressivity capability. Furthermore, input techniques designed specifically for Head-Mounted Displays (HMDs), such as free-hand (e.g., Microsoft Hololens) or dedicated controller (e.g., Oculus VR) tracking, exhibit low levels of social acceptability (e.g., large-scale hand gestures are arguably unsuited for use in public settings) and are vulnerable to cause fatigue (e.g., gorilla arm) in long-term use. Such factors limit their real-world applicability. In addition to these difficulties, typical wearable use scenarios feature various situational impairments, such as encumbered use (e.g., having one hand busy), mobile use (e.g., while walking), and eyes-free use (e.g., while responding to real-world stimuli). These considerations are weakly catered for by the design of current wearable input systems.

This dissertation seeks to address these problems by exploring the design space of intra-hand input, which refers to small-scale actions made within a single hand. In particular, through a hand-mounted sensing system, intra-hand input can include diverse input surfaces, such as between fingers (e.g., fingers-to-thumb and thumb-to-fingers inputs) to body surfaces (e.g., hand-to-face inputs). Here, I identify several advantages of this form of hand input, as follows. First, the hand's high dexterity can enable comfortable, quick, accurate, and expressive inputs of various types (e.g., tap, flick, or swipe touches) at multiple locations (e.g., on each of the five fingers or other body surfaces). In addition, many viable forms of these input movements are small-scale, promising low fatigue over long-term use and basic actions that are discrete and socially acceptable. Finally, intra-hand input is inherently robust to many common situational impairments, such as use that take place in eyes-free, public, or mobile settings. Consolidating these prospective advantages, the general claim of this dissertation is that intra-hand input is an expressive and effective modality for interaction with wearable devices such as HMDs. The

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dissertation seeks to demonstrate that this claim holds in a range of wearable scenarios and applications, and with measures of both objective performance (e.g., time, errors, accuracy) and subjective experience (e.g., comfort or social acceptability).

Specifically, in this dissertation, I verify the referred general claim by demonstrating it in three separate scenarios. I begin by exploring the design space of intra-hand input by studying the specific case of touches to a set of five touch-sensitive five nails. To this end, I first conduct an exploratory design process in which a large set of 144 input actions are generated, followed by two empirical studies on comfort and performance that refine such a large set to 29 viable inputs. The results of this work indicate that nail touches are an accessible, expressive, and comfortable form of input. Based on these results, in the second scenario, I focused on text entry in a mobile setting with the same nail form-factor system. Through a comparative empirical study involving both sitting and mobile conditions, nail-based touches were confirmed to be robust to physical disturbance while mobile. A follow-up word repetition study indicated that text entry studies of up to 33.1 WPM could be achieved when key layouts were appropriately optimized for the nail form factor. These results reveal that intra-hand inputs are suitable for complex input tasks in mobile contexts. In the third scenario, I explored an alternative form of intra-hand input that relies on small-scale hand touches to the face via the lens of social acceptability. This scenario is especially valuable for multi-wearables usage contexts, as single hand-mounted systems can enable input from a proximate distance for each scattered device around the body (e.g., hand-to-face input for smartglass or ear-worn device and inter-finger input with wristwatch usage posture for smartwatch). In fact, making an input on the face can attract unwanted, undue attention from the public. Thus, the design stage of this work involved elicitation of diverse unobtrusive and socially acceptable hand-to-face actions from users, that is, outcomes that were then refined into five design strategies that can achieve socially acceptable input in this setting. Follow-up studies on a prototype that instantiates these strategies validate their effectiveness and provide a characterization of the speed and accuracy achieved by the user with each system.

I argue that this spectrum of metrics, recorded over a diverse set of scenarios, supports the general claim that intra-hand inputs for wearable devices can be expressively and effectively operated in terms of objective performance (e.g., time, errors, accuracy) and subjective experience (e.g., comfort or social acceptability) in common wearable use scenarios, such as when mobile

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and in public. I conclude with a discussion of the contributions of this work, scope for further developments, and the design issues that need to be considered by researchers, designers, and developers who seek to implement these types of input. This discussion spans diverse considerations, such as suitable tracking technologies, appropriate body regions, viable input types, and effective design processes. Through this discussion, this dissertation seeks to provide practical guidance to support and accelerate further research efforts aimed at achieving real-world systems that realize the potential of intra-hand input for wearables.

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List of Publications

This dissertation is based on the following publications.

Chapter3: Nailz: Sensing Inter-hand Input with Touch Sensitive Nails

DoYoung Lee, SooHwan Lee, and Ian Oakley. 2020. Nailz: Sensing Hand Input with Touch Sensitive Nails. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (CHI '20). Association for Computing Machinery, New York, NY, USA, 1–13.

Chapter4: FingerText: Exploring and Optimizing Performance for Wearable, Mobile and One-Handed Typing

(Accepted) DoYoung Lee, JiWan Kim, and Ian Oakley. 2021. FingerText: Mobile, One-Handed, Inter-hand, Wearable Text Entry In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (CHI '21). Association for Computing Machinery, New York, NY, USA

Chapter5: Designing Socially Acceptable Hand-to-Face Input

DoYoung Lee, Youryang Lee, Yonghwan Shin, and Ian Oakley. 2018. Designing Socially Acceptable Hand-to-Face Input. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* (UIST '18). Association for Computing Machinery, New York, NY, USA, 711–723.

All publications in this dissertation have been co-authored with Ian Oakley. He mainly advised and guided the overall part of the publications including the experiment design, analysis, and writing. For the study in Chapter 3, SooHwan Lee and HyunMi Oh supported the user study and provided constructive feedback for the nailz system. In Chapter 4, JiWan Kim supported the overall part of the study; he conducted entire user studies and provided several unique ideas for data analysis. In Chapter 5, Youryang Lee assisted the user study and data analysis in the aspect of social acceptance, and Younghwan Shin took part in the ideation and discussion of the work. Thanks for all of this dedicated supports.

I Introduction

1.1 Wearable Technology

The archetype of current wearable devices was originated from the first glasses developed in 1286 and a pocket watch (which is worn as a necklace or a pendant) developed in 1510. These two main form factors of current wearables can assist humans by enhancing the human vision (glasses) or providing time information from an easy-to-access body location (watch). Over the 20th century, technological advances have brought more functionality to these form factors. For example, in 1968, Sutherland introduced “The Sword of Damocles,” which is regarded as the first augmented reality head-mounted display (HMD) system [1]. The fundamental idea behind the system is to augment the human vision by presenting a perspective image that changes. The user’s motion through a three-dimensional display has become the foundation of today’s augmented reality (AR) system. Similarly, from 1975, the modern style of wearable devices came to be presented as a form of a wristwatch, particularly with the introduction of the Pulsar Calculator (1975) and HP-01 (1977). These two watch form factors of electronic devices gathered public attention because of their built-in calculator and stopwatch that provides interaction through multiple keys under the clock screen. These examples illustrate how they add significant functionality to glasses and watch form factors. However, due to their limited interaction (no other interaction for HMD or preset buttons in watches) and low computational power, it was difficult to use them for other applications.

The current miniaturization trend on digital technology can overcome these limitations. Fingernail-sized processors can run even 3D games within a smartwatch. Meanwhile, cutting-edge touch screens in current smartwatches enable delicate touch inputs that can detect simple drawings even on the 1.57-inch size of screen [2] and the vision system in current smartglasses (or an HMD) can track hand and finger motions in real-time. Such remarkably advanced processors and tracking fidelities enable various forms of inputs, such as touch, mid-air gesture, or speech control. At the same time, the diminutive size of chips enables various form factors, such as glasses, watches, accessories, shoes, or clothes, which can incorporate multiple wearable computers into our daily activities. With these latest technologies and form factors, wearable

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technologies are expected to have considerable impact on diverse application domains, such as health care, education, entertainment, communication, industry, military, or other life activities.

1.2 Inputs for Wearables

This new device category will change the way we use computers. Their high-performance processors and multiple sensors capable of tracking body motions with high precision are expected to enable a seamless integration of wearables into our daily activities. However, to input modalities in wearables, several challenges related to their characteristics are yet to be addressed, such as variety of form factors, diminutive size, proximity to the body, and dynamic usage contexts including mobile and social settings. Due to these inherent challenges, the current input methods, such as touch screen, controller, or mid-air hand gesture, cannot be effectively operated in this class of computing devices. For example, the touchscreen paradigm popularized on larger devices, such as phone and tablet functions in smartwatches, is arguably a poor fit to the small screen, where only limited content can be displayed, and a user's fingers tend to obscure the screen during taps or swipes. Even in terms of hand occupation, touch interactions on the smartwatch is rather inefficient as they require both hands occupied [3, 4], while the mobile phone requires only one hand for operation with a much larger screen [3]. For the smartglass, there is no clear direct input technique adaptation or consensus [5]. Consequently, multiple interaction techniques, such as handheld controller, on-air input of the hands, or a small touchpad on the side of the head, are adapted together. These approaches have some drawbacks, such as the inconvenience of carrying a dedicated input device, the limited expressiveness of a small touchpad, and the social awkwardness of performing in-air gestures or voice control. These factors limit their real-world applicability. Along with these physical difficulties, typical wearable use scenarios feature various situational impairments, such as attention-demanding tasks (e.g., while driving), mobile use (e.g., while walking), social situations (e.g., meeting), and encumbered use (e.g., having one hand busy), that are weakly catered for by the design of current wearable input systems.

Given this background, this dissertation aims to explore improved interactions with wearables to address several considerations and challenges derived by the characteristics of such devices.

For further discussion, I specify the scope of this dissertation in terms of three aspects: level of interaction, wearable form factors, and context. Level of interaction refers to the level of user engagement with the device. Burgy and Garrett [6] classified this aspect into three basic categories: primary task, support task, and control task. In detail, the primary task requires no direct interaction with the device, but the device can still sense the environment passively. Conversely, the support and control tasks require sole interaction with the device. The difference between these two is that the support task assists the user in providing information or accepting input, while the control task involves navigating wearable applications. From these categories, this dissertation will only cover the direct manipulation of wearable devices; the primary tasks, such as context awareness, are not addressed here. In line with this, this dissertation will only refer to smartwatch and smartglass form factors. This is because other form factors of wearables, such as accessories, shoes, and clothes, are typically used for activity tracking, health monitoring, or simple notification [7], with limited interaction. Lastly, regarding context, I focused on typical situational impairments that can impact input on wearables, namely attention-demanding tasks, mobile use, social situations, and encumbered use. These separated scenarios can cover the diverse real-world usages of wearables. In the following sections, I delve into these wearable usage contexts to discuss considerations and challenges.

1.3 Contexts, Considerations and Design Factors

Designing inputs for wearables require an understanding of diverse aspects, including their characteristics and usage contexts. One most distinctive and notably different characteristic of these devices compared to conventional desktop computers or mobile phones is that wearables are continuously worn devices. This inevitably means that they will be used more frequently [8] and intervene more often in daily activities, such as attention-demanding tasks [9, 10], mobile use [4], social situations [11], and encumbered use [3]. Each of these usage contexts has several considerations to be made so as to better support users.

For example, with attention-demanding, tasks such as driving [12], cycling [13], and cooking [14], users should focus on the main tasks for safety purposes [7]. Thus, interactions should be simple and quick to ensure that the system does not demand exceptional attention of the user

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during the interaction. In this regard, the use of eyes-free input [15] or non-visual modalities for output [16] is encouraged to guarantee that the user remains focused on the physical world rather than on the computer screen.

Unlike conventional static desktop computing environments, the mobile context (e.g., walking or running) of wearable devices is crucial. Just as smartphone use in the mobile condition is prevalent [17], wearable devices will also be used in different mobility scenarios. However, mobility is challenging due to situational impairments [18], from simple tasks (e.g., object selection with head gaze [19]) to complex tasks (e.g., text entry on the smart watch [20, 21, 22, 23]), as such interaction increases the task load with potential disturbances [24]. While these can be mitigated through careful design of stable and accurate input while on-the-go, the current approaches that address these challenges remain underdeveloped.

Social situations or public contexts, such as meetings, cafe, or public transportation, are also significant usage contexts, as their characteristics considerably affect willingness to use wearables [11, 25]. When it comes to smartglasses, the issue becomes more critical as large arm motions, such as mid-air gestures or touches on the HMD, are quite obtrusive and likely to attract attention from the public [26]. To avoid this undue attention, the design of the wearable input should pursue unobtrusive and socially acceptable actions, such as microinteractions [27] or natural body motions.

These situations occasionally limit the use of hands due to holding objects or dirtiness of the hands [3]. Such a limitation requires one-handed or no-handed input with other input modalities, such as speech control and head gaze. The one-handed use can leverage the benefits of the hand's high dexterity for wide input space and quick access, while no-handed inputs can provide higher accessibility for diverse situational impairments, such as driving and cooking. Considering these tradeoffs, the wearable input should provide multiple input modalities to support various usage contexts.

In addition to these contexts, in terms of physical property, diminutive size and various form factors are also key challenges. Direct inputs to the device are often limited by a confined space (as in the smartwatch) and eyes-free usage (as in the smartglass). Accordingly, their usage will vary from simple tasks, such as playing music or checking the weather, to more complex

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ones, such as message texting [4], 3D modeling [28], and engaging in educational activities [29]. This dynamic usage condition and the variety of form factors require a versatile input set that can cover several function shortcuts with easily understandable interfaces. Usage contexts of wearable devices include these diverse situational impairments. Therefore, considering these environments and the characteristics of wearables is essential for designing inputs for wearables. For discussion purposes, I consolidated these considerations into the following four design factors that can guide the design of inputs for wearables.

Manipulation: The input should be quick and accurate. As an always-worn device, many applications, including notifications, payments, or music, will be used more frequently within a short period of time [30], and this requires seamless use of wearables to not disturb the user. Thus, these inputs should seek microinteraction [31] inputs to ensure that the interaction duration is short and the users are not distracted from their main tasks. For example, as Ashbrook [32] stated, the time from the first intention of the interaction to the input should have a short life span (less than four seconds).

In terms of accuracy, the system should consider both sensing quality and algorithm performance. For example, the system should be better calibrated so that the touch or vision input can better reflect the user's intention. Likewise, the system should be able to distinguish inputs such as gestures and poses with higher accuracy through improved classification algorithms.

Accessibility: The input should be easily and comfortably accessible in diverse usage contexts. In particular, a highly accessible system is necessary for situational impairments, such as attention-demanding tasks [9], mobile use [4], and hands-occupied tasks [3, 33]. To this end, the input of the wearable device should have eyes-free, one-handed or no-handed, and stable inputs. In addition, the interaction should consider multi-wearable devices use scenario, which raises questions about how to control each device scattered over the body by a single input technique.

Space: The input space should be expressive for more complex tasks in various applications. In particular, it is important to provide a wide set of inputs for both discrete and continuous input [34]. The required expressiveness of input depends on the application. For example, text entry requires 26 keys for multiple letters (or nine keys with multiple letter assignment as in T9 [35]), while map navigation requires precise movement tracking. In addition, complex tasks,

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such as 3D modeling in AR environments, require diverse shortcuts (e.g., copy&paste, undo, and grouping) with various continuous inputs (e.g., color bar control, object movement, and size change). Accordingly, the expressiveness of the input should be considered in relation to the application to be used. Generally, these expressive inputs can be achieved by a physically larger input space (e.g., wider touch surface), various forms of actions (e.g., touch, motion, poses, and deformation of skin), or higher tracking fidelity of sensors (e.g., higher sampling rates in IMU sensors can detect more diverse motion gestures).

Social: The input should seek to reflect and fit the public contexts in which the use of the wearable device is frequent. The interactions should ensure that the control movements required are performed without attracting undue attention. By and large, unobtrusive design [25] or natural gestures [36] are considered key strategies to achieve this social acceptability [37] ,which is a particularly important step for the successful diffusion of wearables [38].

In addition to these, many other factors, such as energy efficiency, privacy, safety, and technology, can affect input design for wearables. However, this work focused on the above four factors because they are highly associated with interface usability and can address many wearable usage scenarios. In this dissertation, these factors were used as a framework for analyzing each input design.

1.4 One-Handed, Intra-Hand Inputs

By reflecting on these challenges and considerations, this dissertation explores the design space of intra-hand input for wearable devices, which are specified as small-scale actions taken using a single hand. This type of input encompasses diverse finger actions (e.g., touches between fingers to thumb and thumb to fingers [39], hand poses, and gestures [40]), as well as touches on other body surfaces (e.g., hand-to-face inputs [41]) through a hand-mounted sensing system. In this section, I highlight that such interaction techniques can provide several benefits in terms of the four design factors mentioned above.

First, for the manipulation factor, intra-hand inputs can be performed quickly and accurately through unique human, proprioception [42], and passive haptic senses [43, 44]. Proprioception, which refers to the ability to sense the relative position of each body part, allows users to make intra-hand input immediately without visual attention. In addition, the haptic feedback, which is readily incorporated in on-body interfaces [45], and the sensory stimulation during intra-hand touches reduce the efforts to verify whether each input was successfully performed [46]. Moreover, the hand is a very appropriate region for microinteractions due to the 27 degrees of freedom (DoFs) of the wrist and fingers [47].

Second, for the accessibility factor, intra-hand inputs are always available for most usage contexts, as hands typically unobstructed by garments and such an input enable the use of the other hand for carrying an object or even engaging in high attention-demanding tasks, such as driving. In terms of mobile contexts such as walking, intra-hand input is robust to disturbances [48] and can reduce distraction by the interaction with eyes-free inputs. In addition, the hand's high dexterity enables easy and convenient access to the thumb and fingers.

Third, for the space factor, intra-hand inputs enable wide design spaces including diverse actions such as tapping [49], swiping [50], drawing [49], posing [40, 51], or flicking [52], as well as large input surfaces to touch, such as the side of the fingers [39], palm [53], and nails [14]. These input primitives can be combined with each other to serve a range of input actions for diverse applications. For example, each finger segment can be used as buttons for text entry [35], while poses and gestures can be used for playing a game [54]. Moreover, continuous input can also be obtained by touch (dragging [55]) or arm motion (finger tap & wrist rotation [56]). These various touch and motion actions incur a wide input space of intra-hand input for diverse applications.

Lastly, for the social factor, microinteractions of intra-hand inputs are typically unobtrusive. For example, the small scale of inputs within a fingertip [57] as less likely to attract undue public attention in diverse social contexts. To better achieve this, the input actions should be carefully designed and the sensor tracking fidelity should be sufficiently high to detect small-scale inputs. In this case, the selection of an input technique (or a sensor) is an important concern. In this dissertation, the intra-hand input was implemented through the system with touch-sensitive fingernails and a motion sensor (Inertia measurement unit; IMU) on the wrist. There are several benefits of using a fingernail as an interactive surface. First, it is a practical site for mounting sensing hardware [58] on its hard plate as this will minimally interfere with the use of the hands,

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and the cosmetic tradition [14, 59] supports this worn accessory. In addition, the tips of the fingers are easily reachable by the thumb and vice versa. In terms of sensing technique, the touch interface is reliable and accurate with its direct contact detection and a motion sensor (IMU) supporting tracking of finger gesture (e.g., finger flick) or continuous actions (e.g., wrist rotation). Throughout this dissertation, this intra-hand input implementation was explored and verified for its applicability as an input modality on wearable devices.

1.5 Claim, Structure, Contributions and Conclusion

The dissertation addresses the general claim that intra-hand input can yield expressive and effective inputs for wearable devices, such as smartwatches and HMDs. The dissertation seeks to support this claim by demonstrating that it holds in a range of wearable scenarios and applications, and with measures of both objective performance (e.g., time, errors, and accuracy) and subjective experience (e.g., comfort or social acceptability). To this end, this dissertation begins with an overview of the general background on intra-hand input by addressing the advantages and limitations of previous research outcomes on intra-hand input within diverse contexts of wearable device use. Then, it follows with carefully selected examples to present different types of design factors that provide evidence to our claim through the multi-research stages of "design - development - evaluation." The discussion is concluded with a summary of three scenarios: underlying design factors, lessons learned, and future works. Specifically, Chapter 2 reviews the general background of intra-hand input over three sections. The first section explores previous literature on intra-hand input considering advantages and limitations, in addition to describing the groundworks for the touch-sensitive fingernail system. Then, it explores contexts of wearable devices characterized by contexts of situational impairments, such as attention-demanding tasks, mobile use, social situations, and encumbered use. The last section reviews state-of-the-art applications and commercial devices that leverage intra-hand input from the perspective of design factors and discuss how intra-hand input will be adapted in future wearable devices.

From this background, Chapter 3 explores the design space of intra-hand input through a touch-sensitive fingernail system. This exploratory design process begins with an ideation workshop in which intra-hand input primitives (taps, flicks, and swipes on the multiple nail

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regions) were generated and a large set of 144 input actions were derived from these input primitives. Next, these input actions were complemented with data from two user studies characterizing the subjective comfort and objective performance (task time and accuracy) of each touch. The conclusion synthesizes this material into a set of 29 viable nail touches, assessing their performance and illustrating how they could be used by presenting and qualitatively evaluating two example applications.

Chapter 4 extends Chapter 3 to investigate the feasibility of intra-hand input for a more complex task in a challenging context: text entry while walking. To this end, the subset of 29 viable nail touches (only tap actions) for the keyboard input was employed and a comparative empirical study on both sitting and mobile conditions was conducted. The results confirm that such a nail-based intra-hand input is robust to the physical disturbances inherent in a mobile setting, and the study data was fed into a multi-objective optimization process in order to design keyboard layouts. A follow-up word repetition study on optimized layout reports up to 33.1 WPM of performance while walking, which demonstrates that intra-hand input can support rapid, accurate, and comfortable typing within a mobile context.

Chapter 5 examines an alternative form of intra-hand input that rely on small-scale hand touches on the face. This form of input is suggested as a solution for multi-wearable device contexts where the hand can play the role of input effector from the proximate distance to the scattered (around the body) devices. Hand-to-face gestures for smartglass have already been proposed as a way to add input expressivity while keeping control movements unobtrusive [41]. This chapter leverages this by utilizing intra-hand input sensors for hand-to-face inputs. However, current knowledge does not address social acceptability for such a technique, while the face, as a publicly visible body region, is exposed. To tackle this issue via the lens of social acceptability, an elicitation study was conducted in a busy public space where pairs of users were asked to generate unobtrusive, socially acceptable, hand-to-face input actions. The outcomes were then refined into five design strategies to achieve socially acceptable input. Follow-up studies on a prototype that instantiates these strategies validate their effectiveness and provide a characterization of the speed and accuracy the user achieved with each system.

Chapter 6 summarizes these separated scenarios and revisits underlying design factors. Then,

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it discusses diverse considerations, lessons learned, and future works. This chapter ends with the conclusion of this dissertation and its major contributions.

From these carefully structured backgrounds and separated scenarios, this dissertation presents several contributions. One major contribution refers to novel artifacts and designs, which include the specific prototypes (e.g., touch-sensitive nails) and interface designs (e.g., nail touch interface and text entry interface). Another contribution concerns the knowledge obtained through developments and the design guidelines or strategies (e.g., design strategies to achieve social acceptability). I also highlight the contributions to methods used in each scenario. For example, unknown input spaces can be explored by extracting common touch input primitives with ideas from workshops by experts and the discovery of various input spaces. Similarly, as suggested in Chapter 5, designing input on the face, where social acceptance is a considerable matter, can be explored by a modified elicitation study in a busy public space. These methods can be used to explore such a novel system and its input space. Finally, this dissertation makes substantial contributions in terms of data on objective performance and subjective experience with one-handed input system in various forms (e.g., intra-hand or on-face) and situations (e.g., while texting, while walking, or in public). The objective data characterize human performance (e.g., time and accuracy) during input, while the subjective data (e.g., comfort and social acceptability) describe user experiences in such settings. These user data can provide clear guidelines to future designers, researchers, and developers to create similar systems more effectively.

In conclusion, I argue that this spectrum of metrics, recorded over a diverse set of scenarios, supports the general claim that intra-hand inputs for wearable devices can be expressively and effectively operated in terms of objective performance (e.g., time, errors, accuracy) and subjective experience (e.g., comfort or social acceptability) in common wearable use scenarios, such as mobile contexts and in public.

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II Related Work

To understand intra-hand inputs and design such a system, this chapter reviews the general background in three sections. The first section begins with an exploration of previous research on intra-hand inputs considering their advantages and limitations, and describes the groundworks for the touch sensitive nail inputs presented in this dissertation. The second section explores contexts of wearable devices from a holistic view, showing clear contrasts to current desktop or mobile usage. More specifically, I emphasize considerations for designing input systems for each context in terms of mobility, public use, and task complexity. Then, I describe how these considerations relate to the design factors presented in the introduction. The last section briefly reviews state-of-the-art applications and commercial devices that leverage intra-hand input from the perspective of design factors and discusses how such a system will be adapted in the future.

2.1 Intra-Hand Inputs

Intra-hand inputs are small-scale actions made within a single hand. These inputs leverage the hand's high dexterity with 27 separate DoFs, including six DoFs in the wrist, four DoFs of each finger, and five DoFs of thumb with a more complicated structure [47]. Particularly, the thumb is more independent compared to other fingers for its position and movement [60], allowing access to the rest of the hand with relative ease. In addition, diverse finger movements, including adduction/abduction and flexion/extension, enable more diverse and delicate movements of intra-hand inputs.

This versatile thumb-and-fingers dynamics present "thumb-to-fingers" or "fingers-to-thumb" inputs with expressive input space through wide touchable hand regions and various input actions. For example, as Soliman et al. [39] consolidated, tap and swipe actions could be performed on a range of touchable and segmented hand areas, such as a segment (e.g., proximal, middle or distal) [34, 35] or the side (e.g., radial, ulnar, dorsal or volar) [61, 62, 63] of the finger. In particular, these segmented finger regions (e.g., phalanx, knuckle, or nail) can be utilized for augmenting the hand as a multiple key input space for issuing commands [64] or text typing [50]. In a different form of action, systems capable of sensing the motions of the hand for the whole

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range provide cursor control [65], drawing letters [66], finch and flicks gestures [52], or sign language pose [67].

The hand's fine dexterity (fine-motor skill) [68] is another highlighting factor for its subtle and socially acceptable inputs [11]. For example, Xu et al. [44, 57] presented a keyboard on tip of the index finger within 2.2cm × 2.2cm of a capacitive touch sensor matrix for invisible and always-available input. Similarly, Hsieh et al. proposed an exemplary glove form factor of input device to support text entry, scrolling, and point-and-select. Their glove design with multiple sensors can capture subtle hand and finger gestures for unobtrusive and socially acceptable inputs. These examples leverage the high tracking fidelity of current sensing technology, which can detect hand and finger positions with high accuracy – leap motion can track the hand and fingers with an average accuracy of 0.7mm [69], a capacitive touch surface can detect the finger position with subpixel level of precision [70], and the IMU device can provide up to 10 µg of precision for accelerometers, which indicates that it will lose its 50 meters of accuracy after approximately 17 minutes (other sensors such as gyro or magnetometer also provide very precise input).

In terms of accessibility, the hand is a well-suited interaction medium as it is typically not covered by garments and the fingers can perform actions subtly and rapidly. These characteristics enable eyes-free and always-available input [34, 44, 55, 71, 72] to the intra-hand input. Moreover, as the interaction does not require any process of picking up, holding, and looking at the devices [42], the inputs are readily accessible to applications such as notifications. Human characteristics, such as proprioception and tactile sensation, also support accessibility of the intra-hand input [16]. For example, proprioception informs where the hand and fingers are, while the haptic feedback [31, 44] informs when the touch was performed. In addition, the intra-hand input is robust to physical disturbances while in motion [73]. Due to these features, intra-hand inputs are accessible to diverse wearable use scenarios.

2.1.1 Sensing Techniques

There are several ways of sensing intra-hand inputs. Input methods that utilize diverse sensors, such as touch, vision, or motion, incur different benefits and limitations depending on the usage environment. This section examines various sensing techniques and their characteristics. For "thumb-to-finger" or "finger-to-thumb" touches, one easy way of detecting these inputs is turning the body into a touchable surface by placing a capacitive touch surface on the finger [44, 57], palm [53], ring [56], or a nail [14]. These input surfaces can delicately and accurately detect small motions [44, 57], while the passive haptic [43, 44] enables easily understandable and performable inputs. In leveraging these advantages, Xu et al. [57] presented a system that can carry out text entry via a capacitive touch sensor pad on the index fingertip. Similarly, Kao et al. [14] presented a nail-mounted gestural input surface that can distinguish on-nail finger swipe and tap gestures with a capacitive touch sensor array. Although these works demonstrated that touch-sensitive body regions can provide quick and accurate input with a flexible printed circuit, which can fit on the curvature on the skin, difficulties are still faced in directly attaching the touchpad to the skin [44], and this may cause unwanted touches while doing daily tasks [74]. To overcome this issues, researchers are underway to develop a thinner and more stretchable form factor, similar to a tattoo [53, 75].

Alternatively, motion data can be used to detect hand and finger movements. This type of input technique is ready-to-use and simple to implement using a built-in motion sensor in the typical smartwatch. For example, Wen et al. [76] presented Serendipity, a technique for recognizing unremarkable and fine-motor finger gestures, such as pinching, rubbing, tapping, squeezing, and waving fingers, using off-the-shelf smartwatches. Their supervised machine learning approach relied on high-fidelity sensor data can achieve an average f1-score of 87

Another way of detecting hand actions is to wear a glove with multiple sensors. The first wired data glove, Sayre Glove released in 1976, can sense the bending of fingers through flexible tubes that contain photocell on one end and a light source on the other to measure the amount of light passing [77]. After this kickoff project, many researchers have added sensors on gloves to detect more exact hand actions and poses. For example, DataGlove [77] can monitor the six DoFs of the position and motion of each 10 finger joints using low-frequency magnetic fields, and power Glove [77] (the first commercially available glove for entertainment) adds resistive-ink flex sensors to capture the bending of each finger. In more recent works, Lee et al. [78] and Jiang et al. [79] present a glove that is sensitive to force exertion with multiple force sensors in each finger segment for keyboard applications that assign multiple letters to each key. Although this

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form factor of input technique is easy to wear and detects intra-hand actions, it is still difficult to wear continuously in daily life because it apparently becomes oily and sweaty [55].

The vision is a common approach in most current VR and AR devices. Thanks to high-resolution cameras and sophisticated processors, these devices can detect the hand poses and track their movement in real-time. This form of input requires a camera mounted on the head [56], shoulder [80, 81], chest [31], wrist [71], or a finger [40, 82]. These vision-based inputs also enable diverse action forms of intra-hand inputs, such as taps [80], pose [40, 51] and gestures [31] including free-hand inputs [83] in 3D spaces with relatively high accuracy [40, 71, 80]. However, there is a limitation in that an occluded hand cannot be captured [80, 84] and the lighting condition can be critical for the RGB-based vision system [85].

In addition to these conventional approaches, many researchers have focused on the bio-sensing technique that utilizes bio-acoustic or electronic signals generated while performing gestures. For example, electromyography (EMG) can detect the electrical signals of muscle activation. Saponas et al. citesaponas2008demonstrating, saponas2009enabling and Haque et al. [86] presented a system that detects EMG signals and translated it to input commands, such as hand-pointing, clicking, and pinching gestures. Bio-acoustic is another popular approach. For example, Amento et.al [87] and Zhang et al. [66, 67] presented a technique that can detect sounds that travel by bone conduction throughout the hand while performing tapping, rubbing, flicking, and unistroke thumb gestures. Similarly, Laput et al. [52] proposed a system that captures bio-acoustic signals by the accelerometer at a sampling rate of 4 kHz and recognizes flicks, claps, scratches, and taps gestures with this. These input techniques can provide always-available and diverse input sets from wrist-mounted high-fidelity sensors. While they are promising for future input techniques, challenges still remain, such as collecting a large set of background data and improving machine learning algorithms for a system that is robust to false-positive inputs in diverse environments [52].

This chapter examined these diverse sensing techniques in terms of their benefits and limitations. When designing a new input for wearable devices, one must carefully select the sensing techniques considering their trade-offs in fidelity sensing, usage environment, action set, and body location. Moreover, the design can yield a multiple-sensor system. For example, Ens et

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al. [56] demonstrated how the combination of hand tracking by vision sensing and touch tracking by the touch sensing on the ring device can be promising for supporting high-precision and low-fatigue interaction by complementing each other. In this manner, future input system design should consider the sensing technique combination to better support the gesture sensing algorithm and reduce the error [86].

2.1.2 Design Factors in Current Sensing Approaches

This section describes several input approaches popularized in current smartwatches and HMD form factors [88, 89], as well as discuss their challenges and opportunities. For a better discussion, each design factor is annotated for each related issue. This section aims is to understand current input channels and their advantages and limitations, which must be considered for designing inputs for wearables.

Touch: The touch interface, commonly combined with a screen, supports accurate and rapid inputs sufficient for complex applications, such as text entry and game playing. In particular, in the case of a touchscreen, the spatial mapping between input and output enables direct interaction with the displayed object intuitively. Most current smartwatches leverage these advantages for operating diverse applications with taps and swipe gestures, as they do in mobile phones. Likewise, the touch interface is also a popular input modality among HMD devices. For example, Google Glass has a touchpad on the temple of the device, and controllers of many VR devices have a touchpad around the thumb.

However, fitting this touch interface into the diminutive size of the wearable surface [Space] is still challenging. For example, the touchscreen is arguably a poor fit to the tiny screen of smartwatches (typically around 1.6 inches), where the fat fingers obscure the contents on the screen and limit the accurate inputs. Similarly, in terms of glasses form factors, users cannot see the small input space directly (the touch surface is on the side of the head for AR or they only can see the front screen for VR), and this makes it more difficult to perform accurate inputs. Moreover, as their input surfaces are typically far from the touching hand (opposite wrist or around the ear), the travel time delays the immediate inputs [Manipulation].

Eye-tracking: Eye-tracking system is being employed in the latest HMD devices thanks to the current high-fidelity cameras. For example, Microsoft HoloLens2[1] and HTC Vive pro eye[2] are utilizing this built-on system for object selection [90] or manipulation of eye movements and blink for VR avatar[3]. These applications leverage the characteristics of the eye, which is always available and very rapid. However, eye-tracking is vulnerable to disturbances in mobile contexts [91] [Accessibility] and enables very limited interactions – blink and gaze[Space]. To deal with this other input techniques such as dwell [92, 93] or other input modalities such as a clicker, speech, or hand-tracking should be combined [74].

Head gaze: Head gaze is used in most HMD devices for its simplicity and higher stability than eye-tracking. Similar to eye tracking, these devices support always available and easy to use inputs. However, for the same reason of eye-tracking, it is vulnerable to mobile context [Accessibility] and has a limited input space[Space].

Hand tracking: High-end HMDs utilize hand movements, poses, or gestures as an input. As this input modality can detect the movement of the hand and high DoF of the finger motions through the camera attached to the device, it can provide suitable input set for diverse applications, such as text entry [94], games [54], and 3D modeling [28] [Space]. However, long-term use of mid-air gesture causes fatigue (i.e., gorilla arm syndrome) [95] and the gestures or finger motions may be occluded by other body regions if the hand is not well positioned [39, 84][Accessibility]. Moreover, in a social situation, mid-air gestures may attract a lot of undue attention from the public [Social].

Speech: Advances in speech recognition technology enables hands-free use of wearables[Accessibility]. In particular, by acquiring the intention of the user from the command, it can provide much simple and rapid use of applications for certain tasks such as make an alarm or play specific music which conventional touch input requires several steps of manipulation [Manipulation]. However, simple tasks involving continuous actions, such as scrolling or zooming in/out, may take longer

[1] https://www.microsoft.com/en-us/hololens/hardware
[2] https://www.vive.com/eu/product/vive-pro-eye/overview/
[3] https://www.vive.com/eu/product/vive-pro-eye/features/

than touch actions as the speech control is typically discrete [Manipulation]. Moreover, it is still difficult to use in public because of its social acceptance [Social] and privacy issues [10].

Controller: A controller is generally used by VR devices in a static and pre-set environment [96]. Their precise orientation and positional tracking through the camera (on HMD or externally pre-installed) and built-in motion sensor are capable to make rapid and accurate 3Dmotion inputs, and by being combined with multiple buttons and touchpad on the controllers, they provide much wider input space for diverse applications such as games, 3D modeling, and teleconferences [Space]. However, their usage is limited to a specific environment and it is cumbersome to bring the controllers around [Accessibility].

Motion based control: Built-in motion sensors installed in most wearable devices enable body motion tracking that support head-gaze interface on the HMD or hand gesture detection in smart-watches. In particular, its high sampling rate and low-power support increase the use of motion control in smartwatches for the activation gesture (Raise arm), wrist gestures (flick in/out), and finger gestures (flick or tap). Motions running on the one-hand only provide higher accessibility than the touch interface (which requires two hands [3]) [Accessibility] and rapid inputs [Manipulation]. In this case, the input set design is particularly important as the large-scale motion gestures can lower the social acceptability and inconvenient gestures can limit the long-term use [Social].

There is no technology that completely satisfies all design factors. Rather, these interfaces are often combined each other. For example, in HMD, head gaze (or eye-tracking) is used for pointing while hand tracking or controller is used for selecting and dragging. Likewise, a smart watch uses a touch interface for main input modality while simple inputs are done by motion control, and text inputs are done by speech. These multimodal inputs complement one another to enables much wider input space and convenient uses.

In addition, this holistic view of current approaches arises further discussions. The decoupling trends between input location and the output feedback location [42] are becoming more dominant due to the small input surface of the wearable devices and their scattering around the body. Body area network [7] and image recognition technology [97] also support this trend by fully

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utilizing the sensor data from each body region or detect the body motions from the camera and thus this input trend can provide a wider input space compared to conventional touch inputs. These can be even more extended with the development of new sensors or techniques. However, such a decoupling may suffer from difficulties to make an easy-to-understand mapping between user action and the input [98].

On the other hand, although wearables are a new form-factor of computing that is always on the body, there is a lack of considerations for the use of the human body itself in the current input modalities [99]. In the research community, there have been long attempts to utilize the body as an input and output platform [45]. These extra input dimensions can open up new interaction opportunities by transforming whole body areas into a touch-enabled surface. In this case, the proximate body area from wearables can be utilized as the input surface, which makes it easier to build easy-to-understand mappings. These areas may include hand, back of the hand, arm, or face which proximate to the smartwatches or smartglass.

2.1.3 Touch-Sensitive Fingernails

This dissertation explored the intra-hand input via capacitive touch sensor on the nail and motion sensor on the wrist. There are several reasons for utilizing this body region and input modalities. First, the nail is a convenient site for finger augmentation: it is rigid and has a cosmetic tradition of worn accessories that minimally interfere with the use of the hands. Some previous works leverage this by mounting hardware object on the nail for objects [58] or measuring finger motions [100, 101]. More closely with this dissertation, Kao et al. [14] describe thumbnails covered with grids of capacitive electrodes capable of supporting input such as simple taps and swipes. Second, the tip of the finger is an easy and convenient site to make a touches [34], suggesting that the fingernails are also easily accessible. Third, the touch input can detect slight touch motions within a small size of a fingernail, and this allows to distinguish even tap and swipe within one fingernail [14]. Lastly, the motion sensor on the wrist can complement the touch modality by providing a motion or gesture detection such as wrist rotation or flick [76].

For these reasons, this dissertation explored nails as an input surface for diverse aspects such as its input space (Chapter 3), accessibility for attention-demanding tasks in a mobile setting

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(Chapter 4), and multi-device use scenario via a lens of social acceptability (Chapter 5). This series of scenario support a better understanding of such a system and the intra-hand inputs.

2.2 Wearable Computing Contexts and its Considerations

Wearable devices have significantly different usage contexts compared to current desktop or mobile computers. To understand these diverse usage contexts, this section reviews studies that examine the characteristics of wearable devices and then discusses their usage contexts and considerations.

First, Rhodes [102] defined the wearable computer as the system that have as many as the following characteristics – 1) Portable while operational: it can be used while walking/moving around. 2) Hands-free use: wearables should minimize the occupation of a user's hands. 3) Sensors: wearables should have sensors to be aware of the physical environment. 4) Proactive: they should be able to communicate this information to the user immediately. 5) Always on, always running: wearables must be always on and working, sensing, and acting.

Likewise, Starner [103] stated that "Wearable computing pursues an interface ideal of a continuously worn, intelligent assistant that augments memory, intellect, creativity, communication, and physical senses and abilities."

For Toney et al. [104], the design of wearable computers should consider diverse aspects, such as function, comfort, mobility, and social weight [105]. He focuses on the social weight, which is a measure of the degradation in social interaction that occurs between users and others due to the use of a computing device, to design a wearable device that contains a vibrotactile display on the shoulder pad for social acceptability.

Amft et al. [106] provided three core factors that characterize wearables: 1) Integration: seamless integration of electronic devices with the user's everyday outfit; 2) Interaction: allowing the user to access the system without interference with his/her ability to interact with the environment; and 3) Situational awareness: Providing the system with the ability to model and recognize user activity and environmental conditions. They argue that wearables should not hinder the activities performed by the user by being virtually invisible, while the device should

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be always active and available without continuous attention of the user.

Lastly, Fletcher et al. [107] also highlighted comfort, ease to use, unobtrusiveness, privacy, and security as aspects that wearables should provide, as health monitoring becomes part of the always-worn device for daily life.

These studies presented diverse design aspects that wearable input interfaces should pursue. One main and notably different context compared to that of existing desktop computers or mobile devices is that of "continuously worn device." From a proximate distance to the user, these interfaces will be used more frequently [30], while their usage duration will be shorter [7]. Accordingly, they will intervene more often in daily routine, which inevitably means that they will be used more in a distracted environment [9, 10]. For example, limited-hands contexts [3] such as driving, swimming, cycling, and cooking, require one-handed or hands-free inputs. Similarly, mobile contexts [4], such as walking or running, require accurate and stable inputs from potential disturbances [24]. Indeed, all these inputs should be comfortable, quick, and simple to use for long-term and immediate use of wearables.

In addition, the subtlety or social acceptability is a crucial issue that wearables should pursue as it considerably affects willingness to use [11, 25]. For example, the use of wearables in public contexts, such as meetings, cafes, or public transportation, require inputs that will not attract undue attention from the public. To achieve this, the input on wearables should be small (e.g., microinteractions [27]) or utilize natural body motions. However, the typical input methods in current smartglass, such as mid-air gestures or touches on the HMD, are quite obtrusive and eventually attract attention from the public [26].

Moreover, wearables should consider diverse application contexts. Especially for HMDs, by augmenting the real world, wearables enable diverse complex applications, such as 3D modeling, games, or education applications. This means that they will require a much wider input space for various functions and shortcuts.

I tackled each of these issues above throughout this dissertation. Chapter 3 explored the wide input space of five touch-sensitive nails and evaluated their objective performances. Then, with a subset of inputs on the same system, Chapter 4 investigated more complex tasks (e.g.,

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keyboard) in a mobile context. Finally, Chapter 5 examines the use of such a system in a different way, namely with hand-to-face touches, in terms of social acceptability. This adds contributions to objective performance data for two prototypes that instantiate user strategies to achieve social acceptability. Through this process, I conclude that intra-hand inputs using touch-sensitive nails are suitable for diverse usage contexts (e.g., wide input space, walking, and in public) of wearable devices in terms of objective performance (e.g., speed and accuracy) and subjective experiences (e.g., comfort and social acceptability).

2.3 Intra-hand Input in Commercial Wearables

This section explores intra-hand input in commercial wearables to understand how they are adapted today and how they will be applied in future designs. Intra-hand input has already been used as an input solution that can provide quick access and comfortable use in various form factors, such as rings, smartwatches, and HMDs. These devices can recognize diverse finger motions, gesture, and touch inputs through built-in high-fidelity input modalities, such as touch, motion, and vision, to control the device itself or surrounding objects.

For example, the Nod[4] presented a smart ring that can augment the finger as an interaction medium to control other gadgets, such as lighting system, music player, or television, through 3D finger motion gestures. These gestures were typically performed by drawing a shape (e.g., drawing musical notes for a music player) or making a motion (e.g., panning for map application) while touching on the ring for activation. To achieve this objective, they impressively packed 70 different components into the ring-sized device and provided a 32,000-dpi accuracy for movement. Although the project was discontinued shortly after the product was launched in 2014 due to the slow growth of the wearable market at that time, they presented a promising aspect of gestural input medium to interact with the ambient computes. Further, the miniaturization trend of digital technology and the development of battery and IoT technologies hint that this type of input device will become popular in the near future.

Regarding the smartwatch, current devices leverage a built-in motion sensor to detect finger

[4]https://nod.ai/about/

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or hand motions. For example, android wear OS[5], which among the mainstream wearables operating systems, provides simple hand motion gestures such as flicking the wrist in/out for navigating information cards or pushing down the hand for opening a notification. This instant access to notifications increases the accessibility of the device and reduces the attention level of the user from the main activity. In addition to these, more recent MAD Gaze[6] provides more than 30 input actions, such as snapping different fingers, turning the wrist, or simple tapping on the back of the hand. Its wider input space enables more complex tasks with its diverse shortcuts. This development trend in smartwatches shows that the future design will enable a more diverse intra-hand input set with a more precise motion sensor and sophisticated algorithms to support quick access to diverse applications with complex tasks.

In terms of HMDs, many of these devices provide hand tracking as a primary input modality through built-in cameras. For example, HoloLens2[7] and Oculus Quest 2[8] provide a similar set of input gestures, which are pinching (thumb and index) for selection, pinching and motion for dragging, and pinching while looking the palm for opening the menu. These discrete and continuous inputs enable diverse applications, such as menu navigation or object control in a 3D space. While their precise cameras enable free-hand 3D motion inputs with high precision, their limited input actions do not fully exploit the potential of the hand. Especially for complex tasks, such as 3D modeling or text entry, head gaze and pinch for many buttons or tasks will no longer be effective. Thus, future design will enable more hand input actions, such as pinch to each finger, flick, swipe, or poses [39] to provide sufficient input space for the needs of diverse applications.

These examples show the potential of intra-hand input for commercial devices to expand the input space of wearable devices. While the current systems are providing a small subset of intra-hand inputs, we can expect improved use of these input spaces with more technology advances and the needs of complex tasks. It is noteworthy that discrete inputs such as tapping can utilize wider input spaces when combined with continuous inputs, such as hand 3D motion. Such a multimodal input can provide much wider input spaces by combining different input modalities. In this context, further research on multimodal input by data from different form factors of

[5]https://wearos.google.com/
[6]https://www.madgaze.com/watch/
[7]https://www.microsoft.com/en-us/hololens/hardware
[8]https://www.oculus.com/quest-2/

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wearables, such as motion input on the smartwatch and hand tracking by the smartglass, is necessary.

2.4 Summary

This chapter explored diverse intra-hand input techniques and their advantages and limitations so as to examine how they are leveraged by nail input systems. Then, by synthesizing the characteristics of wearable devices from several previous works, this chapter presented usage contexts, design challenges, and considerations regarding wearables. This chapter was concluded with an investigation on how the latest devices are using intra-hand input and a discussion on how systems will be adopted in the future. In the following chapters, the design and evaluation process will be presented to validate the claim of this dissertation, that intra-hand input is an expressive and effective modality for interaction with wearable devices such as HMDs. The rationale for the nail input system and the frames of each scenario will be based on this chapter.

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III Nailz: Sensing Inter-hand Input with Touch Sensitive Nails

3.1 Abstract

Touches between the fingers of an unencumbered hand represent a ready-to-use, eyes-free and expressive input space suitable for interacting with wearable devices such as smart glasses or watches. While prior work has focused on touches to the inner surface of the hand, touches to the nails, a practical site for mounting sensing hardware, have been comparatively overlooked. We extend prior implementations of single touch sensing nails to a full set of five and explore their potential for wearable input. We present design ideas and an input space of 144 touches (taps, flicks and swipes) derived from a ideation workshop. We complement this with data from two studies characterizing the subjective comfort and objective characteristics (task time, accuracy) of each touch. We conclude by synthesizing this material into a set of 29 viable nail touches, assessing their performance in a final study and illustrating how they could be used by presenting, and qualitatively evaluating, two example applications.

3.2 Design Factors in Nailz

This scenario examines intra-hand inputs from the perspective of three design factors. First, in terms of the space factor, touch-sensitive nails enable a wide set of 29 viable nail touch inputs, which is comparable to existing controllers such as Oculus quest (10 buttons and two joysticks in two controllers) or HTC VIVE (eight buttons and two touchpads in two controllers). In addition, as suggested in the sample applications (media), wrist rotation and arm motion can also be utilized by being combined with nail touches to create continuous inputs. Second, in terms of the accessibility factor, the comfortability of the system was examined. To this end, the comfort study measured the comfort level of 144 input sets, and these data were used as the base for selecting 29 final input sets. Finally, regarding the manipulation factor, the study conducted a verification study for 29 final input sets and, as a result, the time (1.61s) and accuracy (94.3%) of each input were measured. These objective performances show that nail touch inputs can be readily and quickly performed.

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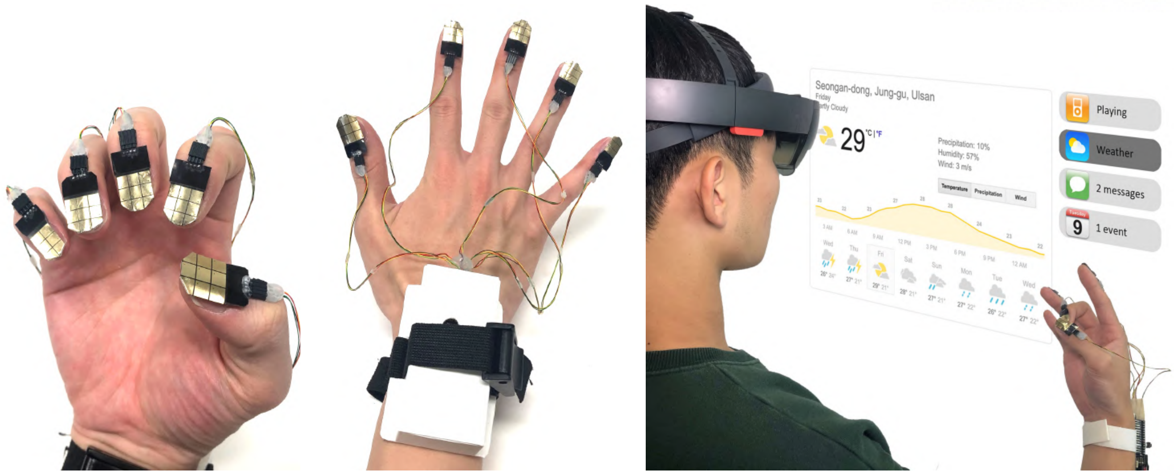

Figure 1: Nailz: five touch sensitive fingernails for wearable input. Left shows two close-ups of nails on a hand, while right shows a user wearing the system during study tasks.

3.3 Introduction

The increasing power and sophistication of wearable devices, in form factors such as smart watches and smart glasses, is enabling new applications in areas such as health care [108], education/tutoring [109], maintenance [110], and transportation [111]. However, the diminutive size and on-body mounting of wearables mean they have very limited spaces and surfaces for traditional input techniques such as controlling a cursor or touching a screen [112]. Existing alternative approaches based on voice-commands or free-hand gestures compromise social acceptability [11] and may lead to fatigue [95] while hand-held touch or motion sensitive controllers require users manage multiple devices and preclude device use during hands-busy tasks [113]. These problems mean that although wearable devices are becoming powerful computational tools, many input tasks remain slow, cumbersome and inexpressive.

Interfaces based on what Shilkrot *et al.* [65] term *finger augmentation* devices can offer solutions to these problems. Worn and operated by the fingers, devices such as rings [72], nails [14] or finger-sleeves [114] can be instrumented with systems such as cameras [40], magnetic trackers [101] or capacitive sensors [115] to support input with a wide range of desirable properties. These include being immediately and continually accessible [116] to users without obstructing normal use of the hands during other activities [73], enabling discreet, subtle or inconspicuous input (e.g., via micro-gestures [83]) and supporting a range of expressive input styles such as pointing or cursor control [14] and/or gestures [117].

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We contribute to research in this emerging area by proposing input via a set of five touch sensitive nails – see Figure 1. This form-factor provides a number of benefits including a mature, reliable and accurate sensing paradigm [118] based on directly detecting contact and that does not rely on complex and potentially power-hungry machine learning [67]. It also supports unencumbered fingers, in contrast to glove systems which cover the inner hand [55]. Compared to systems that track the hand using body-mounted cameras [80], there are no issues related to privacy [119] or field of view – no data about a users surroundings is recorded. Furthermore, input can also be made "arms-down" [84] or out-of-sight rather than directly in front of the body.

Indeed, the intrinsic advantages of this concept has led to prior proposals for nail input systems. However, we note these have considered only single nails, typically the thumb, and input based on a small set of five gestures [14] or a cursor control paradigm [115]. In contrast, we study how a full set of nails can be used to capture input relating to articulation of the hand as a whole – thumb-to-finger [55] and finger-to-thumb input rather than cursor control. We argue data about how a set of touch sensitive nails can be used to sense hand articulation is a valuable complement to prior work proposing the nails as a cursor control surface [14, 115]. Furthermore, due to the inherent complexity of the hand, we argue that viable forms of input on or with the nails will also differ substantially from that discussed in prior work dealing with the touches to inner surfaces of the fingers [34, 55]. In light of these differences, the goal of this paper is to explore the value of input on a set of five touch sensitive nails: what types of hand input are enabled, and what input actions can be reliably and readily performed on such a system?

To answer these questions, we conducted a multi-stage design-driven process. To characterize the input space, we conducted a design workshop to generate interface, interaction and application concepts. Building on the outcomes of this study, we derived a set of 144 input actions occurring on one or more nails. We assessed its viability through two user studies. In the first (N=16), we assessed the subjective comfort of each action. In the second (N=16), based on a fully functional prototype system implementing designs from prior nail systems [14, 115], we captured task time and the distinguishability of each input action using a simple threshold based classifier. We close by consolidating these outcomes into a final set of 29 viable inputs and a revised personalized classifier which we evaluate in terms of both objective performance and subjective opinion. This work contributes to the design of new wearable input techniques by: 1) studying the unexplored sensing configuration of a set of five touch sensitive nails and; 2) by documenting and instantiating the input actions and interface designs suitable for this system based on 3) a characterization of the comfort, time and accuracy of full hand nail-based touch input.

3.4 Related Work

Wearable input systems based on touches between the fingers of the hand have been widely studied due to the fact they promise subtle socially acceptable input [11] that can be conveniently accessed [116] and operated eyes-free [34] while still retaining a large and expressive input space [80]. While some work in this area seeks to capture input directly on a worn device such as a ring, typically via an embedded track-pad [56], this approach is limited by the inherently small size of such systems – Boldu *et al.* [73], for example, use such a system to classify just five basic tap/swipe inputs. A more common approach has been to deploy finger augmentations [65] capable of sensing input on the body through either an indirect sensing technique such as acoustic wave propagation [66, 67, 120], magnetic tracking [101], camera-based computer vision [40] or via the simple expedient of placing a layer of sensing substrate over the skin, for example in a glove [55]. An alternative approach uses cameras or depth cameras mounted on the wrist [51], shoulder or head [80]. Compared to finger augmentation, camera systems have the advantage of tracking full finger movements/positions as opposed to simply finger contacts; disadvantages include threats to privacy and the requirement for the tracked hand to be unoccluded and in the field of view of the camera. We first review this literature in general before turning to prior systems that have instrumented the nail.

3.4.1 Input on the Skin of the Hand

The hand is anatomically complex with 27 separate Degrees of Freedom (DoFs) [47]. The thumb is particularly adroit, accounting for five of these and positioned to access the rest of the hand with relative ease. Prior research has leveraged these properties to explore what both Whitmire

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et al. [55] and Soliman *et al.* [80] term "thumb-to-finger" input. This refers to systems in which the thumb taps [120], force-taps [121], swipes [62] or gestures over regions such as the side of the index finger [61] or the inner surfaces of all four fingers [34, 66] in order to support tasks such as providing a secondary input channel during touchscreen use [61], issuing commands, changing settings or typing [55]. A common approach is to treat each finger phalanx and/or joint as a different input region by, for example, placing a different command on each one [34]. Alternatively, with systems capable of sensing continuous input, a cursor can be controlled [65] or gestures such as letters or shapes can be drawn [66]. Finally, systems capable of detecting pose can capture full hand gestures, such as those involved in sign language [67].

There is also data on human performance with thumb-to-finger input. For example, Huang *et al.* [34] capture how comfortable this input type of input is, highlighting that while touches of the thumb to the inner surfaces of the index and middle finger are relatively easy to perform, touches to the ring and little fingers are more taxing. Objective performance has also been documented: Huang *et al.* [34] also report selection accuracy for different numbers of targets distributed along the length of the fingers; optimal input accuracy ranges from between two (on the little finger) and five (on index/middle) separate targets. In terms of task time, Whitmire *et al.* [55] find that text input on a qwerty keyboard spread over all fingers/phalanxes of both hands supports typing at 16 WPM, which they conclude is a rapid rate for a wearable device. These results highlight the fundamental viability of thumb-to-finger input. If designed appropriately, it is quick, comfortable and easy.

3.4.2 Input on Finger Nails

The nail is a convenient site for finger augmentation: it is rigid and has a cosmetic tradition of worn accessories that minimally interfere with use of the hands. However, in comparison to the wealth of literature on the fingers, it has attracted relatively little research attention. It has been previously proposed as an output surface [122, 123], as a convenient site to mount tracking hardware for objects [58] or finger gestures that are independent [62] or that occur with respect to a sensor mounted on another finger [101] or an external device [100]. Typically such systems track in air movements of the thumb, the most articulate digit. Most relevant to the current

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paper is work that has placed touch sensors on nails – both Kao *et al.* [14] and Lee *et al.* [115] describe thumb nails covered with grids of capacitive electrodes capable of supporting input such as simple taps and swipes and controlling a cursor via a touch of another finger or by touching the thumbnail against the body. This paper extends this prior work by considering a full set of five nails, rather than a single thumbnail, by exploring inputs relating to full articulation of the hand (rather than cursor control) and by providing a thorough description of performance covering comfort, time and accuracy.

3.5 Ideation Workshop

To better understand the input and interaction space enabled by a set of touch sensitive nails we ran a design and ideation workshop with a group of five graduate students (three female, two male, mean age 27) engaged in either Industrial Design (four) or Human-Computer Interaction (one) programs. The goal was to generate a diverse set of interaction ideas we could use as the basis for developing a set of concrete input actions. The workshop took three hours as follows:

Ice-breaking/Priming (30 mins): Introductions and scene setting to establish the topic and input/use context – the workshop focused on using the nails as input for smart glasses. Accordingly, participants watched promotional videos from a set of existing smart glass products (Epson BT300, Google Glass, Microsoft Hololens, Vuzix Blade).

Brainstorming – Tasks (30 mins): Participants generated a set of useful services or tasks that could be performed by smart glasses, such as those relating to messaging, navigation or media applications. This took the form of a brainstorming session in which tasks were noted down on post-its, announced to the room and placed on the wall.

Brainstorming – Input (30 mins): Participants generated input actions, widgets and systems that a smart glass user could operate in order to access services and perform tasks on a device. This session followed the brainstorming format; ideas were kept distinct by using differently colored post-its.

Nail Input – Priming (30 mins): To provide context for the final task, we had each participant don a set of fake nails and showed them videos from a set of research papers [14, 40, 56, 62]

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and products (Nod [124] and Talon, www.talonring.com) dealing with finger augmentation and thumb-to-finger input. In addition to sensing touches, participants were informed the nail system could sense overall hand orientation and rotation.

Brainstorming – Interaction Designs (30 mins): In the final brainstorming session, participants devised interaction concepts based on touching the nails they were wearing and using the input actions, widgets or techniques they had proposed to achieve the original set of tasks or services.

The session closed with debriefing and generated 80 interaction design concepts. These were diverse, but also subject to clear trends. Key variations occurred in the *nails* used, the touch *actions* employed and, to a lesser extent, the nail *regions* touched. In terms of the nails used, half the inputs (48.75%) relied on a single nail (thumb: 18.75%, index: 26.25%, middle:3.75%) while the reminder used multiple nails either simultaneously (e.g. a two finger tap, 22.5%), continuously (e.g. a swipe over two fingers, 2.5%) or as a discrete set (e.g., each nail as short-cut button, but proposed as a group, 26.25%). The nails used in multi-nail proposals were fairly evenly spread – thumb: 33.75%, index: 47.5%, middle: 50%, ring: 50%, little: 47.5%). In terms of actions, taps (60%), swipes (13.75%) and fingers flicks (18.75%) dominated proposals. Finally, nail region was most frequently specified as the tip (10%) and occasionally the edge or side (1.25%) but was mainly not detailed in proposals (88.75%), possibly due to perception of a fingernail as a single location or ”button”.

Beyond this functional classification, we summarized the ideas through an affinity process: a single researcher clustered the full set of ideas based on the final descriptions, notes from the workshop and the summary statistics, ultimately deriving the following five themes (also illustrated in Figure 2).

Symbolic/Pose (21.25%): This collected ideas in which hand poses triggered applications or actions: a thumb-up (sustained contact by all four finger nails with the palm) for a social media like or favorite; an OK gesture of thumb covering index nail to signify approval; a "rock-on" hand gesture (middle and ring nails constrained by thumb) to open a music app; a "V" sign (ring and little covered by thumb) to take a photo.

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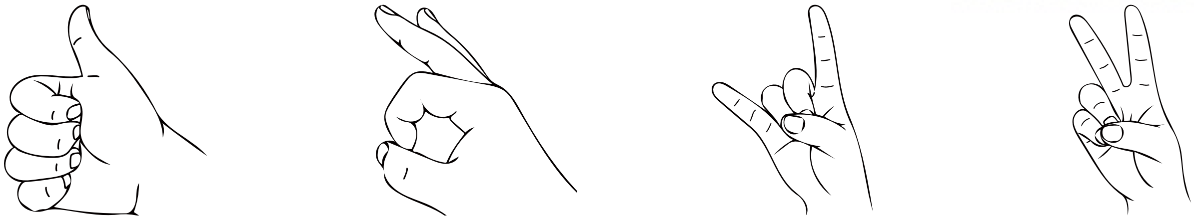
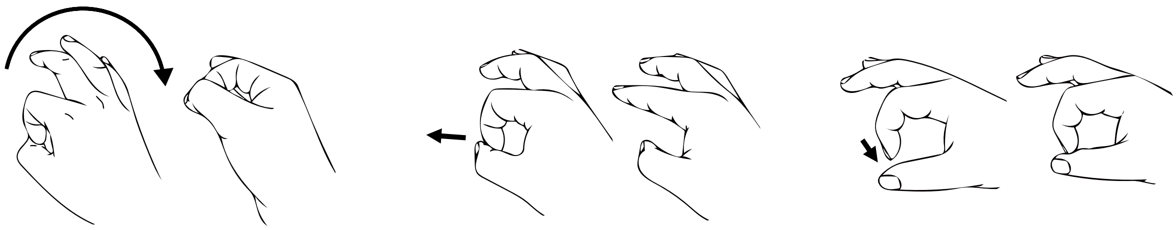
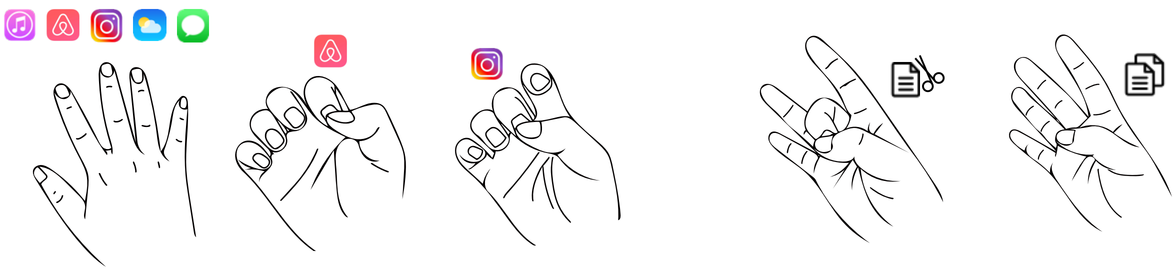


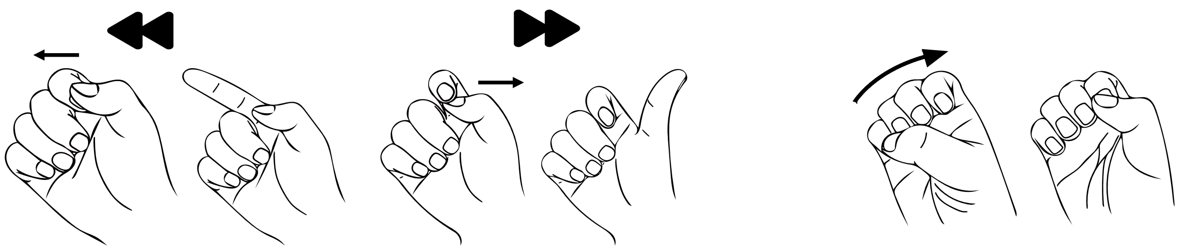
Symbolic/Pose: Hand poses proposed for like (nail tips touching hand), confirm (thumb touching index nail plate), play music and take photo.



Movement metaphor: Touching a nail and twisting to control a setting, flicking the index to delete content and tapping a nail tip to select.



Spatial: Assigning apps or commands to specific nails.



Directional: Directional flicks or swipes for scrolling or navigation.

Primed/Abstract: Swipe nails to delete content, double tap tips to select.

Figure 2: Example designs proposed in the ideation workshop.

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Movement Metaphor (18.75%): Finger and hand motions were applied metaphorically. For example, flicking the index finger out from the thumb was proposed for sending a message, much as the same action might push a physical object away. Similarly tapping the finger was associated with real world button presses for activities such as taking a photo. Associating the same pose with a rotational hand movement was proposed for changing a setting – like gripping and turning a dial.

Spatial (17.5%): The fingers were also divided up spatially, so that different nails were associated with different functions such as launching a specific app, a concept that has appeared in prior work [34]. Additionally, these were qualified by the nail area or nail action being performed. For example, while tapping on the tip of a nail could open an app, holding the whole nail could copy content from it and flicking the finger away could paste into it.

Directional (20%): Proposals were also based on directional mappings. For example flicking either the index (from the thumb) or the thumb (from the index) with the hand facing the user, actions which respectively involve predominantly leftward and rightward motion, were proposed to signify previous/next on an e-book app or media player. Similarly, moving the thumb over all finger nails when they were aligned vertically was proposed for scrolling.

Primed/Abstract (22.5%): Suggestions were also derived from current input technologies. Double tapping nail tips was proposed to select content while swiping across nail tips deleted it, in much the same way that secondary selection mechanisms and swipes are currently used on mobile devices. The use of nails for these basic interactions suggest that users may be able to generalize their existing knowledge about how to operate smart devices to a nail-based input system.

These design themes were frequently combined. For example, the *movement* of rotating a dial was merged with *spatial* mappings such that touching different fingers and rotating could control the volume, brightness, or play back position of media content with different nails. Similarly, the click *movement metaphor* for taking a photo was combined with *spatial* use of the different nails: the index for photo and middle for video.

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3.6 Initial Nail Input Set

We designed an initial set of nail inputs based on both prior work and key variations observed in the workshop: the different *nail(s)* used, *regions* touched and touch *actions*. To create a coherent and complete range of possibilities, we defined each dimension as follows:

Nail(s): Due to the diverse uses of both single and multiple fingers in the workshop, we included all five individual nails (*Single*) plus six nail combinations (*Mult*): all three adjacent finger pairs (e.g. index plus middle but not index plus ring), both contiguous finger triples and the quad of all four fingers (see Figure 3 (e)). The thumb nail was not used in multiple nail inputs – it was inevitably the touching digit.

Nail Region: Although regions varied relatively infrequently in the workshop, touching different nail regions is the dominant way of interacting in prior work [14, 115]. As such, we opted to include five nail touch regions: *Tip*, the distal edge of the nail; *Center*, the plate of the nail; *Root*, the proximal edge of the nail over the lunula; *Inner* side, the lateral edge of the nail facing the first interdigital space (between thumb and index); and the *Outer* side, the opposite lateral edge of the nail that faces away from this space – see Figure 3 (a).

Action: Based on the actions proposed in the workshop, we included *Taps* of the nail, *Flicks* of the finger and swipes over the nail(s) either horizontally (*HSwipe*) or vertically (*VSwipe*) in both directions.

To instantiate these dimensions in a set of concrete input actions, we first differentiated between touches to single and multiple nails. For each action, we then defined the nails and regions on which it could be used. We excluded combinations if they were impossible (e.g., HSwipe on the Inner side of the nail), judged to be extremely challenging (e.g. VSwipe over multiple nails) or hard for a user to meaningfully distinguish (e.g., Flick from different nail regions). For single nail touches, we ultimately included all five nails for all actions. Taps could take place on all five nail regions (25 different inputs in total), Flicks on only the Center region (5 inputs), HSwipes on Tip, Center and Root regions in both left/right directions (30 inputs) and VSwipes on Inner, Center and Outer regions in both up/down directions (30 inputs). Single inputs are illustrated in Figure 3 (a) through (d). For multiple nail inputs, we include all six

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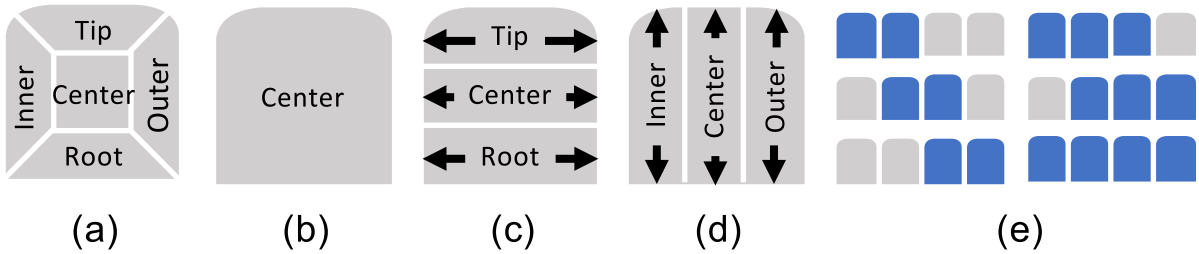

Figure 3: Nail Regions used in Single Tap (a), Flick (b) and bi-directional HSwipe (c) and VSwipe (d) input actions. (e) shows the six contiguous multiple (Mult) nail combinations highlighted in blue.

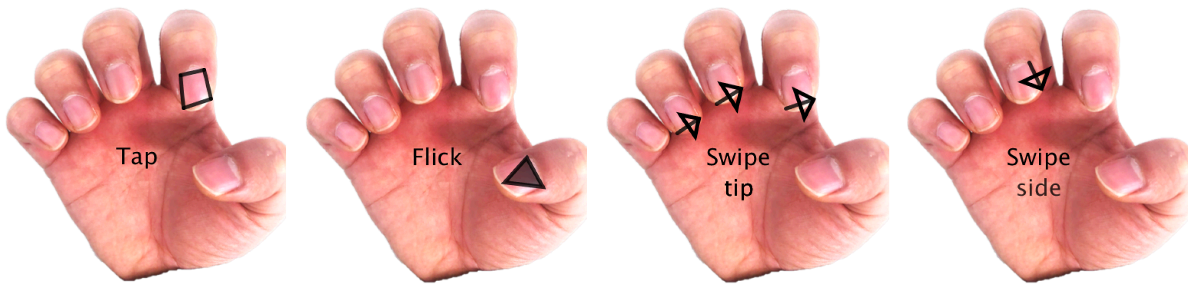

Figure 4: Example finger action study instructions

nail combinations (Figure 3 (e)) for Tap, Flick and HSwipe. *Mult-Taps* could take place on Tip and Center regions (12 inputs); *Mult-Flicks* on center regions (6 inputs) and *Mult-HSwipes* on Tip, Center and Root regions in left/right directions (36 actions). This process led to a comprehensive and intentionally inclusive set of 144 input actions. The rest of the work in this paper sought to refine this set to a more practical and functional subset.

3.7 Comfort Study

We first assessed the 144 input actions by capturing their perceived comfort, a metric previously used to make recommendations about viable finger input actions for use in interactive systems [125, 126]. In line with closely related prior work [34], the study was conducted with participants' unencumbered hands in order to capture comfort ratings in a natural situation, unbiased by the specifics of any prototype sensing system.

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3.7.1 Participants and Method

Sixteen participants were recruited from the local student body via social media channels. All were right-handed, nine were female and seven male and they had a mean age of 22.9 (SD 3.32). Using a one to five scale, they indicated they were fluent users of computers (4.6) and smartphones (4.8) but had little experience with wearables such as smartglasses (2.1). The experiment lasted approximately 30 minutes and the participants were compensated the local equivalent of five USD.

The study had participants try out and then rate the comfort of hand actions shown to them on a laptop screen. They were asked to use their right hands and find the most comfortable way to make each touch before assigning a rating – there was no prescribed method for making each touch. Each hand action was presented using both an image and textual description – see Figure 4. Ratings were captured using a five-point Likert-scale (1: very uncomfortable, 5: very comfortable, as in [34]), and each item in the set of hand actions appeared twice in a random order: in total we captured 288 ratings per participant or 4608 ratings in total.

3.7.2 Results

We first performed a reliability check by calculating the mean per-user Pearson correlation between the two sets of ratings each generated [126]. This was 0.62 (SD: 0.12), indicating a moderate to strong relationship between the ratings assigned to repeated actions. This suggests participants were able to assess and report their comfort reliably and consistently and increases confidence that the data captured is valid. The overall mean rating reported in the study was 3.41/5.0, a figure prior work has suggested indicates high comfort [34]. Figures 5 and 6 present a summary of the comfort ratings for each nail, action and region and highlight that ratings varied considerably. Following prior work [125], we explored differences in these data statistically. We used the processes outlined by Wobbrock *et al.* [127] and applied the Aligned Rank Transform (ART) followed by factorial repeated measures ANOVA and pairwise *post-hoc* contrasts incorporating Bonferroni corrections. Our analysis involved eight separate ANOVAs, so applied a conservative alpha threshold of $p < 0.00625$ (0.05/8).

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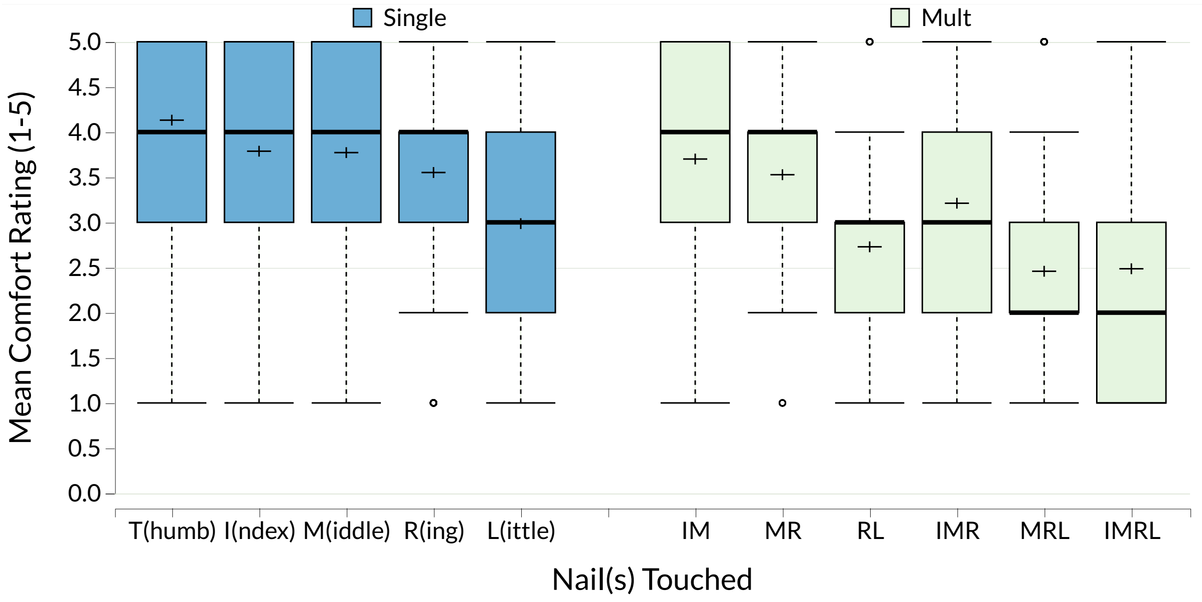

Figure 5: Comfort ratings for nail(s). Means marked by plus symbols.

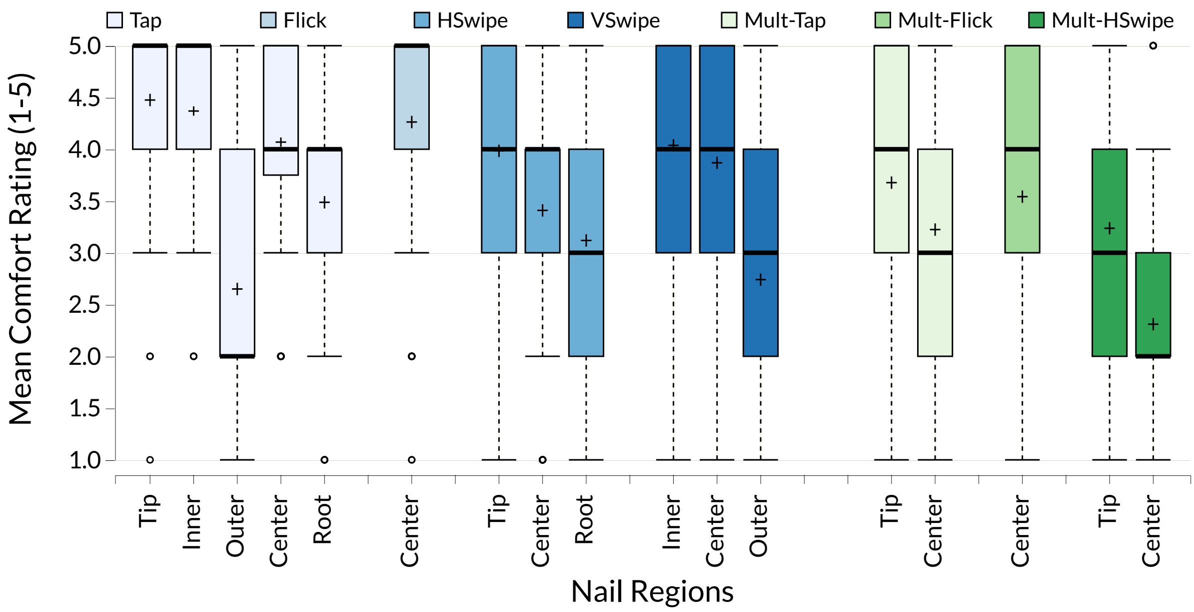

Figure 6: Comfort ratings for each action and region. Means marked by plus symbols.

Action	*Variable(s)*	*F-Value*	*DOF*	*p*	η_p^2	*Post-hoc contrasts*
Tap	Nail	29.18	4, 360	0.001	0.24	All significant at p<=0.003 except I-M, I-R and M-R (non-significant)
	Region	111.38	4, 360	0.001	0.55	All significant at p<=0.01 except Tip-Inner (non-significant)
Flick	Nail	5.76	4, 60	0.001	0.28	I-L (p=0.03), M-R (p=0.01), M-L (p=0.003)
HSwipe	Nail	47.22	4, 435	0.001	0.3	All significant at p<0.001 except I-M, I-R and M-R (non-significant)
	Region	62.09	2, 435	0.001	0.22	All significant at p<0.001
VSwipe	Nail	30.99	4, 435	0.001	0.22	All significant at p<=0.005 except T-I (p=0.042) and I-M, I-R and M-R (non-significant)
	Region	191.22	2, 435	0.001	0.47	Both Outer-Inner and Outer-Center significant at p<0.001
Tap-Mult	Nail	16.64	5, 165	0.001	0.36	IM-MR not significantly different. IM and MR significantly different to all other combinations (p<=0.002)
	Region	24.8	1, 165	0.001	0.13	N/A
Flick-Mult	Nail	9.33	5, 75	0.001	0.38	IM different (p<=0.01) to all bar MR and IMR (non-sig.); MR sig. different to MRL and RL (p<=0.01)
HSwipe-Mult	Nail	76.46	5, 525	0.001	0.42	All significantly different (at p<=0.005) except IM-MR, IMR-MR, IMRL-MRL and MRL-RL
	Region	96.06	2, 525	0.001	0.27	All significantly different at p<0.001

Table 1: Aligned Rank Transformed ANOVA and post-hoc test results from comfort study. Data from non-significant tests and tests with low effect sizes ($\eta_p^2 <= 0.1$) are not presented. Nails denoted by initials: T(humb), I(ndex), M(iddle), R(ing), L(ittle)

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Seven ANOVAs examined all data from a particular input action involving either single or multiple fingers using both nail and nail region (except for flick actions, which did distinguish between regions) as independent variables. Table 1 summarizes the outcomes, omitting non-significant results and those with lower effect sizes ($\eta_p^2 <= 0.1$) for brevity. We note there were no significant interactions with effect sizes over 0.1, which suggests the *post-hoc* contrasts, which can be invalidated by interactions after ART procedures, remain valid. This analysis indicates that, in terms of the nail variable, single nail touches to the thumb were significantly more comfortable than to other fingers and touches to the little finger significantly less comfortable; comfort ratings for the other single fingers were similar and between these extremes. Multi-finger inputs involving the little finger were also rated as significantly less comfortable than those involving two or three of the other fingers. In line with prior work [34], these results indicate users feel reduced comfort when touching the little finger. In terms of the region variable, touches to the outer and root were significantly less comfortable than touches to the inner and tip, with touches to the center falling between these extremes for simple actions such as tap.

The final ANOVA compared data from each of the seven actions involving the Center region. We focused on this subset of data as Center is the only region present in all seven actions—we can therefore compare actions without confounds due to variations in region. Unsurprisingly, it showed significant differences and the largest effect size in the study ($F(6, 90) = 26.5$, $p<0.001$, $\eta_p^2 = 0.64$); the input actions are quite varied. *Post-hoc* contrasts indicated single finger and simpler inputs were more comfortable. Specifically, Flicks were rated more comfortable than VSwipes ($p = 0.04$), HSwipes ($p < 0.001$) and all multi-finger actions (all $p < 0.001$). Similarly, Taps and VSwipes were more comfortable than HSwipe, Tap-Mult and HSwipes-Mult trials (all $p < 0.001$ bar VSwipe-HSwipe at $p = 0.03$). Additionally, Taps were more comfortable than Flick-Mult ($p = 0.011$) and HSwipe-Mult trials less comfortable than HSwipes ($p = 0.003$) and Flick-Mults ($p < 0.001$).

Its worth informally contrasting the comfort data in this study with that reported by Huang [34] for the inner surfaces of the fingers. The most directly analogous data is for single taps on the dominant hand. Huang reports three ratings per finger ranging from 4.8/5 (left index distal phalanx) to 2.1/5 (right little proximal phalanx) and ultimately select seven finger regions due to their high comfort, defined as mean results over 3/5. In the current study, the mean ratings for the optimal three regions (tip, inner, center) on all nails all equal or exceed a mean rating of 4.07/5 – 15 tap locations in total. While this comparison is speculative, we suggest it indicates that simple nail touches may be both more comfortable and expressive than touches to the finger phalanxes. A candidate explanation for this is the relatively small scale of the movements involved in nail touches, compared to the stretching required to touch to areas such as the proximal phalanxes of the fingers. We note that while this comparison does not constitute formal proof, it does serve as supporting evidence that nail touches are a comfortable way to make input with the fingers.

3.8 Nail Sensor System

Encouraged by these results, we developed a working prototype that senses touches to all five fingernails. There are two approaches to developing touch sensitive nails in the literature. NailO [14], implements an impressively miniaturized 4mm thick standalone device featuring sensing, power, and communications all on the thumbnail. However, arguing that a device as thick as 4mm would interfere with use (and their empirical objectives), Lee *et al.* [115] designed a touch sensing nail system composed of a 0.3mm thick flexible PCB on the nail wired to a wrist mounted device with all other functionality. Our objectives align more closely with Lee *et al.*, so we opted for a similar implementation.

We created three different flexible PCBs based on mean nail sizes [128] for the thumb, index/middle/ring and little fingers. Figure 7 shows the sizing, spacing, electrode count and arrangement for each PCB. In each board, capacitive sensing was handled by an MPR121 micro-controller mounted on the bottom of the PCB and designed to be positioned behind the nail on the distal phalanx of the finger. The nail portion of each PCB was glued to a standard cosmetic artificial nail. To improve robustness, the front tips of the PCB were curled around the nail pad, preventing the PCB from detaching during use and ensuring the tip of the nail was touch sensitive. A layer of thermoplastic adhesive was applied to the area containing the micro-controller to create a smooth, comfortable and insulated bottom surface to the whole PCB. Each nail prototype was approximately 1mm thick and flexible enough to fit snugly on a

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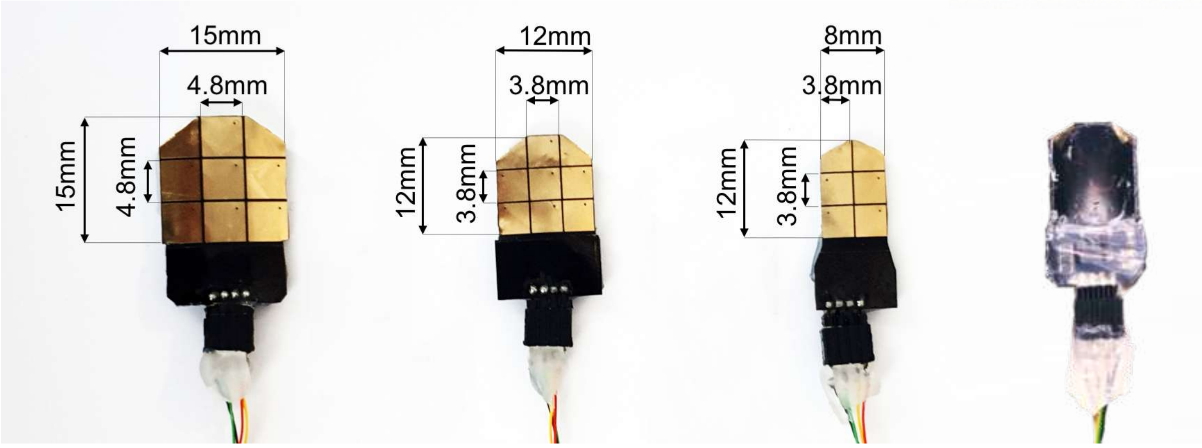

Figure 7: Nail touch sensors, showing electrode size and arrangement: thumb (left); index, middle and ring (center-left) and; little (center-right). The top corners of each board are rounded to mimic the shape of a human nail. The black sections sit behind the nail on the distal finger phalanx. Right image shows underside of thumb sensor mounted on a cosmetic artificial nail with thermoplastically insulated circuitry.

wide range of nail shapes. We firmly adhered it to participants' nails using commercial adhesive gel pads.

All five nails in a set were wired to a single Arduino MKR1010 mounted on the wrist with lightweight AWG32 wires that did not restrict finger motions. The wrist unit also featured an IMU (BNO080) configured to measure raw accelerometer data from wrist/hand motions. All data was captured and transmitted over USB to a host PC at a rate of 100Hz. In terms of the specific data captured, we followed numerous prior implementations [129] and sampled raw and baseline capacitive sensor readings from each electrode to derive a grayscale touch image representing the location and intensity of contact with each nail. On the host PC we processed each image using a typical process: we up-scaled it by a factor of three, identified a dominant touch area by using flood fill to segment separate contacts and selected the largest and, finally, calculated image moments to summarize this contact as an ellipse with properties of location, size (major/minor axis length), angle and eccentricity [130]. We also retained all raw touch images to support subsequent analysis.

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3.9 Performance Study

This study used the full set of 144 inputs actions and the nail prototype system. All visuals were presented on a PC screen. It sought to complement the comfort study by collecting objective performance data: the time it took to perform each input action; the raw touch sensor data, and; accuracy based on a threshold based input classifier we developed (see below). The goal was to use this data to help select a final set viable input actions that can be performed rapidly and that are readily distinguishable from each other.

3.9.1 Participants, Procedure and Design

Sixteen undergraduate students participated in the study (mean age of 22.9 (SD 1.65), 9 males, all right handed). They were fluent computer (4.6/5) and smart-phone (4.8/5 users) and screened for average or larger nail size [128]. The experiment took 40 minutes with each participant compensated with 10 USD. To encourage good performance, an additional 20 USD was awarded to the two top performing participants (determined using a normalized weighting of time and accuracy).

Throughout the study, participants were seated at a desk in front of a laptop computer. The study began with participants donning the nail sensor and wrist processor unit on their dominant hand. The study task and input actions were then explained and participants completed a familiarization session (max two minutes) where they could freely ask questions, try input actions and see a visualization of their inputs on the laptop. After ensuring all actions and study instructions were understood, the main trials began. To start each trial, participants needed to press the space bar on the laptop with their dominant hand– the one wearing the prototype. This ensured all input actions started from a similar "hands-occupied" pose. A depiction of one of the input actions was then shown, (as in the comfort study) on the laptop and participants were asked to perform this action rapidly and accurately. After an initial nail touch, the instructions changed to show a circular cursor and a grey highlight illustrating the nail regions that they needed to touch to successfully complete the trial. Trials terminated on release of all nails, or timed out after ten seconds. Trial duration was defined as the period between the initial

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key press and final release of the nails. Breaks between successive nail touches of 200ms were allowed, as pilot testing indicating small gaps in multiple nail touches occurred frequently. After each trial, participants received feedback as to its correctness.

Trials were presented in 144 randomly ordered blocks, each containing four repetitions of the same input action. Trials resulting in touches to incorrect nails (e.g., index when middle was requested) were considered invalid and repeated. Furthermore, the first trial in each block was discarded as practice. We therefore retained a total of 432 trials involving touches to correct fingers per user (6912 in total). The goal of this structure was to screen out clear errors (wrong fingers) and to reduce the impact of examining and interpreting the study instructions on the measured performance: for input action, we captured data from a standard hand pose (pressing a key) but only immediately after participants had practiced it.

3.9.2 Nail Input Recognizer

We created a simple decision tree to classify nail touches from the five sensors to one of the 144 nail inputs. We first omitted data from the first and last 50ms of each touch, effectively ignoring touches less than 100ms in duration. This was because initial and final stages of a touch could vary strongly in position and velocity as different finger regions came into contact with the sensor [131]. Furthermore, we observed very short touches may represent inadvertent contact with the nails. In cases where the resultant set of touches spanned multiple nails, we tested for invalid sets (e.g., use of the thumb or non-contiguous finger nails such as index and little) and screened the results to create valid combinations by removing the thumb or the temporally shortest touch.

Based on the touched nails, we then determined the touch action. We differentiated flicks from other events by examining IMU data in the period immediately 100ms after release of the nails—we used a threshold on the peak summed magnitude of accelerations along X and Y axes (i.e., those capturing information from finger/wrist flexion movements and omitting deviation). Touches not classified as flicks were checked for movement on the nail. Specifically we examined the SD of both x and y motion and, in the case of multi-finger taps, the temporal order of touches to different nails (sequential/simultaneous). We classified sequential touches, or those exceeding

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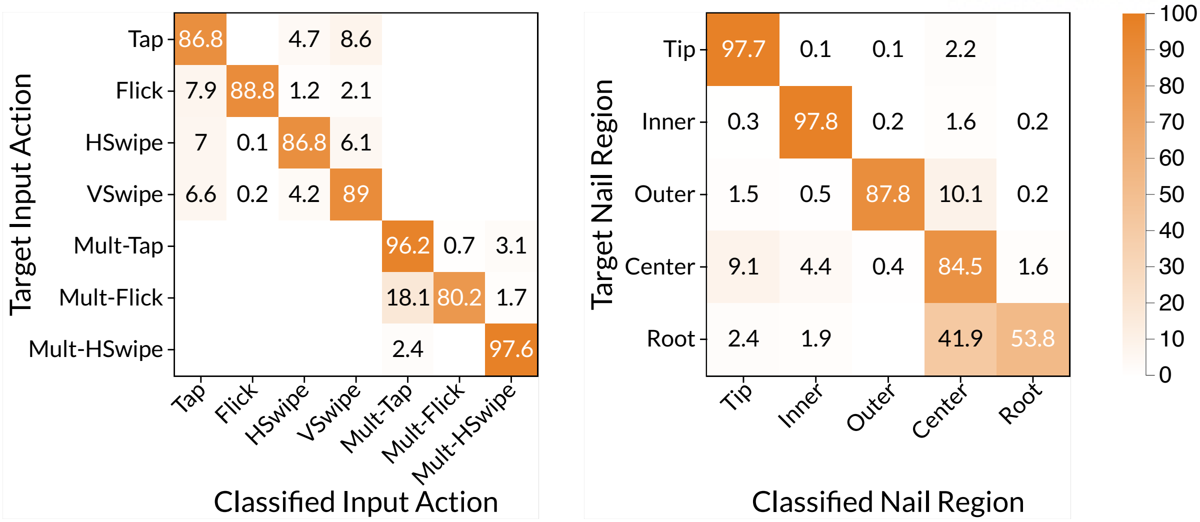

Figure 8: Confusion matrices for classifying input action (left) and nail region (right). Data shown in percentages so rows sum to 100.

a specific threshold to classify swipes in both horizontal or vertical directions. Any remaining unclassified touches were considered taps. Finally, we classified nail regions by calculating mean touch position and dividing each nail into five equally sized areas, as illustrated in Figure 3 (a). The two thresholds used in this initial recognizer were established via iterative testing during system development. They were intended to support subsequent empirical study and we do not expect them to be optimal. We considered peak acceleration over 0.41g to signify a Flick and SD of x or y motion during a touch over 0.26 sensor units (1.25mm on the thumb and 0.99mm on the fingers) to signify a swipe.

3.9.3 Distinguishing Input Actions

In the trials we retained for analysis, the mean accuracy among all 144 input actions was 74.2%. We analyzed classification errors in order to better understand how people make input on touch sensing nails and iterate on and improve our system by refining and simplifying the set of input actions it supports.

Nail(s). We recorded 574 inputs (7.67%) to wrong nails, with the majority (5.93%) occurring in multiple nail touches. These problems fell into three categories: *mistakes* (the wrong nail(s), 1.34%); *missing* (omitted nail(s) 4.37%) and; *excess* (extra nails, 1.95%). Mistakes combine genuine user error, (e.g., misinterpretation of the study instructions) and performative errors such as using the thumbnail to touch the outer region of a target finger nail. Missing errors predominantly occurred with Mult-HSwipe (84.0%) and/or on touches to three or four fingers (74.5%). Excess touches tended to occur on multiple nail touches, particularly those involving ring and little fingers (84.7%), as users ”slipped” onto adjacent fingers during input.

Actions. Figure 8 left shows a confusion matrix for actions: the overall mean accuracy is 90.5%. High mis-classification rates occur for flick and between single Tap, HSwipe and VSwipe. This is likely due to a combination of non-optimal thresholds for peak acceleration and movement SD and also to the small size of the nail—there is limited space to perform the movements required to clearly differentiate taps and swipes.

Regions. Figure 8 right shows confusion matrices for the nail regions throughput the study (overall mean accuracy: 80.8%). Tip and Inner showed good performance, with Center, Root and Outer more substantially overlapped, suggesting participants struggled to reliably differentiate between them.

3.9.4 Time Results

Task completion time data for each nail, region and action are shown in Figures 9 and 10. We analyzed the time data following procedures from the comfort study: eight repeated measures ANOVAs; Greenhouse-Geisser sphericity corrections applied when indicated; a conservative alpha threshold of $p < 0.00625$; followed up with Bonferroni corrected *post-hoc* t-tests. Table 2 summarizes the significant results, omitting non-significant results for brevity. Due to the comparatively low effect sizes, we opted not to conduct follow up testing on interactions found in the HSwipe action.

In general the results in Table 2 show fewer differences than the comfort data. This is in line with prior suggestions that users can tolerate a range of comfort levels before than objective performance will be impacted [126] and highlights the importance of rigorously gathering this type of qualitative data. The Tip nail region offers significantly faster performance than other regions in three of the four of the input actions it features in (Tap, HSwipe and Mult-HSwipe). Similarly, the Inner and Center regions also enable faster performance in a more limited set of

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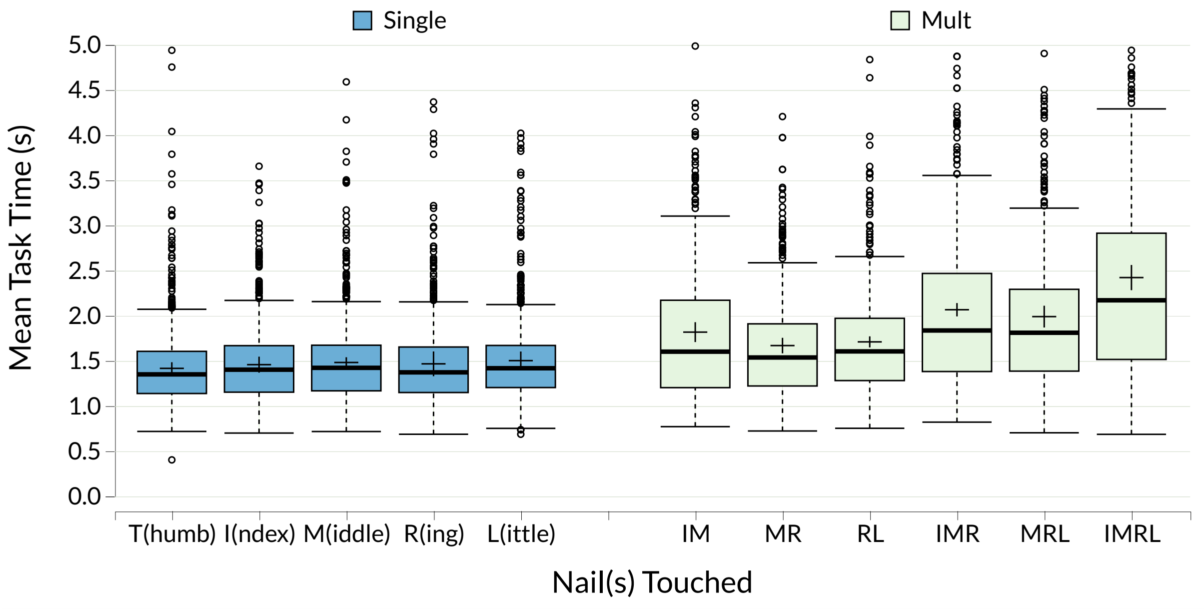

Figure 9: Task completion time for single/multiple nail inputs. Plus symbols mark means. Outliers greater than 5 seconds not shown.

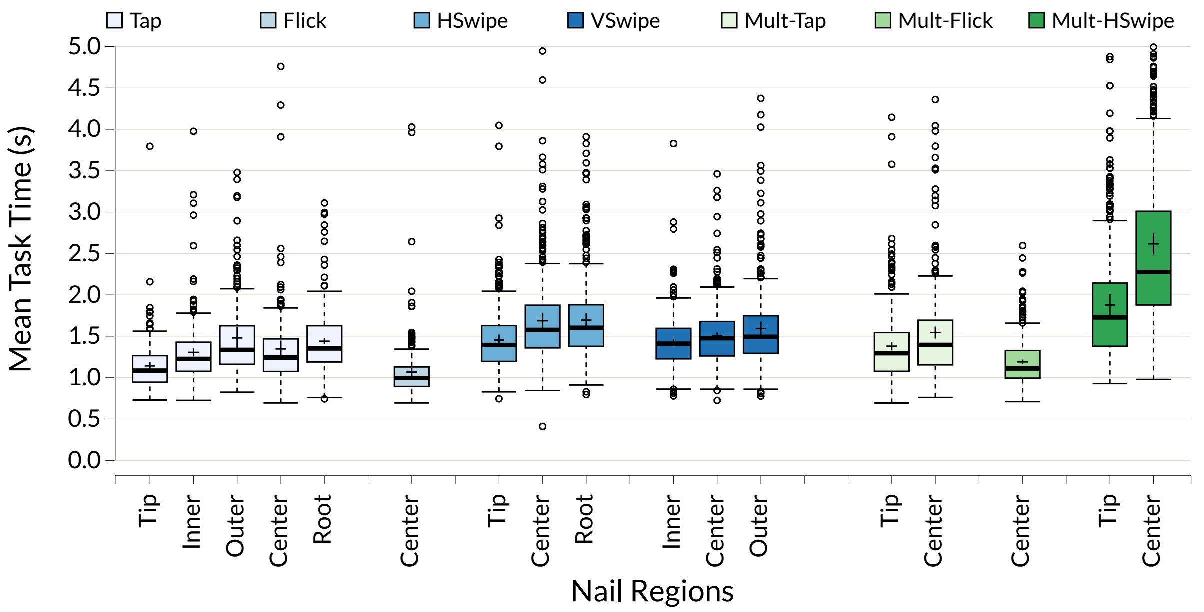

Figure 10: Task completion time for each action and region. Plus symbols mark means. Outliers greater than 5 seconds not shown.

Action	*Variable(s)*	*F-Value*	*DOF*	p	η_p^2	*Post-hoc test results*
Tap	Region	10.57	4, 60	0.001	0.413	Tip significantly faster than Inner, Outer, Root (all $p <= 0.002$); Inner significant faster than Outer ($p = 0.033$)
HSwipe	Region	15.03	1.36, 20.44	0.001	0.501	Tip significantly faster than Center ($p = 0.0076$) and Root ($p = 0.0001$)
	Nail:Direction	4.46	4, 60	0.003	0.229	N/A
	Nail:Region	2.89	8, 120	0.006	0.162	N/A
VSwipe	Region	7.57	2, 30	0.002	0.335	Inner significantly faster than Outer ($p <= 0.0085$)
Mult-HSwipe	Nail	29.94	3.07, 45.98	0.001	0.666	Touches to fewer fingers significantly faster (all $p < 0.0017$) except IM-IMR and IM-MRL (both non-significant)
	Region	28.99	1.41, 21.15	0.001	0.659	Tip significantly faster than Center ($p < 0.001$) and Root ($p < 0.001$). Center faster than Root ($p = 0.002$)

Table 2: ANOVA and post-hoc test results on time data from performance study. Data from non-significant tests are not presented. Fingers denoted by initials: T(humb), I(ndex), M(iddle), R(ing), L(ittle)

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circumstances. These results suggest these regions should be prioritized. We also note the effect of the nail variable in Mult-HSwipe reflects the increased distance travelled when more nails are involved in a touch; it is inevitable.

We conducted a final RM-ANOVA on time data from each of the seven actions involving the shared center region. As with the comfort study, we opted to focus on only this region as it is the only one to be used in all seven actions, therefore avoiding potential confounds in the the analysis due to the different regions used in each action. This test revealed significant differences ($F(2.78, 41.76) = 47.34$, $p < .001$, $\eta_p^2 = 0.759$). Flicks were performed rapidly, with single Flicks significantly faster than all other actions bar Mult-Flicks ($p < 0.037$), which were in turn faster than all other actions bar single Taps ($p < 0.008$). In contrast, HSwipes were performed slowly, with single HSwipes significantly slower than single VSwipes ($p = 0.04$) and Taps ($p = 0.009$) and Mult-HSwipes inevitably slower than all other actions (all $p < 0.001$)—in contrast to other inputs this action involved a sustained and time consuming movement across between two and four fingers. Based on this limited set of differences, we conclude that objective performance with a wide range of different input actions on the nails is viable: while some actions may be particularly readily executed (e.g., Flicks), the majority of basic actions such as Taps and VSwipes can be perfomed with quite consistent speed.

Its also worth discussing the numerical data. Task times in the study capture performance of an input action from a ”hands-busy” pose of pressing a key to start the trial: given this constraint, we believe the mean per trial task time for the whole study of 1.64s represents strong performance and reflects the ready physical availability of the nails as a site for thumb-to-finger [65] and finger-to-thumb touch input. We note there is no directly comparable task performance time data from prior nail based input systems: Kao *et al.* [14] report only classification accuracy while Lee *et al.* [115] report data for touches of the thumb nail to the face, a quite different scenario. Regardless, we note their data for tap inputs ranges from 1.48 seconds for an error-prone ”land-on” selection method to 2.52s for a more reliable ”lift-off’ technique. Our data, composed of a wide range of different input actions, lies towards at the bottom end of this range—touches between the fingers can in general, be performed more rapidly than touches to the face, most likely due to their familiarity. While further data and comparative studies are required, we believe the current study is sufficient to support the idea that a wide range of thumb-to-finger and finger-to-thumb touches to the nails can be performed rapidly by users.

3.10 Revised System Design

Based on both study results, we revised the system design in terms of the input actions it supports and the recognizer it uses to classify them. To demonstrate the revised system is both expressive and useful, we created several example applications to showcase its functionality. We describe this work below.

3.10.1 Final Input Set

We refined the input actions to 29 options, 20.1% of the original set. We included actions based on the following criteria and goals. Actions in the set should be:

Comfortable, defined as actions that score over the mean (3.41) comfort score. We discarded the majority of multiple nail inputs and less comfortable finger regions (root and outer).

Distinguishable, via selecting actions that were more reliably recognized and by providing redundancy. This was achieved by assigning different actions to different regions (e.g., center for Mult-Tap tap and tip for Mult-HSwipe)

Diverse, achieved by retaining some examples from the majority of input actions.

Consistent, achieved by making exceptions to prior heuristics to create a coherent set. For example, including a set of input actions on the little nail that match those on the other nails, even though its comfort and performance results were reduced.

The final input actions included 25 Single nail inputs: ten Taps (on each nail Tip and Center); ten VSwipes (on each nail Inner region in both up and down directions); five Flicks (on each finger). Multiple inputs were restricted to the pair of index and middle fingers. There were four in total: Mult-Tap on the center region; Mult-HSwipe on the tip in left and right directions) and Mult-Flick on the center Region.

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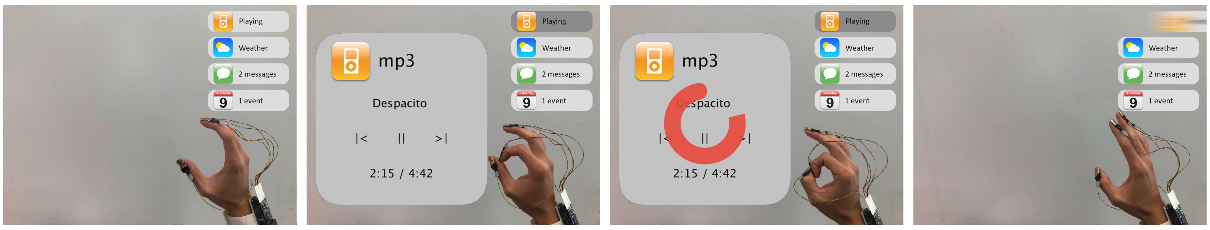

Figure 11: Notification application showing how nail touches can access multiple functions (e.g. open, delete) seamlessly

3.10.2 Revised Recognizer

We revised the recognizer based on study data and the reduced input set. Firstly, we merged center region with root and outer for tap and ignored touches to ring and little fingers during multiple nail input. Secondly, we optimized thresholds using a brute force search to minimize misclassifications in the initial study. We set new thresholds as $0.38g$ for peak acceleration and 0.13 sensor units (0.625mm for thumb and 0.5mm for fingers) for movement SD. Finally, we leveraged the redundancy of regions to actions by modifying thresholds according to the region touched. Specifically, for touches on the Inner region we halved the threshold for VSwipe detection while for touches to the Tip or Center, we doubled it. This made the system more sensitive to and resilient against small movements, depending on whether or not they were expected for a given region. Together, this boosted accuracy to 88.7%.

3.10.3 Sample Applications

To showcase how the final set of input actions could be used to control a wearable device, we developed sample information management applications for a typical wearable: smart glasses. These embody and express key qualities of input via finger augmentation—movements are small in scale (i.e., composed of mirco-gestures [83]) and performable eyes-free [72]. We describe two examples in detail below, and developed other applications (e.g., calendar, weather) using similar designs.

Notifications. We developed a system to manage notifications through nail touches. When a notification arrives, it can be peaked at by tapping the nail tip; transitioning to holding the center provides an expanded view. When finished, the notification can be left on the stack by simply removing the touching finger, or deleted by flicking the nail - see Figure 11 If there are multiple notifications, the top four can be assigned to each of the fingers in vertical order, providing immediate access to each without scrolling.

Media. We explored metaphors in the context of a media playback application. Users can play/pause content through tapping on the index and middle nails, a configuration in which the pair of fingers resembles a pause icon (||). Similarly, a thumbs-up hand pose (all finger tips in contact with palm) marks favourite items while horizontal swipes left/right signify previous/next song operations. For continuous input, nail touches can be combined with motion data: tap and hold the index tip while rotating the hand to control the playback position. Finally, vertical swipes up/down on the thumb nail adjust the volume higher or lower.

3.11 Verification Study

A final study evaluated use of the revised 29 item input action set, recognizer and example applications. We sought to: assess classification accuracy; explore the impact of threshold personalization; capture performance in a more realistic task and; solicit qualitative comments, reactions and feedback.

3.11.1 Participants and Method

We recruited ten participants from the local student body via social media channels. All were right-handed, 5 were female and they had a mean age of 24.1 (SD 3.14). They indicated they were fluent users of computers (4.2/5) and smartphones (4.5/5) but had little experience with wearables such as smartglasses (1.8). The experiment lasted approximately 45 minutes and the participants were compensated 10 USD. The experiment contained three stages, each separated by a short break. The goal of the first stage was to compare performance results with the previous study and provide data for personalizing thresholds for each user. The procedure followed the performance study but used the reduced set of 29 input actions. In the second stage there were four trial blocks (the first treated as practice), each containing all 29 actions presented in a random order. The goal of this stage was to explore performance when users were not aware

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of the input action they would be need to make. Moreover, data from this stage was intended to validate the personalized recognizers from the first stage. In the final stage, we showed the two applications described in the prior section to participants, had them try out and experience these for 10 minutes and then conducted a semi-structured interview to capture their reactions and opinions. The interviews were audio-recorded and transcribed. For this stage of the study, participants wore the Microsoft HoloLens and all UI content was shown on this device. In total, this study retained 870 trials in the first stage, 870 trials in the second stage and approximately 60 minutes of transcribed interview contents.

3.11.2 Results

The mean per trial duration and accuracy of the first and second stages was (1.43s / 1.61s) and (89.7% / 88%), improvements over the prior study. This suggests users benefited from the smaller number of actions and had little difficulty with the more challenging task in the second stage. Wrong finger errors were also low throughout: 1.1% in both stages. This indicates reducing multiple finger inputs was an effective strategy. Despite the data derived thresholds used in the first stage, single finger Flick remained prone to misclassification with Tap (11.3%) and VSwipe (2%) and Tap and VSwipe were also often confused (5.7% and 14.7%). This suggests user performance of these actions is diverse: fixed thresholds are not ideal. Accordingly, we used a brute force search to find per-user thresholds that minimize classification errors in the first stage of the study. We applied these thresholds to the second study of the study, leading to a classification accuracy of 94.3%. Figure 12 shows confusion matrices for personalized action and region classification thresholds. This result indicates that personalization or adaptive approaches are effective and likely be required to yield an effective nail input system.

Comments from the third stage of the study were transcribed and analysed using affinity diagramming to identify clusters and themes. Participants highlighted qualities including: "convenient" (P0, P1, P5, P6); expressive, "various operations are easily done" (P8, P9) and; ease of access (P2, P6), or as both P7 and P8 noted "no other equipment is needed". Nailz was favourably compared to mid-air gestures by P3 and P8 noted using nail touches was "less tiring, simpler and socially acceptable". Participants also felt many of the input actions were

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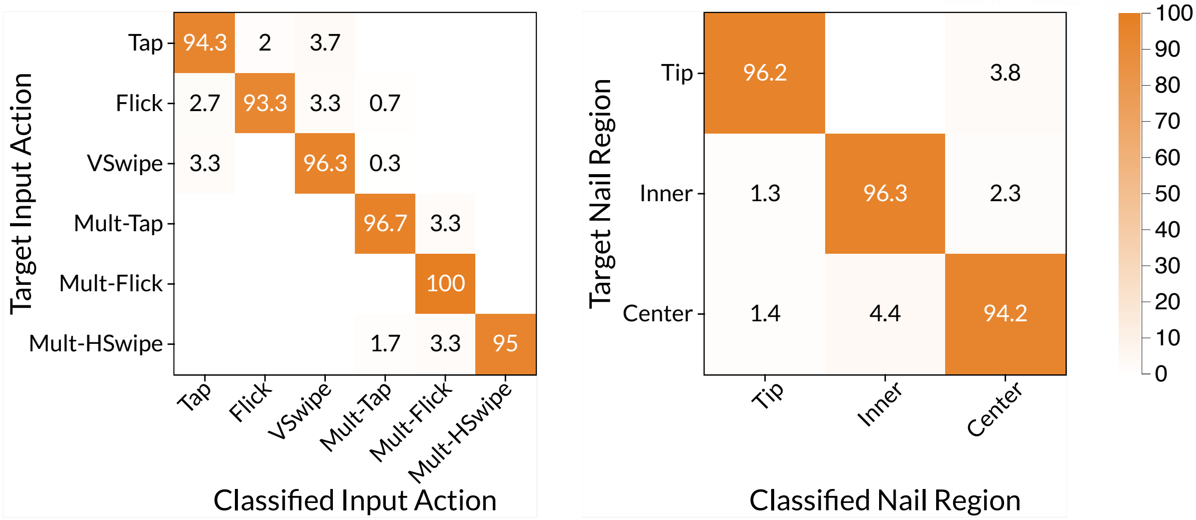

Figure 12: Confusion matrices for classifying input action (left) and nail region (right) using personalized recognizers on trials from the second stage in the verification study. Data shown in percentages.

readily learnable. P0 remarked: "play/pause and next/prev songs are well matched with Nailz action" and changing playback position with rotations was just "like rotating a knob". P3 and P4 valued familiar actions, referring to uses of flicking to delete and long tap to open notifications as "intuitive". Similarly, P1, P2, and P9 appreciated the use of directional mappings between finger/hand movements and interface contents—they were "well matched each other". There were worries about "unfamiliar mappings" (P2, P4, P5, P6), but also a consensus that "it become easier after some time" (P4, P5, P6). The comfort and utility of some of the input actions was questioned, particularly by three participants who stressed "input on little nail is frustrating" (P0, P5, P7), possible due to Midas touches as the "little finger is curved, so little nail was touched unintentionally" (P9). Consequently "real world use will involve more wrong touches" (P5). Some of the input actions were felt as designed to mitigate this problem: P0 suggested long tap to open "can prevent mistakes". In general, we conclude participants were positive on Nailz as a viable always available, eye-free and socially acceptance input system for wearable computing.

3.12 Discussion and Conclusion

This paper aims to characterize how a set of touch sensitive nails can be used to control other wearables such as smart glasses or watches. The data provides a useful complement to prior

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nail touch [14, 115] and finger articulation systems [34, 80]. One key point of comparison is recognition accuracy. In a system based on a single thumbnail, Kao *et al.* [14] report accuracy among five input actions—cardinal swipes and a long tap—to be 92.3% [14]. The data in this paper, encompassing all nails and a more diverse 29 item final inputs set achieves an improved accuracy of 94.3% using personalized recognizers—this is a strategy that should be further pursued in the future. This accuracy figure also compares well to prior work on camera tracked finger augmentation—Soliman *et al.* [80] report correct touched finger identification rates of 90.2% (vs the 98.9% reported here) and can recognize one of eight action types with an accuracy of 91.06%. We suggest the direct sensing paradigm we use may be inherently more accurate than camera tracked systems. We also extend prior work by reporting additional metrics. Specifically, we add to the limited prior reports of task times (of thumb nail touches to the face [115]) and comfort (of touches to the inner finger phalanxes [34]) with comprehensive data on thumb-to-finger [55] and finger-to-thumb nail touches. These show that nail touches can be performed rapidly—in a mean of 1.61s the final stage of the verification study, a figure at the lower of the 1.32s to 2.448s reported for taps triggered by land-on and lift-off actions by Lee *et al.* [115]. In addition, nail touches are comfortable—the 144 touches we studied were rated with a mean of 3.41/5 which compares well to the mean of 3.34/5 for 12 touches to the inner fingers in Huang *et al.* [34]).

In conclusion, this paper explores finger input for wearable computing via the novel form factor of set of five touch sensitive fingernails. It explores the design space of this system, presenting a large set of 144 possible inputs and characterizes the comfort, distinguishability and time taken to perform each of these actions using a fully functional prototype. We close by evaluating a final input set refined by data from the earlier studies and capturing qualitative comments about example applications. We show that touch inputs on the nails are expressive, can be comfortable and efficiently performed and are readily recognized using simple criteria.We believe that the range of small scale inputs supported, the simple classification scheme and the speed with which participants performed all testify to the viability of this approach. Future work should improve sensor hardware (e.g., via on-skin films [53]), integrate the system with signal propagation approaches to finger input for improved flick classification [52], examine more sophisticated recognition schemes and personalization processes (e.g., unsupervised learning) and study nail touch input in more realistic settings, such as in the field.

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IV FingerText: Exploring and Optimizing Performance for Wearable, Mobile and One-Handed Typing

4.1 Abstract

Typing on wearables while situationally impaired, such as while walking, is challenging. However, while HCI research on wearable typing is diverse, existing work focuses on stationary scenarios and fine-grained input that will likely perform poorly when users are on-the-go. To address this issue we explore single-handed wearable typing using inter-hand touches between the thumb and fingers, a modality we argue will be robust to the physical disturbances inherent to input while mobile. We first examine the impact of walking on performance of these touches, noting no significant differences in accuracy or speed, then feed our study data into a multi-objective optimization process in order to design keyboard layouts (for both five and ten keys) capable of supporting rapid, accurate, comfortable, and unambiguous typing. A final study tests these layouts against QWERTY baselines and reports performance improvements of up to 10.45% WPM and 39.44% WER when users type while walking.

4.2 Design Factors in FingerText

This scenario examines the intra-hand inputs from the perspective of two design factors. First, in terms of the accessibility factor, the first study showed that there was no significant impact of walking on the performance of nail touch inputs. Moreover, the final study on word repetition input, which was conducted under the walking condition, reported up to 31.3 WPM of text entry speed for optimized keyboard layouts, which is comparable to previous similar studies on word repetition on tablets (up to 39 WPM with bimanual keyboard gesture input) [132] or on the palm (up to 10.1WPM with optimized keyboard layout) [133]. Second, in terms of the manipulation factor, these results show that such a system can carry out a complex task such as text entry.

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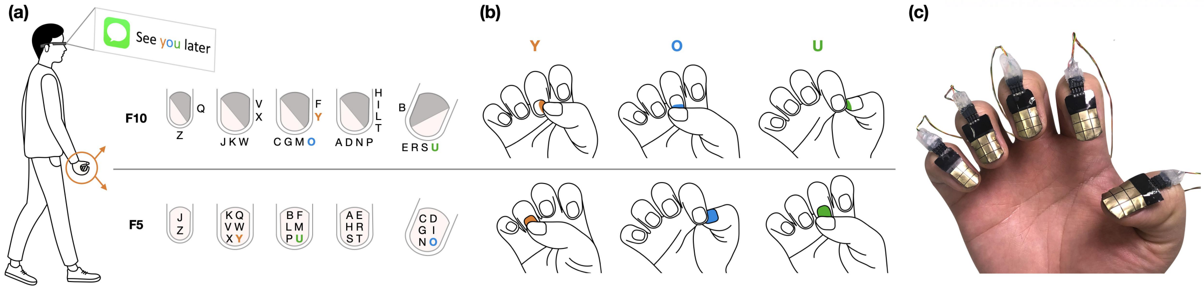

Figure 13: FingerText, a one-handed text entry system for touch sensitive nails. (a) shows two keyboard layouts: a ten key layout (*F10*) based on distinguishing between touches to the side and tip of each nail and a five key layout (*F5*) based on detecting a single touch event on each nail. (b) shows the sequence of inputs needed to type 'YOU' on both F10 and F5 layouts. (c) shows the set of nail touch sensors.

4.3 Introduction

Text entry on wearable devices poses considerable challenges. Touch input spaces may be small [134], imprecise [20] or out of view [135]. Displays are also often small [136], or offset from input spaces [137]. Solutions to these problems involve techniques such as multi-stage character selection [138, 139], limited graphical feedback [140], bespoke gestural alphabets [135], and optimized keyboard layouts [78]. In addition, wearable devices inevitably target scenarios in which users are situationally impaired [141]: distracted [12], with one hand busy [142], or while mobile [143]. These situations demand wearable text entry systems that can be operated with one hand and while engaged in common activities such as walking. While researchers have begun to tackle situational impairments during wearable device use, such as enabling single-handed input [144], research on wearable device text entry while actually mobile is in its infancy, and remains focused on two-handed form factors such as touch input on smartwatches [137, 145].

However, mobility matters. Interaction on-the-go is a prevalent use scenario for smartphones [17] and the de facto design of such systems for stationary settings [146] has contributed not only to reduced input effectiveness and efficiency but also exacerbated social problems such as distracted walking [147] (or *twalking*), a potentially dangerous practice that has been banned in several US cities [148] due to perceptions of the risks it poses at pedestrian intersections. Explicitly designing for mobility aims to cater to, alleviate, or ameliorate these concerns—if we can better support and facilitate effective input, we can reduce the impact of user distraction. We argue these perspectives should also be applied to wearables. Indeed, while research on wearable interaction while on-the-go remains sparse, existing studies highlight unsurprisingly similar trends—mobility decreases input effectiveness [18, 137] and reduces performance in reading tasks [149], problems that can be mitigated, at least in part, through careful interaction design informed by data describing user performance in input tasks while mobile [143].

One promising design candidate for text entry in this space uses *intra-hand input*, defined as the combination of both thumb-to-finger [50] and finger-to-thumb touches. In such systems, a hand-worn or remote sensor, for example, a touch surface [150], depth sensor [39] or RFID tag [151] tracks contact between one or more fingers of one hand to register input events, most commonly taps and/or swipes. This type of in-hand input has been previously suggested as particularly appropriate for on-the-go interaction [152], an assertion supported by evidence indicating that performance of in-hand swipes (on a ring sensor) is robust to the disturbances caused by both walking and running [153]. The simplicity and ready availability of this modality have also led to diverse text-entry designs. Whitmire et al. [50], for example, distribute the characters of a full qwerty keyboard over the finger segments of both hands. A pair of touch-sensitive gloves tracks thumb touches to these regions and achieved a Words per Minute (WPM) of 16. Wong et al. [35] and Lee et al. [78] both propose broadly similar designs for single-handed use and report substantially lower WPMs: 5.42 and 6.47 WPM respectively. In a variation of this approach, Xu et al. propose a miniature keyboard spread over the distal phalanxes of either one [44] or both [57] index fingers; touch typing on these surfaces reached performance levels of between 13.3 WPM, for one hand, and an impressive 23.4 WPM for both. Finally, Fashimpaur et al. [94] use an external camera tracking system in conjunction with a Head-Mounted Display (HMD) to achieve WPMs of 12.54 for a two-handed keyboard design based on a probabilistic text entry system and touches to only the fingertips. While these text-entry projects have remained focused on stationary input, they effectively highlight the potential of thumb-to-finger input to support accurate, rapid, and fully wearable text entry.

We extend this work by considering the impact of, and designing expressly for, mobility. We first use the previously proposed form factor of a fingernail sensor system [150, 154] to assess input performance between sitting and walking conditions, logging both speed and accuracy (N=12). We contrast this data, showing no significant differences in performance in terms of speed or accuracy. We then combine these results with previously published data on the comfort of intra-

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hand finger touches [154] and simulations of the word-level accuracy of candidate keyboard layouts [155] in a quad-objective optimization process intended to generate key arrangements that can support high levels of user performance. Based on a balanced consideration of the results, we select two candidate keyboard layouts: *F5* and *F10*. *F5* is based on sensing single touches to each finger while *F10* assumes a higher fidelity system capable of distinguishing two touches per nail. Figure 13 (a) and (b) illustrate the layouts and how text input was performed in the system. We close by using our fingernail sensor system to evaluate both *F5* and *F10* layouts against QWERTY derived baselines in a word repetition task [156] while users are walking (N=16).

The contributions of this work are: 1) an evaluation of the impact of walking on intra-hand input performance; 2) an exploration of the design of keyboard layouts for intra-hand input that considers variations in sensing fidelity, in terms of the number of finger touches that can be detected, and uses computational methods to balance the competing concerns of speed, accuracy, comfort, and support for unambiguous word-level text input; 3) the *F5* and *F10* keyboard layouts selected to optimize performance and comfort for systems capable of detecting either one or two touches per finger and; 4) an evaluation of text entry performance using *F5* and *F10* while mobile, ultimately achieving WPMs, in a task simulating expert performance, of 31.3 and 25 respectively. This performance represents improvements of 9.47% and 10.45% over QWERTY baselines. The data, designs, and results we report, and methods we present, will help future researchers, designers and developers create more effective wearable text entry systems for mobile settings.

4.4 Related Work

4.4.1 Wearable Text Entry

Text entry is a ubiquitous and challenging input task typically achieved, at high levels of performance, through large dedicated input devices such as keyboards. As computing devices have diversified into smaller mobile and wearable form factors, a considerable body of research has sought to enable rapid text entry on devices such as tablets [157], smart phones [158] and wearables such as finger sleeves [57] and rings [159]. The extremely small size and atypical input and output spaces of many wearables have led to a particularly wide range of proposals. A common approach involves adapting smartphone touch screen techniques to watches [138] or glasses [160]. Envisioning advanced finger trackers, researchers have also proposed external systems to track in-air finger strokes, thus supporting input actions that resemble those used in traditional keyboards and enabling rapid, accurate performance [94, 161]. Other proposals have sought to leverage the specific touch input capabilities of deployed wearable devices to create entirely novel schemes, such as a one-dimensional gesture input system [135]. More recently, text entry research has also begun to design for the situational impairments under which wearable devices are likely to be operated. WrisText [144], for example, targets one-handed use, recognizing that wearable device users may be engaged with everyday tasks such as holding a bag. Similarly, TipTex [44] and BiTipTex [57], based on miniature touch input surfaces mounted on the index finger(s), note that they may be accessible even when a user is holding a bag in the same hand as the device. Inspired by this work, we argue that successfully designing for mundane situational impairments, such as encumberment or walking, is likely to be a key factor in the eventual viability of any wearable text entry technique.

Text entry systems based on touches among the fingers of one hand are particularly relevant to this paper. A common approach has been to define touch input regions on the inner surfaces of the fingers. Whitmire et al. [50] applied this approach to both hands and a continuous input surface to create an unambiguous QWERTY keyboard. They demonstrated text entry speeds of 16 WPM after training, at a cost of encumbering both hands with a full glove input device. Other projects have explored a similar modality, but focused on single-handed use, arguing it is more practical in wearable settings. A major challenge in this work has been dealing with the reduced number of possible inputs this entails. Solutions include Jiang et al. [79]'s use of six input regions on the index and middle fingers with a two-stage input process (as in Zoomboard [138]) to uniquely specify characters, Lee et al. [78]'s use of nine input regions (i.e. adding the ring finger) each with three pressure-levels and [35]'s use of a similar 9 key layout with advanced word prediction techniques. While promising, these approaches have yielded somewhat limited text entry speeds of 5.42 [35], 6.47 [78] and 9.28 [79] WPM, after training. This is likely due to factors such as the time cost inherent in multi-stage selection processes (e.g., increased KeyStrokes Per Character (KSPC) [162]), reductions in input accuracy associated with eyes-free

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pressure input [163], the use of finger regions, such as the proximal phalanxes, that prior work has identified as uncomfortable [49], or reliance of QWERTY based layouts that may be poorly suited to the form factor of input on the fingers.

We build on this prior work by exploring typing on the nails. This finger region has not previously been studied in the context of text entry and we identify a number of reasons why it may be particularly suitable for this form of input. Firstly, the nails have been linked to improved comfort ratings [154], compared to those reported on the finger phalanxes. The nails may also offer greater input expressivity than the phalanxes, as they enable the thumb to be used as an additional touch surface [150], complementing input on the fingers. Each nail also supports several distinct touch regions [154] in close proximity, a fact that may support more rapid text entry times. Finally, nail wearables [59], unlike those mounted on the inner surfaces of the fingers, do not block tactile perception and intrinsically encumber the hand. In sum, nail input may be able to achieve comfortable, expressive, rapid, and unencumbered wearable text entry, a goal that is enticing and worthy of study.

4.4.2 Mobile Input

Mobility is a critical situational impairment for wearables. As with other mobile device form factors [146, 164], performance in tasks involving both viewing content [149] and performing input [18] on wearables drops while walking. However, work to understand and mitigate the impact of mobility on wearable interaction remains in its infancy. The majority of work to date [143], including in the area of text entry [137, 145], focuses on the relatively mature form factor of the smartwatch and deals with two-handed use — the watch is worn on one wrist and its screen tapped by the other hand. This input scenario closely models, and the reported results unsurprisingly follow, those for two-handed smartphone use [165]. While some work, such as Boldu et al. [153]'s touch-sensitive ring, which supports reliable input of swipes during a range of mobility conditions, highlights the potential for reliable wearable input while moving, we are not aware of work that empirically examines text entry while mobile on wearable devices other than the smartwatch. Indeed, researchers have recently identified exploring the performance of wearable typing systems while mobile as a key area for future work [79].

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The studies in this paper are the first to address wearable, single-handed text entry while mobile. We seek to complement prior work on single-handed wearable text entry, which has focused on encumbered use — situations in which either one [144] or both hands [57] are occupied but the user is stationary. While this prior work demonstrates effective and elegant solutions for hands-busy use, we argue that many of the techniques it relies on, such as motion-based input [144] or micro-movements of the thumbs [57], will lose effectiveness in genuinely mobile settings. Walking will likely interfere with motion input, magnify the impact of encumbrance [166] and disturb acquisition of small targets [167], factors that suggest that the ability of these previously proposed techniques to support reliable and effective input while users are on-the-go may be extremely limited. On the other hand, we argue that the intra-hand touches we study, based on relatively large motions of all fingers relative solely to one another, may be highly resilient to the impact of walking [153]. A major goal of this paper is to establish the veracity of this claim.

4.4.3 Keyboard Optimization

In order to design a text entry technique, the letter assignment problem [168] refers to the process of allocating characters to input actions [169]. Key factors constraining this process are the number of characters that need to be supported and the number of input actions that are available. In wearable text entry systems, the number of input actions is typically less than the number of characters [35, 44, 49]. Input actions are therefore associated with multiple characters and word prediction techniques [170] are used to disambiguate input and enable accurate text entry. It is common to view the letter assignment problem as one of the multiple objectives, with different possible character arrangements resulting in different (and usually conflicting) performance profiles in terms of metrics such as text entry speed [171], input accuracy [144], comfort [78], word-level accuracy [155], or similarity to existing layouts [172], among others (see [168] for a full review). Multi-objective optimization, using processes such as evolutionary algorithms [158] or branch-and-bound integer programming [173], provides tools to help designers balance these concerns and select keyboard layouts that achieve a desired balance between objectives. They have been widely deployed to, for example, tweak QWERTY to boost performance without requiring retraining [156], reduce ambiguity in gesture keyboard designs [158] and improve the placement of infrequently used special characters [168]. In this paper, we leverage these methods by deploying an evolutionary algorithm to evaluate candidate key assignments on our wearable and mobile text input system in terms of input speed, comfort, accuracy, and the ability to uniquely specify words.

4.5 Experimental Platform

All work in this paper used a set of five fingernails mounted capacitive sensors to track inter-hand touches, an approach also used by Lee et al. [154] and, in single nail systems, also by both Kao et al. [150] and Lee et al. [174]. We selected this approach as it supports relatively fine-grained tracking of up to five touches to each nail [150]. Furthermore, an informal comparison of published data characterizing the comfort of nail touches [154] against that for finger phalanx touches [49] suggests the former may be more comfortable for users. In addition, we expected that the reliability and robustness of capacitive sensing solutions would be greater than that of camera-based solutions—these remain at an early stage of development and while body-worn systems have been presented [39], even relatively recent work on text entry has relied on research-grade external motion capture systems [94] to support the high level of fidelity required for rapid, unambiguous sequences of input. In contrast the nail based capacitive sensing system we used is fully wearable and does not limit the user movement range.

We based our system on that presented by Lee et al. [154] and refer interested readers to this prior work for a more complete description. In brief, our sensor is composed of five separate modules, each attached to the nails of one hand. The modules consist of flexible PCBs (0.3 mm thick) mounted on commercial cosmetic nails and are attached to a user's nails using a standard fixative. Each nail has nine individual capacitive touch electrodes arranged in a square grid, bar the little finger whose narrower form supports six electrodes in two columns. Electrode sizes range from 3.8mm (on the fingers) to 4.8mm square (on the thumb). At the base of each nail sensor, each flexible PCB extends over the distal phalanx of the finger and contains an MPR121 micro-controller. This monitors the electrodes, reporting contact data in the form of an analog "touch heatmap" [175] at 100 Hz. During each sensor read, these heatmaps are processed to extract the largest contact region (via blob detection). We then calculate image moments to

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describe the region's centroid, angle, and dimensions. The centroid is considered the contact point on the nail. Each MPR121 is wired to a wrist-mounted Arduino MKR1010, via AWG32 gauge wires that do not restrict finger movement. The Arduino communicates with WiFi and UDP to a host computer. In terms of feedback, all studies reported in this paper used an Epson BT 200 Head Mounted Display (HMD) to present instructions and interfaces to users. This device provides a 23° field of view and a 30Hz update rate. All visual content on this device was controlled by the host computer via a wireless UDP connection. Figure 13 (c) shows a user's hand wearing the nail sensor.

4.6 Metrics Study

This study was designed to contrast performance with intra-hand touches between stationary and mobile conditions. We sought to document and characterize the performance changes that may occur with this form of input when users are mobile. In addition, it sought to complement existing data on the performance on individual intra-hand touches [39, 49, 150, 154] with data on how such touches are performed sequentially, as in a continuous process of typing. Data about the performance of all possible pairs of inputs in a system is required to support text entry optimization approaches that leverage bi-gram frequencies to create efficient and accurate input—they allow the fastest and most reliable input sequences to be assigned to the most common character pairings [169, 171]. To the best of our knowledge no prior work has captured a data set characterizing intra-hand input while users are mobile, nor one that systematically documents the performance of pairs of intra-hand finger touches. The study was approved by our university's IRB and was run in full compliance with governmental and institutional recommendations/restrictions for safety and social distancing.

4.6.1 Design

The study examined three independent variables: *pose* (sit/walk), *start-touch* and *end-touch*. Start-touch and end-touch had ten possible levels, each corresponding to the tip or side of one of the five fingernails. The study followed a fully repeated measures design: all participants completed trials in all conditions. Pose was balanced, with half the participants completing

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walking trials before sitting and the other half vice versa. Each unique combination of start- and end-touches formed a block within each pose condition. These blocks were randomly presented to the participants. Each block was composed of four repetitions of the start- and end-touch. The first repetition was discarded as practice. In addition, if a participant performed the requested pair of touches incorrectly, they were required to re-complete it. In total, this led to the retention of 600 correct trials per participant: two poses by ten start-touches by ten end-touches by three repetitions.

4.6.2 Participants

A total of 12 participants (seven male, five female, eleven right-handed and one mixed-handed) with a mean age of 23.08 (SD 1.67) completed this study using their dominant (right) hand. All were university students. On average, they self-rated themselves as highly familiar with computers (4.67/5.0, SD 0.65) and smartphones (4.83/5.0, SD 0.39) but only passingly familiar with virtual and augmented reality technology, such as the Epson smart glass system used in this work (2.0/5.0, SD 0.6). The study took approximately 50 minutes to complete and each participant was compensated with the equivalent of 30 USD in local currency.

4.6.3 Measures

We measured time and errors for pairs of touches. Time measurements were defined as the duration between initial contact with the start-touch finger region until initial contact with the end-touch finger region. Errors were defined as the number of times a participant failed to correctly select both start- and end-touch finger regions. In addition, during the walking conditions, we measured the overall distance participants travelled and used this to infer their average walking speed.

4.6.4 Procedure

The experiment took place in an unused class room. The study began with participants reading instructions, signing consent, and completing demographics. They then donned the study

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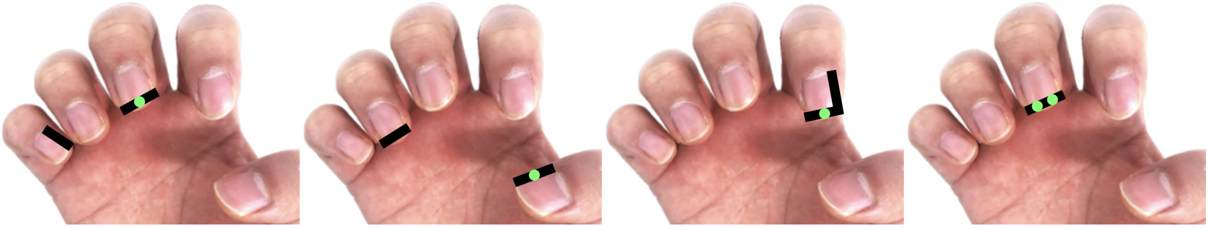
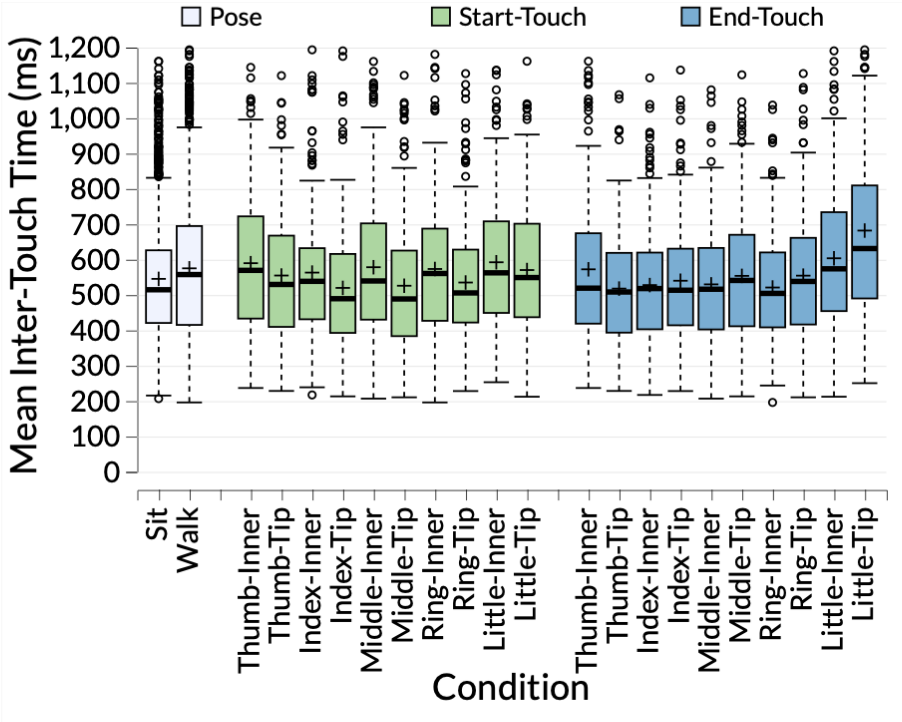


Figure 14: Example study instructions depicting sequential touches between different fingers/regions (left and center-left), different regions on the same finger (center-right) and, on the same region (right). A green dot indicates the start touch region and two green dots signify a double-tap.

equipment, in the form of the nail sensor system on their right hand and the Epson HMD on their head. In order to provide control input, such as starting and stopping a trial, participants' also held a wireless mouse in their left hand, such that they could comfortably press its buttons. Next they performed all ten single nail touches to ensure they understand the input modality and that the system was worn comfortably. They then completed randomly presented (and never repeated) study trials until satisfied they were familiar with the format and instructions (five trials on average). The actual study trials then began. In the sit condition, participants sat in a chair without an arm rest, while in the walk condition they continuously walked a 30-meter figure-of-eight shaped route around a set of desks. They were requested to walk at a comfortable speed. A break of at least 5 minutes was enforced between the two pose conditions.

Each trial in the study followed a similar structure. First, participants clicked the wireless mouse and the experimental instructions were shown. These depicted the start- and end-touch regions, as highlights superimposed over a graphical image of a hand. Figure 14 shows example instructions. Participants then performed a pair of touches, following the shown instructions, and the trial ended and the next began. In between trials participants were able to rest if needed. Throughout the study, participants were asked to maintain a natural "arms down" posture, with their hand in free space near their waist or thigh. While we did not mandate eyes-free input, in practice this posture led, almost universally, to eyes-free performance of the intra-hand touches (see Figure 13, a).



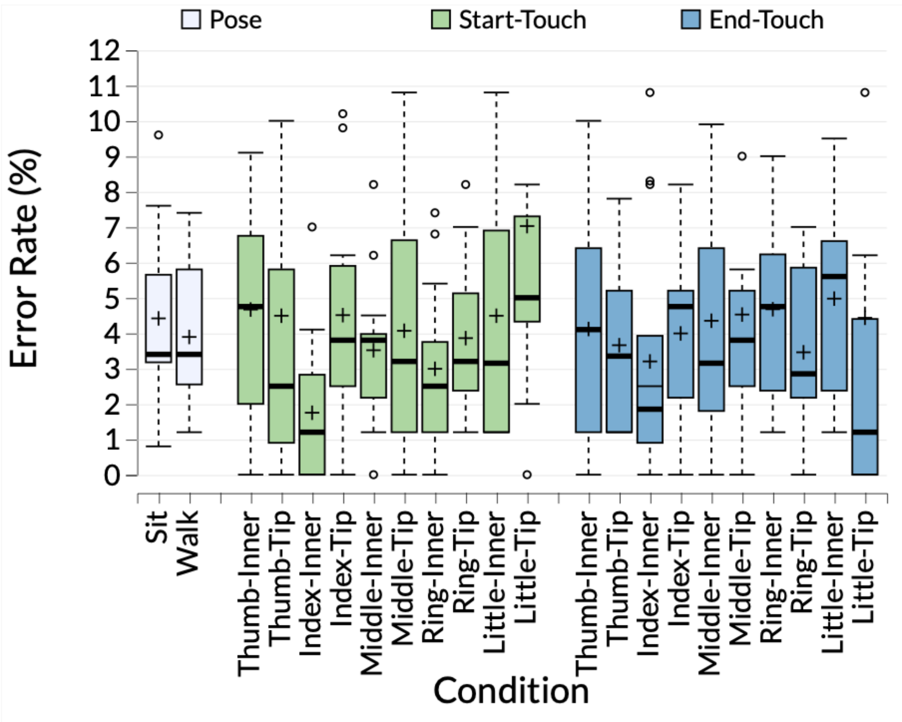


Figure 15: Box plots from the metrics study. Upper shows time data from all conditions for all main effects. Under shows error data, collapsed to the individual independent variables, for all main effects. Means are marked by '+' symbols.

4.6.5 Results and Discussion

We recorded a total of 7653 trials, including errors. We excluded 29 trials (0.38%) due to data loss caused by system failures, leaving a total of 7175 correctly completed trials and 449 error trials. To analyze time, we initially removed outliers by examining the correct trial data set as a whole, an intentionally conservative strategy, and excluded 150 trials (2.1%) with data over three standard deviations from the mean. We used mean imputation in the two (0.08%) cases when all a participant's data for a given condition was removed. We then plotted the data: Figure 15 (upper) shows the main effects for time for all three dependent variables. Time data showed minor violations of normality in 8% of the individual conditions (i.e., 16 of the 200 combinations of pose, start- and end-touch). As ANOVA is widely viewed as robust to such distortions [176, 177], we analyzed time data using three-way repeated measures ANOVA, incorporating Greenhouse-Geisser sphericity corrections where indicated, on the variables of pose, start-touch, and end-touch. The significant results were a two-way interaction between start- and end-touch (F (81,891) = 7.55, p<0.001, $\hat{\eta}_G^2$=0.18) and individual main effects of both start- and end-touch (F (9,99) = 6.19, p<0.001, $\hat{\eta}_G^2$=0.029 and F (81,891) = 12.71, p<0.001, $\hat{\eta}_G^2$=0.10, respectively). Pose did not lead to significant differences in the speed at which participants performed tasks.

Errors for the 200 individual conditions were not normally distributed — all individual conditions showed a median and inter-quartile range of zero. Furthermore, the data was predominantly discrete, with per participant error counts for individual conditions either zero (85.79% of trials), one (11.08%), or two (2.29%) and rarely greater (0.84%). This meant we were unable to apply Aligned Rank Transforms (ARTs) [178], a widely deployed technique to correct normality violations and deploy factorial parametric statistics, as they are designed for continuous data and inflate type I errors when applied to discrete data [179]. Accordingly, we opted to collapse the three individual variables and examine the main effects using non-parametric statistics. As this entails three separate tests, we applied an alpha value of 0.0167, equivalent to using Bonferroni correction. The collapsed data is plotted in Figure 15. Neither a Wilcoxon test on the pose variable ($W = 60.50$, $p = 0.52$), nor Freidman tests on start- and end-touch (respectively $\chi^2 = 17.6$, $p < 0.04$ and $\chi^2 = 10.8$, $p < 0.29$) led to significant differences. Finally, rather than leave the error data interactions entirely unexamined, and based on the presence of highly sig-

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nificant interactions in the time data, we collapsed pose and performed a two-way factorial RM ANOVA on start- and end-touch. The goal was to explore whether the interaction in the time data was also present in the error data. The results suggest it was: they revealed a significant interaction ($F\ (81,891) = 1.92$, $p<0.001$, $\hat{\eta}^2_G=0.11$) and a main effect of start-touch ($F\ (9,99) = 2.06$, $p=0.04$, $\hat{\eta}^2_G=0.03$) but not end-touch ($F\ (9,99) = 0.33$, $p=0.96$, $\hat{\eta}^2_G=0.005$). Given the normality violations in the data, these parametric results may have low validity. We include them as a speculative analysis due to the particular relevance of an interaction between these variables to work reported in this paper.

These results suggest that the main factor impacting performance was the relationship between the start- and end-touch finger regions—the interactions led to the largest effect sizes in the study. Rather than depend on which finger is touched, speed (and possibly accuracy) in the dual touch task we studied depended on the relationship between the start and end points. The confirms both our expectations and the general consensus in prior work [78, 169, 171]. We plot these relationships, for both time and errors, by reporting pairwise mean data in Figure 16. We opted not to conduct statistical pairwise comparisons on this data as both a large number of tests this would entail and the limited size/scope of our study would render these of questionable validity. Furthermore, the evidence in the interaction effects—that the performance of sequential intra-hand touches depends on the specifics of both start and end touches—is sufficient to support our main experimental objective and validates our goal of capturing data on the performance of sequential touches in order to support the design of optimized text entry input systems for intra-hand touch. Regardless, review of the raw pairwise means suggests several reassuringly expected trends. We observe that repeat selection of the same region (shown on the diagonal from left-top to bottom-right) leads to very strong performance; there are also noticeable benefits in sequential selection of two different regions on the same finger over two regions on different fingers (mean error rates of 2.58% versus 4.76% and task times of 520ms versus 583ms); the thumb and, particularly, the little finger, situated at the extremes of the hand, tend to yield lower performance and; there is a general (and anticipated [49, 154]) cluster of high performing regions on the index and middle fingers. These common-sense observations support the validity of the data we report.

In addition to these main results, we recorded an overall mean walking speed of 2.42 km/h

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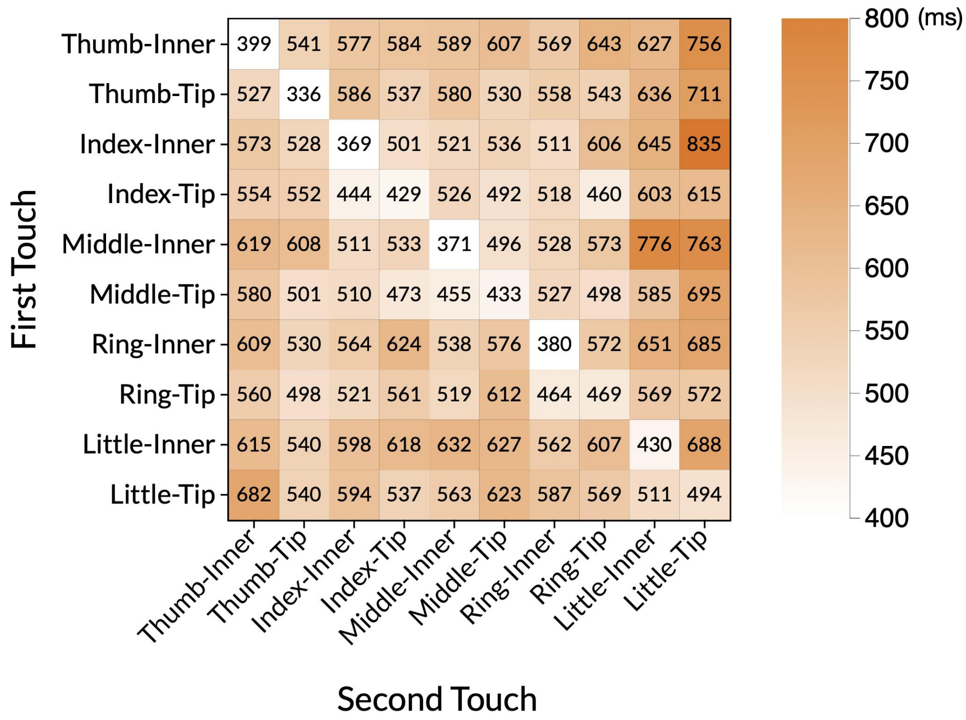

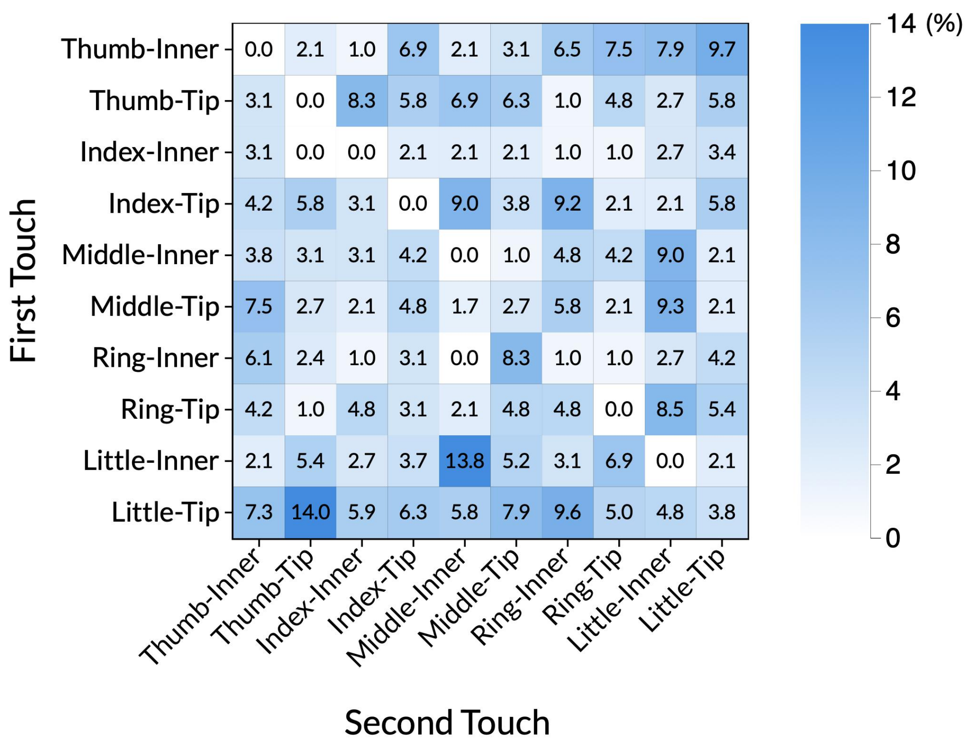

Figure 16: Raw mean results for all combinations of start- and end-touch in the metrics study. Upper shows time data (ms) while under shows error data (%).

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(SD 0.52, min 1.41, and max 3.07), almost identical to that reported in prior accounts of mobile HMD use dealing with tasks such as reading [149]. While our study design does not support any formal comparisons with this literature, we suggest that the bespoke pictorial study instructions we used (see Figure 14) are unlikely to yield a lower mental load that of the highly practiced task of reading text. The fact that participants were able to both process our study instructions (shown on the HMD) and perform our input tasks while maintaining walking speeds at levels previously recorded during solely visual HMD use suggests that the intra-hand input we studied has limited impact on walking speed. While future studies would be required to confirm this preliminary suggestion, it does provide additional evidence of the viability of intra-hand input while on-the-go.

4.6.6 Conclusion

We draw two high level conclusions from the study. First and foremost, walking had no significant impact on performance. Both time and errors remained stable between sitting and walking poses. This, combined with the representative walking paces participants achieved, suggests that intra-hand input is a good candidate modality for wearable interaction while on-the-go. Users should be able to operate systems with intra-hand touches when walking with much the same ease as they can while seated. This is an extremely positive result given the widely documented performance reductions in other forms of touch input while walking [164]. We hope it spurs future work on this modality in mobile settings. Secondly, the relationship between start- and end-touches matters. This is of critical importance for the typing scenario we study as it suggests that keyboard layouts will need to take account of this relationship in order to support good user performance—simply applying existing (e.g., QWERTY) or default (e.g., alphabetical) layouts that do not consider this relationship will likely serve to limit the speed (and possibly the accuracy) with which skilled users are able to type. On the other hand, keyboards that ensure that commonly typed character sequences are achieved by a series of touches that can be performed rapidly and reliably may be able to boost performance to peak levels. The remainder of this paper explores how this can be achieved.

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4.7 Keyboard Layout Optimization

Building on the results from the metrics study indicating the performance of sequential intra-hand input varies significantly based on the start- and end-touches, we conducted a keyboard layout optimization process to explore the range of possible designs. We considered hypothetical systems that are capable of detecting either single or a pair of touches to each nail and, to provide a rounded exploration of the space of possibilities in tractable computational time, used genetic algorithms, specifically NSGA-II [180], to achieve this. The goal was to generate five key (*F5*) and ten key (*F10*) layouts that are representative of optimal performance for each of these input scenarios. For 10 key layouts, we used the full set of data from our metrics study. In contrast, for five key layouts we used the subset of data from trials in the 25 conditions involving pairs of touches to nails tips. In both cases, our process was as follows: we first defined four metrics for assessing key layouts—speed; accuracy; comfort and; confusability. We selected these metrics to emphasize performance over concerns such as familiarity [78]. We then performed optimization processes for each metric individually in order to generate minimums and maximums for normalization. Next we ran multi-objective optimization using the normalized metrics. Finally, we used the resulting Pareto fronts, representing the sets of solutions in which no metric is dominant, as the source from which we selected final layouts for further study. We provide additional details on these processes in the sections below. Furthermore, Appendix 4.12 shows the mathematical formulations.

4.7.1 Metrics

4.7.1.1 Speed Speed metrics for letter assignment problems typically combine temporal costs for arbitrary pairs of physical inputs with the bigram probabilities in a given text corpus. The goal is to design layouts that minimize the time taken to enter frequently occurring letter pairs. A common way to achieve this is via Fitts' law (e.g., as in the Fitts-Digraph model [169, 171]), an approach that models the time required to press pairs of keys in sequence as a function of the physical distance between them. However, for the type of intra-hand input we study, Fitts' law models are inappropriate. The physical distances between targets (i.e., fingertips) vary continuously due to diverse finger articulations such as correlated motions—involuntarily movements occur among other fingers during the intentional movement of one finger [161]. In addition, transitions that involve changes in the touching finger in addition to the touched finger (e.g., a touch to index with the thumb followed by a touch to thumb with the index) may result in higher costs than situations in which only the touched finger changes (e.g., the thumb touching the index then the middle fingers), irrespective of their proximity. As such, rather than use a Fitts' law derived model, we opted for the simple expedient of a function based on mean time costs for each possible pair of sequential inputs: the period between initial contact with the first finger region to initial contact with the second finger region. This approach is achievable due to the limited number of finger regions (5 or 10) considered in this work. Our speed function combines this data with bigram probabilities from Norvig [181] to model the overall time cost of a given letter assignment using the standard quadratic formulation of this problem [168].

4.7.1.2 Accuracy We modelled accuracy using a similar mechanism to speed. We first assigned a cost for each possible pair of touches by multiplying their individual accuracy scores together. This represents a conservative view: if one touch in a pair is wrong, both are considered to be wrong. Using this strict metric during optimization was intended to ensure that more challenging input pairs were not assigned to high probability bigrams. We then combined pair input accuracy with bigram probabilities to model the overall accuracy cost of a given letter assignment: a second quadratic term.

4.7.1.3 Comfort We used comfort ratings for nail touches from the literature [154] and followed Feit [168]'s recommendation to treat "ergonomic costs" such as comfort in terms of individual input events, rather than a property that emerges from pairs of events. The intuition here is that comfort ratings relate to the experience of specific input actions and cannot be meaningfully combined into an aggregate rating for a pair of actions. The cost function for comfort was therefore formulated as a linear term: it was simply based on the ratings for individual nail regions and the frequency with which individual characters occurred in our corpus.

4.7.1.4 Confusability In key assignments in which multiple characters are assigned to each key, input is ambiguous. However, the sparsity of valid character sequences makes such systems

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effective: although each sequence of inputs can stipulate a range of possible character strings, only a small number correspond to actual words, meaning that word-level input remains relatively unambiguous [78, 144, 170, 182, 183, 184]. We included an assessment of the uniqueness of entered character sequences in our optimization process for a number of reasons. Firstly, the number of keys in our target *F5* layout is low—it requires a minimum of five to six characters assigned to each key. This will inevitably increase the number of valid words expressed by any given sequence of selections. In addition, our intuition was that accuracy, speed, and comfort metrics may result in grouping frequently selected letters, such as vowels, on the same high performing regions, an outcome that would likely substantially reduce the word-level accuracy of an ambiguous input system. Introducing a cost relating to the ability of layouts to accurately specify word-level input should be able to mitigate these problems and lead to layouts that balance the need to achieve a high level of input performance (e.g., that are fast, accurate, and comfortable) with the ability to unambiguously specify words.

A key challenge with this approach is substantial computational resources required to calculate the word-level accuracy of ambiguous character input [155]. While such computations are reasonable for a design process that evaluates the performance of tens to hundreds of manually selected key layouts [144], they are infeasible in the genetic algorithm driven optimization process we planned. To model this cost in a more tractable way we applied Lesher et al. [155]'s notion of pre-calculated confusability matrices. Based on a given text prediction algorithm, these matrices contain sums of the frequency with which all pairs of letters are mistakenly selected for each other in a given text corpus. During optimization, the cost of a particular key assignment is then calculated as the sum of matrix cells for all letters assigned to each key. We derived confusability matrices using Lesher et al. [155]'s optimal k-gram algorithm (implemented via word frequencies for the top thirty thousand most common words from Brants and Franz [185]) and a 322210 word corpus formed by combination of three mobile text entry data sets [186, 187, 188]. We used these matrices to assess the confusability of all layouts during our optimization process. This metric serves as a final (albeit relatively simple) quadratic term in our optimization process.

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4.7.2 Normalization

In order to perform multi-objective optimization, all metrics need to be normalized so that variations in the units and scales each is expressed in do not unduly impact the process. A common way to achieve this is via approximating the minimum and maximum scores for each metric via independent optimization processes [158]. To achieve this, we used the NSGA-II algorithm [180] implemented in Pymoo [189] to determine the individual minimum and maximum scores for each of our four metrics for both *F5* and *F10* layouts. In total this involved 16 separate optimization processes: four metrics by two layouts by two endpoints. Each process involved 100 separate optimization runs, each configured with a population and offspring size of 300 and set to terminate after model improvements trailed off [190]—the default. We constrained the minimum number of letters that could be assigned to each key in both *F5* and *F10* to be one and the maximum to be, respectively, six and four. We derived these limits from the minimum numbers required to produce a valid arrangement (i.e. six keys in *F5*), and the four character/key limit used in prominent prior similar systems such as T9 [184].

4.7.3 Multi-objective Optimization

We used the same platform (NSGA-II/Pymoo) to conduct multiple objective optimization using the normalized metrics for both *F5* and *F10* layouts. We weighted all metrics equally and followed the same process used during normalization: 100 separate runs, population and offspring sizes of 300, default termination criteria and character assignments constraints of between one and six for *F5* and one and four for *F10*. We merged the results of all runs for both layouts, culling redundant solutions, to create four dimensional Pareto fronts for both *F5* and *F10* layouts. We visualize the fronts, composed of 3964 and 2297 layouts respectively, and in terms of their scores for all four de-normalized metrics in Figure 17. Inspection of these images reveals trade-offs between all metrics for the ten key case, but that the metrics of time, accuracy, and comfort tended to align for five keys. A clear trade-off was maintained between these three metrics and confusability throughout.

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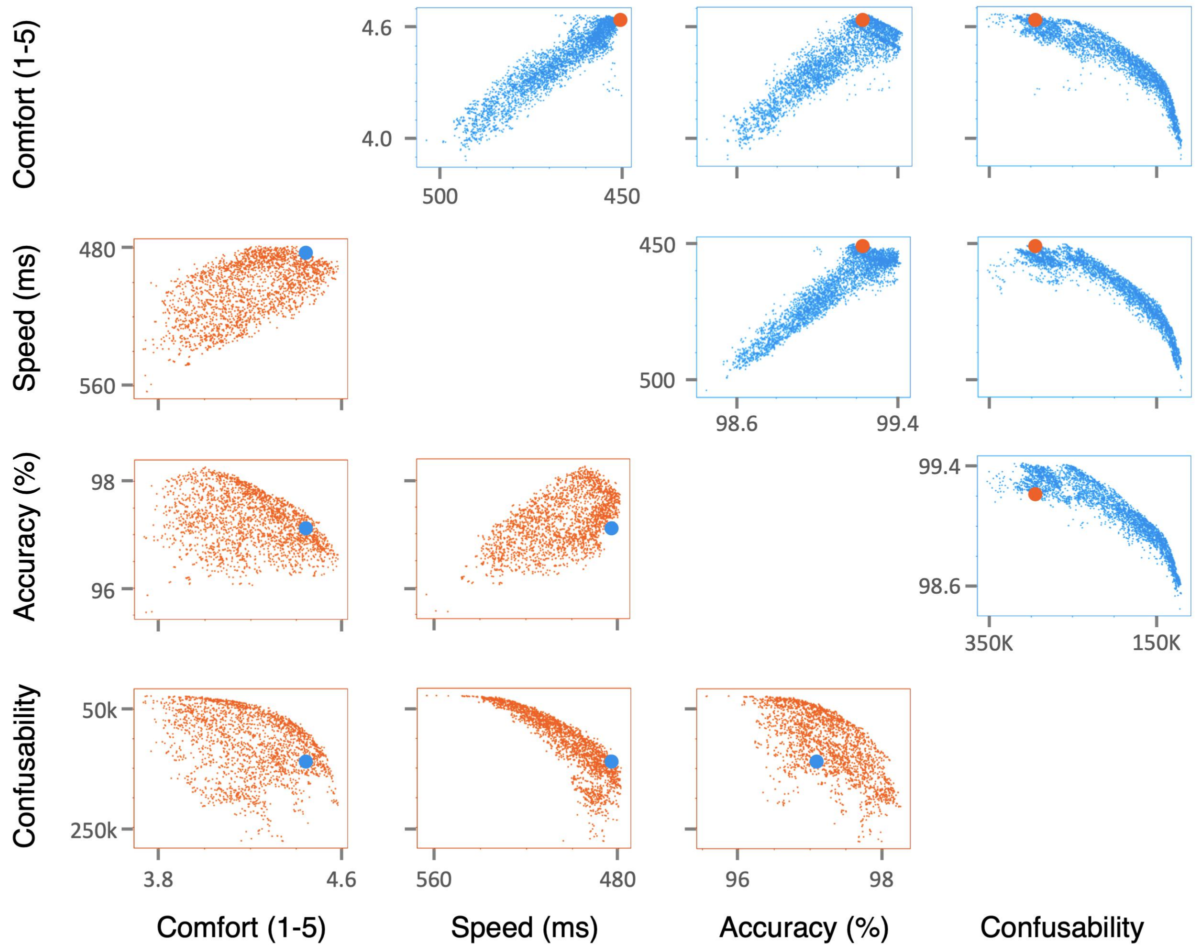

Figure 17: 2D projections of Pareto fronts from optimization processes for both five (in blue, top-right) and ten (in orange, bottom-left) key layouts for all six possible pairs of speed, accuracy, comfort, and confusability metrics. In each figure, top, right quadrants represent better performance. Large red dots indicate the locations of the F5 (in top-right charts) and F10 (in bottom-left chart) layouts. During layout selection, speed, and comfort metrics were emphasized.

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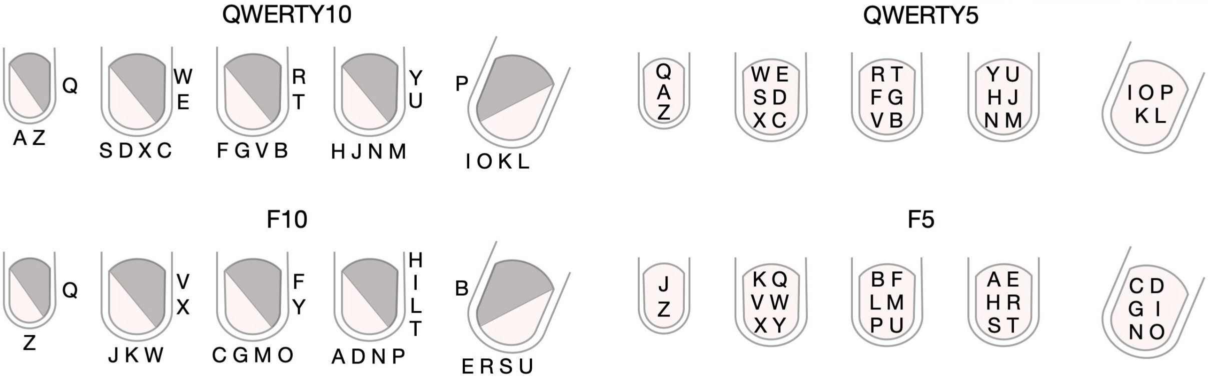

Figure 18: Keyboard layouts assuming either one or two touches each nail are possible. Figure illustrates QWERTY inspired baseline layouts and the *F5* and *F10* layouts produced via the multi-objective optimization process described in this paper. In all layouts, little finger is shown on the left and thumb on the right. In layouts based on two touches to each nail, characters are shown to the side or front of the nails to denote touches to the edge (darker area) or tip (lighter area) of the finger.

4.7.4 Results and Layout Selection

We selected optimal key layouts through a detailed review of those on the Pareto fronts. This was a multi-stage process. Firstly, to better interpret speed data, we calculated the projected WPM figures [191] for all Pareto front layouts. Secondly, to better contextualize the confusability metric we used, we augmented it by similarly calculating Gong et al. [144]'s *disambiguation score*. This metric expresses, for a given corpus of example words and dictionary of word frequencies, the mean rate at which a specific number of inputs on a specific key layout returns the intended example word with the highest probability. While calculating this metric is not computationally tractable during optimization, it is achievable for the relatively limited number of layouts on our Pareto fronts. We specifically calculated rates, assuming three entered keys, for which the correct word has the highest probability (*top1%*), is within the top three highest probabilities (*top3%*) and is within the top five highest probabilities (*top5%*). The goal was to better illustrate how a given layout may perform with respect to a text entry system capable of recommending lists of up to five high-frequency words for selection during typing. We note this analysis supported the validity of [155]'s confusability metric: over both *F5* and *F10* Pareto front layouts, Pearson correlations with top1, top3 and top5 scores showed very strong relationships of between 0.949 and 0.988. Finally, we created *Q5* and *Q10*, baseline qwerty-inspired designs for our five and ten key form factors (see Figure 18) and calculated scores for these on all metrics—see Table 3

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Table 3: Performance metrics for selected F5 and F10 keyboards layouts and QWERTY derived baselines. *Norm* columns contain normalized scores, which are summed in the final column.

Keyboard	**Speed (ms / WPM)**			**Accuracy (%)**		**Comfort (1-5)**		**Confusability (#)**					**Normalized**
Layout	Value	WPM	Norm	Value	Norm	Value	Norm	Value	Norm	Top1%	Top3%	Top5%	**Value Sum**
QWERTY10 (Q10)	538	27.9	0.34	95.9	0.43	3.952	0.31	108863	0.25	91.3	98.9	99.7	1.332
F10	486	30.9	0.06	97.13	0.21	4.455	0.07	140154	0.34	88.1	97.7	99.1	0.685
QWERTY5 (Q5)	494	30.4	0.45	98.56	0.39	4.064	0.35	191122	0.17	81.7	95.1	97.8	1.369
F5	453	33.1	0.05	99.21	0.10	4.654	0.01	293959	0.42	70.1	88.6	93.7	0.582

for details. The goal of these activities was to provide a context for selecting novel designs.

We then reviewed all metrics for saliency. As shown in Figure 17, accuracy was generally high and did not vary substantially (95.6% to 99.4%) across either Pareto front; as such, we did not consider it during layout selection. In contrast, speed (450ms-563ms), comfort (3.73/5-4.67/5) and confusability (25512-353001) varied more considerably, with particularly clear trade-offs between layouts that achieve greater input speed and comfort and those that have reduced confusability. Based on the relatively strong performance of qwerty baselines in terms of confusability, we opted to select *F5* and *F10* layouts that emphasize improved user experience in terms of fast and comfortable input, while maintaining the best possible confusability (and thus top1, top3, and top5) scores. Figure 18 shows the final selected layouts and Table 3 their scores on all metrics. We note that both *F5* and *F10* target 10% or greater improvements in both speed and comfort over QWERTY designs. We also highlight that while the *F10* layout achieves relatively strong performance in terms of confusability, when compared to similar single-handed wearable input systems in the literature (e.g., 85.9% top1 and 95.3% top3 scores for Gong et al. [144]'s WrisText versus 88.1% and 97.7% for F10), the low number of keys on the *F5* inevitably compromises performance (to 70.1% and 88.6%) on this metric. In order to be usable, *F5* would require support from advanced word and sentence level prediction techniques. We selected it for further study in order to explore the extremes of user performance—to examine whether layouts that represent near peak values for comfort and speed actually provide the predicted benefits when real users actually type.

4.8 Text Entry Study

We conducted a final study to evaluate our *F5* and *F10* layouts against QWERTY baselines and validate how the metrics in the optimization process were reflected in the objective performance

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and subjective comfort of mobile wearable text entry. We used a word repetition task [156] as these can emulate expert levels of performance in relatively short study sessions and prior authors have shown they provide good estimates for performance in phrase level text entry tasks [132, 156, 192]. Due to the lack of differences observed in the metrics study, we opted not to re-examine the pose variable and all tasks in this study were conducted while participants were walking. The study was approved by our university's IRB and was run in full compliance with governmental and institutional recommendations/restrictions for safety and social distancing.

4.8.1 Design

The study followed a repeated measures design with two independent variables: layout *type* (qwerty/optimized) and number *keys* (five/ten). All participants completed trials in all four layouts and both variables were balanced. Specifically, half the participants completed qwerty conditions before optimized and the other half vice versa. Within each of these groups, half of the participants always completed five key conditions before ten and the others ten before five. For each condition, participants completed 20 blocks, each containing seven trials, each involving typing one repetition of a single word. This design, and the word set, are taken from prior work [156, 193]. The word set is "the and you that is in of know not they get have were are bit quick fox jumps lazy on". It contains all the English letters and approximates both monogram and bigram frequencies. In total, we recorded 560 trials from each participant: four experimental conditions by 20 blocks by seven trials.

4.8.2 Participants

Sixteen participants (11 male, all right-handed, mean age of 24.5 (SD 3.1)) were recruited from the local university via social media channels. As in the metric study, they were highly familiar with computers (4.44/5.0, SD 0.73) and smartphones (4.75/5.0, SD 0.58) but only passingly familiar with virtual and augmented reality technology (2/5.0, SD 0.73). The study took approximately 90 minutes to complete and each was compensated with approximately 20 USD in local currency. Furthermore, to motivate participants to make input as quickly and accurately as possible, we awarded an additional 20 USD to two top performers.

4.8.3 Measures

We measured input speed, accuracy, and subjective comfort. For speed and accuracy, we used the standard metrics of Words Per Minute (WPM) [191] and Word Error Rate (WER)[156]. For comfort, participants completed a subjective assessment directly after every block in each condition. Specifically, participants provided a comfort rating on a one to five (uncomfortable to comfortable) scale, a process modelled on that used by Lee et al. [154], the source of the original comfort ratings used in this work. In addition, we once again logged the distance walked in each condition in order to subsequently calculate the walking speed.

4.8.4 Procedure

The study procedures, by and large, followed those used in the metrics study - participants walked around a figure of eight in the same classroom wearing the same equipment - nail sensor on their dominant (right) hand, HMD and wireless mouse. The study began by showing a visualization of the first layout (as illustrated in Fig 20) each participant was to experience and explaining how the characters were mapped to the finger regions. In particular, in the case of the Qwerty keyboards, additional explanations were given to ensure participants recognized the layout. Then they entered several (max five) randomly presented words to familiarize themselves with the system and then started the first condition. Each condition involved display of the 20 blocks in random order. The seven trials in each block involved display of the same word on the HMD, which participants were instructed to type. For typing feedback, we followed prior work [35, 144] by showing the first character on a key for the initial keystroke (e.g., C for F5 thumb) and the most likely word prefix for all further keystrokes. In the study, as we sought to verify whether our optimized layouts resulted in increased performance and/or comfort in a simplified task (as in [156]), we did not provide facilities for correcting errors. Rather, participants were simply instructed to type as rapidly and accurately as possible, without rectifying any mistakes. Individual trials were separated by breaks in which the participants were required to click the wireless mouse to move on. After completing a block, participants entered a comfort rating. As they were mobile, this frequent process was integrated into the wearable input system: participants tapped their thumb to indicate a very comfortable experience (5/5),

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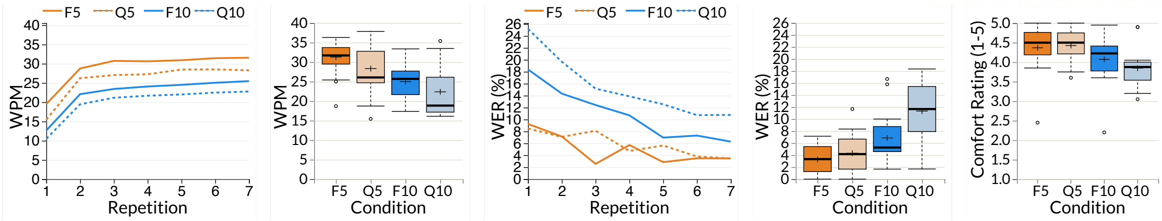

Figure 19: WPM (left-two), WER (center, center-right) and comfort (right) results from the text entry study. Line charts show how mean performance for each metric changes with repetition number. Box plots for WPM and WER are derived from data from the final three repetitions and represent expert performance. Comfort box plot summarizes all data.

their little finger to indicate a very uncomfortable one (1/5) and their other fingers to indicate the intermediary ratings. After completing each full condition, there was an enforced break (minimum 2 minutes).

4.8.5 Results

We first processed the 8960 trials recorded in the study by excluding the 330 outliers (3.3%) with a WPM over 3*IQR apart from the 1st and 3rd quartile. Forward fill imputation was used to ensure we retained complete pairwise data for all layouts and participants. We then plotted the WPM and WER data by repetition—see Figure 19 (left and center). These show substantial improvements during early repetitions, as the time spent in processes such as visual search reduces, and stable performance during latter repetitions as physical limitations become the constraining factors [156]. As our interest was in expert level performance, we conducted two-way RM-ANOVA on data from the final three repetitions for both WPM and WER metrics. These data are shown in Figure 19 (left-center and center-right). WPM showed no interaction, but significant main effects of *type* ($F(1,15)=4.59$, $p<0.05$, $\hat{\eta}^2_G=0.23$) and *keys* ($F(1,15)=79.1$ $p<0.001$, $\hat{\eta}^2_G=0.84$). WER showed an interaction ($F(1,15)=7.54$ $p<0.001$, $\hat{\eta}^2_G=0.33$) and also, again, main effects of *type* ($F(1,15)=7.56$, $p<0.05$, $\hat{\eta}^2_G=0.34$) and *keys* ($F(1,15)=65.2$ $p<0.001$, $\hat{\eta}^2_G=0.81$). In addition, we conducted RM-ANOVA on the mean comfort ratings (Fig 19, right). The interaction was significant ($F(1,15)=20.2$, $p<0.001$, $\hat{\eta}^2_G=0.02$), as was the main effect of *keys* ($F(1,15)=67.68$, $p<0.001$, $\hat{\eta}^2_G=0.14$).

Interpreting these results, we note the prevalent significant effects and particularly large effect sizes for *keys* indicate very robust performance improvements, at least in terms of speed

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and accuracy, when dropping to one key per finger from two: minimizing the number of keys per finger is a desirable approach for future systems. Furthermore, the moderate effect sizes for *type* suggest that the optimization process we conducted, and layouts we selected, were able to improve over baseline designs. Specifically, F5 improved by 9.47% (WPM) and 23.68% (WER) over Q5, and F10 by 10.45% (WPM) and 39.44% (WER) over Q10. These represent meaningful performance boosts. In addition, we saw few benefits of the QWERTY layouts in the early trials in each block—initial performance and learning curves were not noticeably better. We suggest participants were not able to map their knowledge of QWERTY to the form factor of their fingers and there may be few advantages to pursuing such layouts in the type of wearable system considered in this paper. The interaction effects can largely be explained by differences between *F10* and *Q10* that are weaker (WER), or absent (comfort), between *F5* and *Q5.* We conclude that improving layouts through optimization was somewhat less impactful in the five key case.

It is interesting the highlight how the study results either confirm or refute our expectations. Based on our optimization and layout selection process, we expected to see improvements in speed and comfort but not accuracy over qwerty baselines. While speed improvements materialized, these also translated into unexpected benefits in terms of accuracy, but comfort was not strongly boosted. Possible explanations for this may be that our metrics study failed to model the challenges, in terms of accuracy, of finger typing. Longer sequences of inputs may be required for this. In addition, the comfort ratings we used were extracted from a prior article dealing with individual touches to the nails [154]. These may not be directly applicable to the continuous input scenario we studied. As comfort is acknowledged to be an important factor in intra-hand touch input [78, 79], further work to understand how to best model comfort during wearable typing is currently required.

Finally, we note that the overall mean walking speed was 2.43 km/h (SD 0.61, min 1.49, and max 3.48), closely following that reported in the metrics study. This suggests that the word input task has a limited impact on walking speed and that our text entry system may be suitable for users on-the-go.

4.8.6 Discussion

It is worth contextualizing the results from this study with prior work that uses similar assessment methods [156], a similar single-handed text entry scenario [35, 78, 79] or addresses wearable text entry on-the-go [137, 145]. While no other work exists at the overlap of these three spaces, we are able to draw a number of interesting parallels and conclusions by examining each issue in turn. In terms of methods, Bi and Zhai [156] use a similar repeated word entry task for evaluating gesture typing keyboard layouts. Their findings align well with ours: text entry times stabilize from the third repetition and mean WER reach as high as 13.54%, figures similar to ours and due, at least in part, to the fact the task restricts participants from correcting errors. While it is not possible to draw strong performance parallels between such different input methods, these similar trends do suggest our methods did enable us to capture performance indicative of genuine expert use.

We can make more direct comparisons with work on in-hand text entry: using variations on single-handed taps to the finger phalanxes, Wong et al. [35], Lee et al. [78] and Jiang et al. [79] report input speeds of between 5.42 and 9.28 WPM. While the speeds reported in our study (between 22.38 and 31.3 WPM) clearly exceed these figures, this positive contrast must be considered in the context of study tasks used. These prior projects have sought to train users on keyboard layouts, over periods where that learning process is likely incomplete. As such, the performance they report does not represent the type of expert use we study—it is more likely "hunt and peck". In addition, our lab-based methods may overestimate the ability of skilled intra-finger typists. Regardless, our work does point towards appropriate strategies for maximizing performance in this area: reduce the number of different input actions by using ambiguous keyboards; focus on the most comfortable and easy to reach finger regions; optimize keyboard layouts; expect few benefits from using existing layouts such as QWERTY and; do not rely on prolonged or challenging input (e.g., pressure [35, 78] or multi-stage selection [79]).

Finally, in terms of mobility, prior work has established times for touchscreen typing on smartwatches: 9.019 WPM [137] in conjunction with smartglasses and 18-30 WPM using a range of input types on a standalone watch (handwriting recognition, keyboard and gesture keyboard) [145]. While this two-handed input differs greatly from that studied in this paper,

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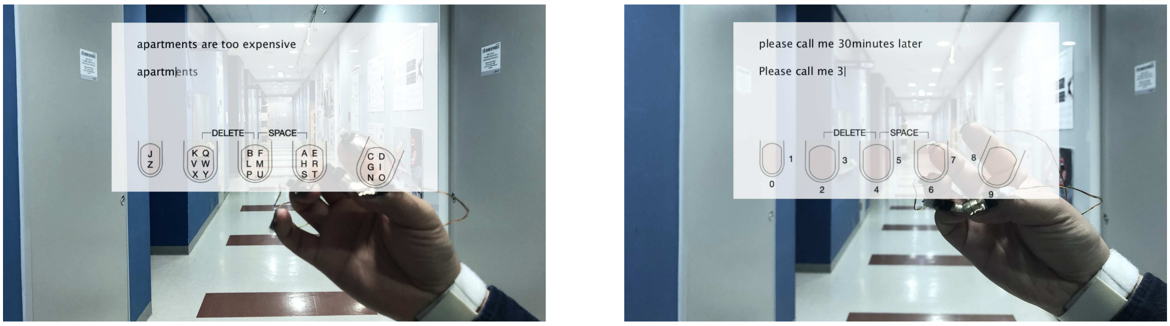

Figure 20: Nail touch based text entry system for mobile typing. It extends the system used in the study by integrating required keys (e.g., space, delete), a word selection interface and a hand close gesture to access a numeric keypad.

we again note our one-handed WPMs contrast relatively well and suggest that in-hand typing interfaces may be a particular viable design candidate in this area. Rather than write on the tiny screen of your watch, it may be better to simply type with your hand [44, 57].

4.9 Text Entry System Design

Building on the positive results of this study, we developed a full text entry system for nail based in-hand input. This used the *F5* layout based on its strong performance in terms of speed, accuracy, and comfort. We added space and delete functionality using chords, or touches to a pair of fingers, and simple gestures [154]. Specifically, the space key was assigned to a simultaneous touch to index and middle fingernails and delete to touch to middle and ring nails. In order to facilitate rapid access, space and delete could also be redundantly accessed by swipes left and right over any nail. In addition, we developed a word suggestion and auto-complete system [144] capable of displaying the top five most likely words based on the currently typed characters. These suggestions were displayed above each finger in the HMD interface and could be selected by a dwelling (for 500ms) on the associated nail. Finally, alternative key layouts, such as for numbers or punctuation, were toggled by closing and re-opening the fist, an action that simultaneously triggers touches to all four fingernails. By integrating these diverse input modalities [154] (e.g., chord, dwell, and swipe) it was possible for the system to provide full keyboard functionality using only the nail sensors. Figure 20 shows an overview of this system. The next step for this project is to evaluate this full featured wearable text-entry system.

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4.10 Limitations

A number of limitations impact our work. Many relate to its scope. At the highest level, we do not consider the broader implications of using wearable devices while mobile; we just focus on the typing experience. However, typing, or working with text in general, may exact a toll in terms of mental workload that would have implications in terms of, for example, safety. This may, in practice, preclude the design of such systems. While our work is motivated by the real world prevalence of mobile smartphone typing, the frequency with users genuinely would (or should) type on wearable devices is currently unknown: existing research on wearable device use patterns is relatively sparse and limited to the smartwatch form factor [8, 194]. Our studies could also be broader in scope. For example, we limited ourselves to two touches per finger, and focused on nail touches. While these are reasonable in terms of scope for a single paper, it would be interesting to explore systems that support more touches (e.g., five [150]), and/or other finger regions (e.g., the inner phalanxes [49]) and sensing systems [39]. Furthermore, our final study used only QWERTY derived baselines; another obvious baseline to study is alphabetical, a form used in prior predictive systems such as T9 [184]. Additionally, it would be valuable to compare performance directly against other current systems, such as head gaze or hand pointer-based keyboards. Longer multi-session text entry studies [195] capable of documenting learning curves and true expert performance with our layouts and system would also effectively complement the studies presented here. Furthermore, a study including the word suggestion and auto completion system and other keyboard functions (e.g., delete, space, and mode change) will generate valuable data about performance of more complex, realistic, and naturalistic typing tasks.

In addition, our optimization process could also be extended. For example, we could use alternative optimization approaches capable of guaranteeing the quality of solutions in terms of provably correct bounds [173]; we could apply weights, in a grid search pattern, to our multi-objective optimization process to more completely populate the Pareto set of solutions [158] and; we could conduct extended manual local searches in the regions around returned solutions—such structured local searches may improve the quality of the results [196]. Finally, we could also extend our treatment of mobility to consider other scenarios, such as travel or public transit [197], or conduct studies in-the-wild, in genuinely mobile settings (rather than the lab). Exploring the viability of wearable text entry in a broad range of mobile scenarios would be highly valuable.

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4.11 Conclusion

This paper argues that text entry systems on wearables need to be designed to support mobility. As with smartphones, designing solely for stationary settings will result in systems that achieve low levels of performance when users inevitably opt to use them while mobile [146]. The resulting increased workload and frustration will lead to poor user experiences and potential societal harms—wearable device use while mobile may become unnecessarily hazardous. We explore the design of wearable text entry systems by documenting performance with the promising modality of intra-hand input. Our initial study confirms our expectations about the robustness of intra-hand input under mobile conditions. While walking, both input times and error rates show no significant changes in performance. Building on these positive results, we conduct a multi-objective optimization process that seeks to balance the properties of input speed, accuracy, comfort, and ability to unambiguously specify words. We ultimately select two layouts: *F5* that relies on a single touch to each finger and *F10*, which assumes two touches to each finger can be detected. Our selection process emphasizes the speed and comfort of input while seeking to minimize reductions in the ability to unambiguously specify words. A second study shows these layouts provide performance improvements over QWERTY inspired baselines: they are up to 10.45% faster and 39.44% more accurate. While their ambiguity is increased (by 14.2% to 0.6% in terms of Gong et al. [142]'s disambiguation score) compared to QWERTY designs, we close by presenting the design of a word completion system that for our intra-hand input modality that we believe can mitigate these concerns and ensure users can achieve rapid, comfortable and accurate text entry performance using a wearable input device and while mobile.

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4.12 Appendix: Optimization Process

This appendix includes objective functions used during the overall process and for each of the individual metrics. We recommend Feit [168] for a more comprehensive review and discussion of each of the individual metrics.

4.12.1 Objective Function

The objective function for the overall optimization process is:

$$O(l) = (1 - time(l)) + acc(l) + comf(l) + (1 - conf(l)) \tag{1}$$

where our overall goal is to minimize the time costs, maximize the accuracy, maximize the comfort, and minimize the confusability of layout l (all metrics are normalized).

4.12.2 Speed

Speed was a quadratic term in our optimization process:

$$min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{M} \sum_{l=1}^{M} p_{ij} t_{kl} x_{ik} x_{jl} \tag{2}$$

where x_{ik}, x_{jl} are binary decision variables indicating that a symbol $i(j)$ is associated with a nail region $k(l)$, p_{ij} is the frequency of the letter pair ij, and t_{kl} is the mean time it takes to touch nail region l after touching nail region k. We have a 26 letters (N) with 5 or 10 nail regions (M).

4.12.3 Accuracy

Accuracy was a second quadratic term:

$$max \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{M} \sum_{l=1}^{M} p_{ij} a_{kl} x_{ik} x_{jl} \tag{3}$$

Terms are identical to equation (2) save for a_{kl}, defined as the mean accuracy of touching nail region l after touching the nail region k.

4.12.4 Comfort

Accuracy was a linear term:

$$max \sum_{i=1}^{N} \sum_{k=1}^{M} p_i c_k x_{ik} \tag{4}$$

where x_{ik} is the binary decision variable denoting whether or not a symbol i is mapped to an input action k, p_i the frequency of the symbol i, and c_i the comfort rating of touching the nail region k.

4.12.5 Confusability

Confusability was a third quadratic term:

$$min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{M} (C_{ij} + C_{ji}) x_{ik} x_{jk} \tag{5}$$

where C is a confusability matrix [155] containing how frequently a symbol i is wrongly predicted to be a symbol j (for a given word prediction algorithm and data set) and x_{ij}, x_{jk} are binary decision variables that denote whether the two symbols are assigned to the same nail region (k)

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V Designing Socially Acceptable Hand-to-Face Input

5.1 Abstract

Wearable head-mounted displays combine rich graphical output with an impoverished input space. Hand-to-face gestures have been proposed as a way to add input expressivity while keeping control movements unobtrusive. To better understand how to design such techniques, we describe an elicitation study conducted in a busy public space in which pairs of users were asked to generate unobtrusive, socially acceptable hand-to-face input actions. Based on the results, we describe five design strategies: miniaturizing, obfuscating, screening, camouflaging and re-purposing. We instantiate these strategies in two hand-to-face input prototypes, one based on touches to the ear and the other based on touches of the thumbnail to the chin or cheek. Performance assessments characterize time and error rates with these devices. The paper closes with a validation study in which pairs of users experience the prototypes in a public setting and we gather data on the social acceptability of the designs and reflect on the effectiveness of the different strategies.

5.2 Design Factors in Hand-to-Face Input

This scenario explores the extension of intra-hand input by exploring hand-to-face input using touch sensitive nail. This extension is particularly important in that it explores other body regions beyond the hand, and this exploration can suggest a new input method to handle various form factors of wearables. For example, the system can control a smartwatch by nail touches with watch usage posture or control the HMD by nail touches with the face. Within this context, this scenario examines the hand-to-face inputs from the perspective of three design factors. First, regarding the social factor, an elicitation study was conducted to generate diverse ideas on hand-to-face inputs in a public setting. The results were consolidated to generate five design strategies to achieve socially acceptable and unobtrusive inputs. Then, the validation study on the two prototypes that instantiate these strategies generally validated the design strategies. Second, regarding the space factor, the results of the elicitation study suggested viable face

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regions and actions for hand-to-face inputs, and ear, chin, and cheek were explored as an input space. Lastly, as for the manipulation factor, the validation study also assessed the time (2.5s, 2.4s) and accuracy (8.9%, 21.5%) performances of two prototypes. These objective performances show that hand-to-face inputs can be readily and quickly performed.

5.3 Introduction

Augmented Reality (AR) Head-Mounted Displays (HMDs) are an emerging consumer technology that promise to impact activities as diverse and fundamental as education [198], accessibility [199], health care [200] and entertainment [201]. Understandably, AR has long attracted attention in the Human-Computer Interaction (HCI) research community [202]. However, while aspects such as tracking fidelity, display quality and computing power have advanced considerably to produce today's high-end products, input and interaction technologies are less mature. Current commercial systems feature on-headset touch surfaces (e.g., Google Glass) or hand controllers in the form of touchpads (e.g., the Epson BT-300) or hand-held clickers (e.g., Microsoft HoloLens) as key interaction channels. While these systems can be effective, they offer limited input areas and, in the case of hand-held controllers, are cumbersome additional devices that disrupt or preclude system use during mundane, everyday tasks and activities in which the hands are busy.

Recognizing the need for input systems for AR glasses that leave the hands unencumbered, a considerable body of research has explored topics ranging from wearable peripherals, such as belts [203] or rings [56], to in-air gestural input [11] and on-body touches [133]. One focus for work in this latter area has been on using the face as a site for input – what Serrano *et al.* [41] term *hand-to-face* input. The face is appealing as it is easy to access with a touch, typically unobstructed by garments and proximate to smart glass hardware. Facial touching is also a common human behavior [204]. Prior work has shown that input on the face can be useful in tasks such as navigation, video browsing [41] or basic selection and pointing [205] through schemes such as swiping and tapping on the cheek [41], thumbing the nose [206] and stroking the hair [207].

While this work effectively demonstrates the viability and diversity of hand-to-face input,

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it is also fragmented, piecemeal and technologically opportunistic. By this we mean that proposals typically target highly specific body sites such as the ear [208], nose [206], cheek [209] or hair [207] with the goal of exploring interactions that can be effectively performed by users and detected by a predetermined sensor setup, such as electrooculography (EOG) glasses [206], optical range finder arrays [209] or capacitive braids [207]. We argue there is a need to improve our understanding of how users conceive of touches to the face as an input modality [41] to better inform future design and development efforts. Specifically, we argue that a key omission in our current understanding relates to the social acceptability [210] of facial touches - how comfortable users feel performing or observing this type of input in real life situations. This issue is particularly important as the face is an exposed, publicly visible body region and AR systems are ultimately intended and expected to be used in everyday settings and spaces, situations in which many forms of publicly observable input may be considered socially unacceptable [11].

We studied this issue in a multi-stage research process. First, we conducted an elicitation study [211] of input via facial touches with pairs of users in a public setting – a coffee shop. Users created and rated interface proposals according to how comfortable they felt performing them in various settings [26]. We contribute both this novel combination of elicitation and social acceptability methods and the study results in the form of strategies for designing socially acceptable hand-to-face input techniques for AR/wearables. Building on these strategies, we then created, implemented and evaluated two input systems, one based on camera tracked touches to the ear, the other on a touch-sensitive thumb nail. These activities contribute a novel sensing setup (camera tracking of touches to the ear) and input approach (nail to face touches) as well as empirical characterizations of user performance and recommendations for how these systems be configured to support effective, expressive input. We close the paper with a study in which participants used our techniques in a public setting and contribute a qualitative assessment of their social acceptability that serves to validate the techniques with respect their original design intentions. In this way, we showcase the value of our design strategies for creating socially acceptable hand-to-face input techniques for AR/wearables.

5.4 Related Work

There is a large and rapidly growing literature dealing with on-body input. One key focus is on developing sensing solutions based on, for example, signals that propagate through the body [120], camera-based tracking [40], or thin sensing films [43]. While most of this work focuses on point touches, researchers have also emphasized that much more can be done with the skin. It is highly flexible and readily deforms, providing additional channels for input [212]. For example, Weigel *et al.* [213] applied elicitation methods to understand the potential of skin deformation for interaction design, highlighting its emotionally rich and evocative qualities.

While the majority of this work focuses on the hand or forearm, touches to the face are a common behavior that interaction designers can also leverage. Basic studies of face touching behavior indicate it occurs frequently – at rates of 15.7/hour for the mouth, eyes and nose [204] through 24/hour [214], 40/hour [215] and up to 54.3/hour for the whole face [216]. In early work to explore the value of these touches for device input, Serrano *et al.* [41] conducted an elicitation study and concluded that fairly standard finger strokes (swipes, two-finger pinches and circles) on the cheek were an optimal design candidate. Subsequent studies characterized empirical input performance (using a high end optical motion capture system) and a lab-based assessment of social acceptability indicated participants felt that smaller and simpler gestures such as swipes were unlikely to attract undue attention.

Recent work has focused on taking hand-to-face input out of the lab by broadening the design space and constructing viable sensing systems. This later task is challenging and the expressivity of current systems is low. For example, Lisserman *et al.* [217] created an array of capacitive sensors that fit behind the ear; they reported that two touches to the ear can be detected accurately (99%) but performance with three or more touches drops steeply (to 86.6% or lower). Kikuchi *et al.* [208] expand on these ideas with a system that uses in-ear optical sensors to detect five ear deformations – four directional pulls and a press – with an accuracy of up to 89.56%. Yamashita *et al.* [209] describe a broadly similar system that deploys an array of optical sensors embedded in glasses, and focused on the skin of the face, to track five pushes to the cheek with an accuracy of 89.8%. In closely related work, Lee *et al.* [206] use off-the-shelf EOG glasses to detect five actions (rubs and left/right flicks and pushes) on the nose with an

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accuracy of up to 96%. Finally, Dierk *et al.* [207] present a proof of concept system featuring actuated hair braids that use swept frequency capacitive sensing to detect touches along their length.

While much of the practical work in these projects involves building effective input technologies, a key goal underlying their explorations of hand-to-face input is the idea that it is an appropriate way to interact in public settings. For example, Lee *et al.*'s [206] primary motivation for their system is to create discreet input primitives, while Dierk *et al.* [207] stress the public and social aspects of hair in the design guidelines that informed their prototype and Kikuchi *et al.* [208] are inspired by the idea that the ear can be touched "naturally without worrying about provoking stares". While the inherent unobtrusiveness, subtlety or social acceptability of hand-to-face input is an appealing idea that is well grounded in the literature capturing the regularity of facial touches, we note is a largely unexamined assertion – it has tended to be claimed rather than assessed. In other words, despite a growing research interest in developing hand-to-face input systems, there is a lack of design knowledge about the types and forms of hand-to-face touch that are appropriate for public settings.

5.4.1 Subtlety, Unobtrusiveness and Social Acceptability

Although they have seen scant attention in studies of hand-to-face input, issues of subtlety, unobtrusiveness and social acceptability have attracted research attention in closely related areas. Early work emphasizing the subtlety [218] and unobtrusiveness [219] of input actions focused on wearable technology and argued these qualities are requirements to achieve social acceptability. The subtlety of an interface has also been operationalized as the frequency with which it can be used without an observer noticing [220]. Building on these ideas, social acceptability has been defined as whether an input action is deemed appropriate by both the user issuing it, and observers watching it, in the context in which it occurs [221]. It has been applied to assess the viability of general body gestures (e.g., foot tapping or head nodding) and mid-air gestures of [210], or around [26], mobile devices. This work typically shows a predetermined set of gestures to participants via video, or requires them to enact such a set. Participants then rate where (e.g., home, restaurant, workplace) and in front of whom (e.g., alone, with family, friends,

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strangers) they would either be willing to (or feel comfortable performing) each gesture. This approach has generated a range of useful outcomes. Rico *et al.* [210], for example, highlight the importance of subtle, comprehensible, and familiar movements in maximizing social acceptability, while Ahlström *et al.* [26] provide concrete recommendations for creating socially acceptable in-air gestures based on pragmatic qualities such as gesture size, location, and duration and Montero *et al.* [221] provide a useful classification of gesture social acceptability based on the whether the input actions and/or resultant outcomes are observable.

5.5 Hand-to-Face Elicitation Study

Elicitation studies involve participants creating input actions for a given set of tasks [211]. The resultant actions are analyzed for factors such as their agreement across participants [222] and categorized according to salient design properties, such as their form or complexity [223]. This study sought to understand how users conceive of hand-to-face input in a social setting. It moves beyond prior work [41] by focusing on social acceptance and unobtrusive or subtle actions during the input creation phase and by including an evaluation of these qualities by both participants and observers. In this way, it seeks to generate design knowledge that can support creation of novel socially acceptable input techniques for AR/wearables.

5.5.1 Experimental Design, Tasks and Setting

Study tasks were adapted from prior work [41, 211] and are shown in Table 4; each participant was asked to generate hand-to-face input actions for each task. Following Morris [224], we deployed three methods to improve study outcomes: production, priming and partnership. Production relates to generating multiple proposals; participant's generated two and selected a favorite. Priming involves providing illustrations and examples to help participants move beyond existing designs from other contexts. We achieved this by showing participants a 90 second video depicting a wide variety of hand-to-face input actions, which they were encouraged to try out, and giving them a demo of the Microsoft HoloLens. Finally, partnership relates to performing elicitation activities in groups. We achieved this by recruiting pairs of participants (all strangers) and having them generate interface proposals alternately – this enabled them to

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build and reflect on their partner's ideas.

To focus the study on social acceptability, we further adapted typical elicitation methods. To improve the ecological validity of the proposed actions, the study was conducted in a busy public place – a coffee shop. Participants were also instructed to generate unobtrusive or subtle actions, suitable for use in the public setting of the study, and both they and their partners rated all favored input proposals for social acceptability and how obvious the input action was. This provided both author and observer perspectives on social acceptability [210]. To assess social acceptability, we used Ahlström *et al.*'s [26] questionnaire; this asks what situations and individuals a participant would feel comfortable performing an action in. For obviousness (or unobtrusiveness), we adapted the social acceptability questionnaire to ask in which locations an action would be obvious. We also included a seven-point Likert scale rating actions from "not obvious" to "very obvious". In total, participants answered four questions per favorite input action generated by both themselves and their partner.

5.5.2 Participants and Procedure

Twenty participants (10 males, mean age 22.6, one left-handed) completed this study in ten pairs. All were either students or recent graduates at UNIST and they were compensated with approximately $15. Participants self-rated as highly familiar with smartphones (4.5/5) and computers (4.5/5), but had no or limited experience of HMDs and AR. Each study session began with an introductory video showing example actions and a demo of the HoloLens. Participants then began generating and rating input actions, alternating making the initial proposal with their partner. Half the participant pairs generated proposals for tasks in the order shown in Table 4

Table 4: Task list used in elicitation study

Task Type	Tasks		
System	Open Delete Copy	Close Accept Paste	Select Decline Take Photo
Navigation	Next Zoom in Rotate anti-clockwise	Previous Zoom out	Pan (any direction) Rotate clockwise

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and half in the inverse order. While generating proposals, they were encouraged to think aloud in order to expose their design intentions to both their partner and the experimenters. After both participants in a pair had generated two proposals and selected a favorite, they rated these for social acceptability and how obvious they were. The experiment took approximately two hours for each pair and, in total, 320 favorite gestures were produced: 16 tasks by 20 participants.

5.5.3 Results and Data Processing

Favored actions were evenly split between first (57%) and second (43%) proposals, highlighting the value of Morris *et al.*'s [224] production recommendation. We first calculated agreement over the proposals [211] attaining an average score of 0.082 which indicates relatively low agreement throughout the study. Agreement scores peaked at 0.11 for the select task; five participants chose the action of tapping the cheek. As the goal of this study was to generate diverse proposals relating to socially acceptable input actions, and participants' task instructions reflected this, we do not view the low agreement scores as problematic; the diversity they hint at is more appropriate for our goals. Based on our goals and this outcome, we opted not to calculate a consensus set of input actions.

We next classified actions according by the *face site* and *hand action* used (Table 5). As in prior work [41], the cheek was popular (27.2% in the current study vs 34% in prior work), but our data saw more emphasis on the chin (18.2% vs 7%) and ear (10.3% vs 7%) over areas such as the forehead (5.6% vs 16%). This again likely reflects the differing experimental instructions – in the current study participants tended to avoid prominent features such as the forehead in order to generate socially acceptable or non-obvious/unobtrusive actions. Hand actions tended to be swipe-like strokes (27.9%), or various forms of tap (e.g., tap, push, long-tap: 29.9%) over more unusual types of input. A long tail of alternatives for both classifications doubtless contributed to the low agreement scores.

To aid in our interpretation of this data, we derived numerical *acceptability scores* from the questionnaire results from all participants and input proposals and used these figures to calculate means for each face site and hand action category. Acceptability scores were generated as follows. For the three nominal questions, participants checked between zero and seven/eight options to

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represent either the situations or individuals/groups they would feel comfortable performing an input action in or in front of [26] and the situations in which an input action would be obvious. For each question, we calculated the percentage (0-1) categories selected. The Likert scale captured how obvious input actions were (0-7 scale). Based on the idea that selecting more locations/situations indicates increased social acceptability, the acceptability score was the mean of the percentages from the nominal questions and the normalized (0-1) score from the Likert scale. The results are shown in Table 5. In terms of face region, the highest scores are on the ear, neck and temple, which suggests that input areas away from the center of the face may be appropriate for hand-to-face designs. The lowest scores are reserved for areas such as the hair, whole face or nose, regions where input actions were either large or front-and-center. These trends were also evident in the scores for hand actions – tap, a small discreet movement, rated best, while spread, a large action involving moving all five fingers out from a central pinch, scored poorly. Similarly, actions such as fold, universally applied to the out-of-the-way ear, scored highly. While we believe these ratings are useful, one caveat to their interpretation is that they are based on varying numbers of example proposals. For example, the rating for swipe is the aggregate of many (27.9%) proposals, while the score for fold is derived from a handful (1.7%). Variations in the number of input proposals in any given category is an inevitable outcome from an elicitation study.

5.5.3.1 Generation Strategies Building on these analyses and classifications, we sought to understand participants' strategies for creating socially acceptable or unobtrusive inputs by constructing a taxonomy, a common outcome from elicitation studies [211, 223], of their approaches. To achieve this goal, two experimenters reviewed the proposed actions, think aloud notes, summary statistics and questionnaire data independently, then created initial categorizations and discussed the outcomes until they reached consensus. Ultimately, of the 320 proposals, 83 were unclassified and 237 were assessed as exemplifying one or more of the following five strategies (bracketed figures show count, mean acceptability score): miniaturizing (51, 0.72); obfuscating (24, 0.76); screening (27, 0.71); camouflaging (185, 0.71) and; re–purposing (39, 0.69). The 83 unclassified gestures achieved a mean acceptability score of 0.6 and 58 actions fell into two categories, 11 into three and three into four categories.

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Table 5: Distribution and acceptability scores for face region and hand action in the elicitation study. Unless otherwise specified (e.g. palm, back), all hand actions involved the finger. The 23 hand actions that were proposed in less than 1.5% of input proposals are not shown.

Face Region	*Selection Freq.*	*Acceptability Score (0-1)*	*Hand Action*	*Selection Freq.*	*Acceptability Score (0-1)*
Cheek	27.2%	0.75	Swipe	27.9%	0.76
Chin	18.2%	0.75	Tap	16.6%	0.81
Ear	10.3%	0.79	Push	7.3%	0.67
Hair	7.0%	0.67	Long-Tap	6.0%	0.77
Lip	5.6%	0.71	Grab	4.3%	0.75
Forehead	5.6%	0.70	Palm-Swipe	4.0%	0.76
Neck	5.3%	0.80	Pinch	3.7%	0.79
Temple	4.3%	0.79	Flick	3.3%	0.76
Nose	4.3%	0.70	Palm-Place	3.0%	0.76
Cheekbone	3.6%	0.78	Pull	3.0%	0.75
Eye	3.6%	0.72	Palm-Push	2.0%	0.78
Eyebrow	3.3%	0.76	Spread	2.0%	0.67
Whole Face	1.7%	0.70	Fold	1.7%	0.80
			Back-Swipe	1.7%	0.73
			Twist	1.7%	0.70

The first three strategies involve hiding input actions. *Miniaturizing* is simple. It relates to keeping movements as small as possible and is closely related to previously observed strategies to achieve social acceptability in gesture input [210]. *Obfuscating* represents the use of a face region that is naturally hidden from observers in front of a user, such as the back of the neck or, when the head is turned, the ear. *Screening* involves the use of the hand to hide the input action, such as movements of the thumb on the face while it is obscured behind the fingers. The remaining two strategies seek to avoid arousing attention, even if actions are observed. *Camouflaging* refers to creating input actions based on unconscious or non-communicative facial touches such as scratching the face or running a hand through the hair. Finally, *re–purposing* entails using clear and explicit intentional actions, such as nodding the head (when touching the chin) or purposefully adjusting the hair. Figure 21 shows representative examples of these five strategies.

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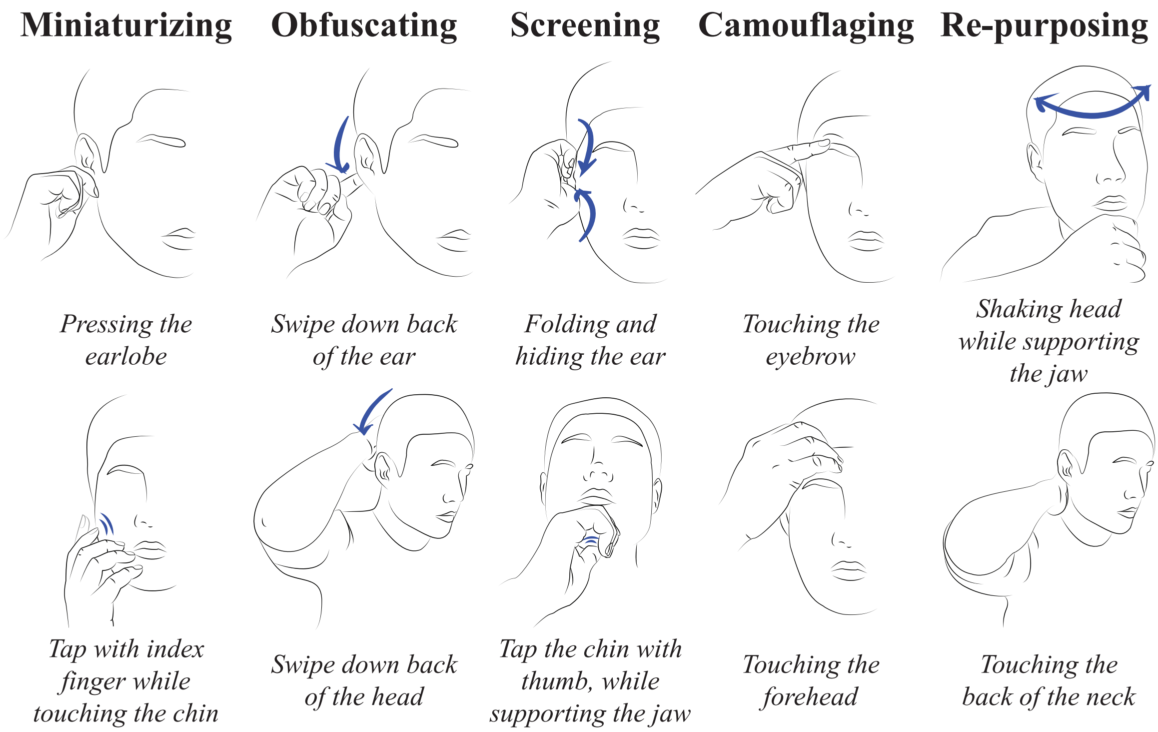

Figure 21: Examples of the five design strategies. *Miniaturizing* illustrates small finger movements, such as taps on or presses to the skin. *Obfuscating* shows input actions intended to be hidden to the side of or behind the head. *Screening* involves concealing input movements within or under the hand. *Camouflaging* masks input actions in seemingly unconscious movements, such as rubbing the eyebrow or scratching the forehead. *Re-purposing* relates to co-opting clear and explicit gestures, such as nodding the head or massaging the neck, as control inputs.

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5.6 Case Studies

To explore the value of the data and design strategies captured in, and derived from, the elicitation study, we developed two prototype hand-to-face input systems. These designs directly reflect outcomes from the elicitation study: they use the most commonly proposed face sites and finger actions; they instantiate different combinations of the design strategies and; each prototype was adapted from specific user proposals (see Figure 21 for examples). For each prototype, we describe the designs, implementations and empirical studies that assess if they are effective at supporting hand-to-face input tasks.

5.6.1 Case Study 1 - EarTouch

The first case study is a system for input on the skin of the ear; it builds on prior work that has explored input on this body site [208, 217]. This site was selected as the ear was the third most popularly selected face site in the elicitation study and it embodies several of the design strategies. Specifically, it supports *obfuscating* input, as the ear can be hidden from an observer simply by turning the head, *miniaturizing*, as the available space for input on the ear is small, and *camouflaging* in that input actions could be disguised as common actions such as scratching. Additionally, prior work on ear based input has achieved quite limited expressivity, reporting reliable recognition of between two [217] and five [208] input actions. Accordingly, we sought to boost this performance.

To achieve this our EarTouch implementation used a high resolution, low latency camera tracking system. While this approach borrows from wearable input devices for the hand [40], we know of no prior systems that have used cameras to track touches to the ear. We argue a camera based approach will increase sensing resolution while reducing weight and hardware complexity compared to existing capacitative sensing implementations [217] and that it can support detection of a broader range of input actions (e.g. tap, dwell, swipe) than prior work on in-ear sensing [208], which is basically restricted to detecting large ear deformations due to actions such as bending or squeezing. Our implementation leveraged the fact that current AR HMDs protrude from the side of the head at the temple (e.g. HoloLens, 2.5cm) and involved

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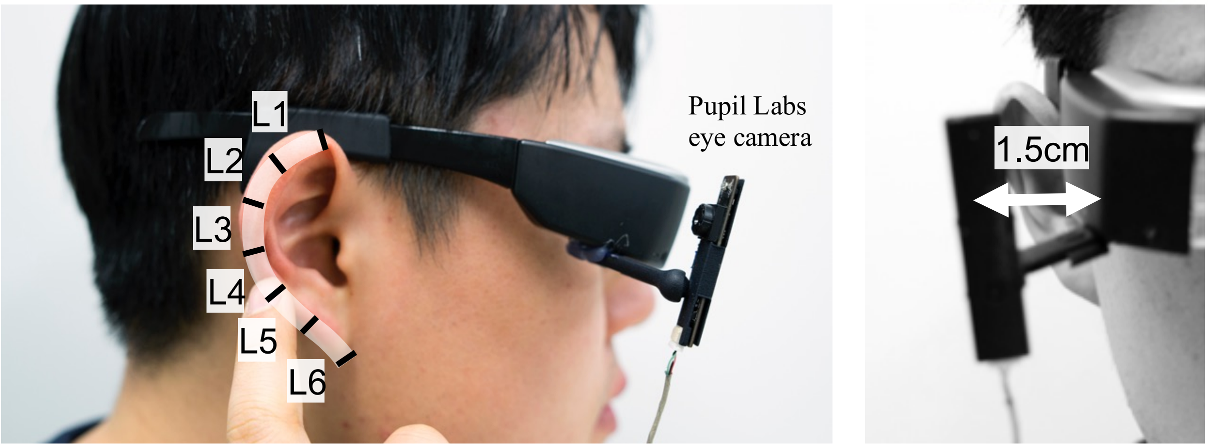

Figure 22: EarTouch device prototype. Left: targets used in the study shown mapped on the ear. Right: tracking camera mounted to the HMD.

mounting a backwards facing Pupil Labs eye camera [225] on a Epson-BT200 AR HMD to capture a clear view of the ear - see Figure 22. We expect a camera to track the ear could be mounted within the housing of many current HMDs. Although originally intended for eye-tracking, the Pupil camera's ball-and-socket joint and adjustable focus lens allowed us to readily track the ear. We configured the camera to capture 480x270 pixel images at 30Hz and connected it to a PC to perform image processing and extract ear touches. The PC transmitted the resultant data to the Epson glasses in real time via OSC/UDP over WiFi; latencies were less than 7ms, creating a smooth user experience.

The image processing system to extract ear touches was straightforward. After participants donned the glasses, we manually adjusted the camera to capture the region around the entire ear. We then extracted the ear's rough outline by segmenting the video feed by optical flow regions during head movement or when objects were moved directly behind the head. In such situations, the view of the ear is static, while the background moves rapidly. We use this initial ear region to sample the ear's color hue and refine the area based on color segmentation. Using these techniques, we achieved an easy to acquire, reliable and stable model of the shape of the ear. Additionally, we were able to re-use the hue data from the ear to capture the location of touching fingers as they came into contact with the ear; ear and finger skin were relatively similar in hue. Based on this approach, we defined the touch contact location as the normalized point at which the largest finger (or skin hue colored region) intersected the ear outline. To smooth irregularities in this data, we applied a linear easing function prior to sending it to the Epson glasses. We also discarded the first and last 100ms of finger contact data in order to focus

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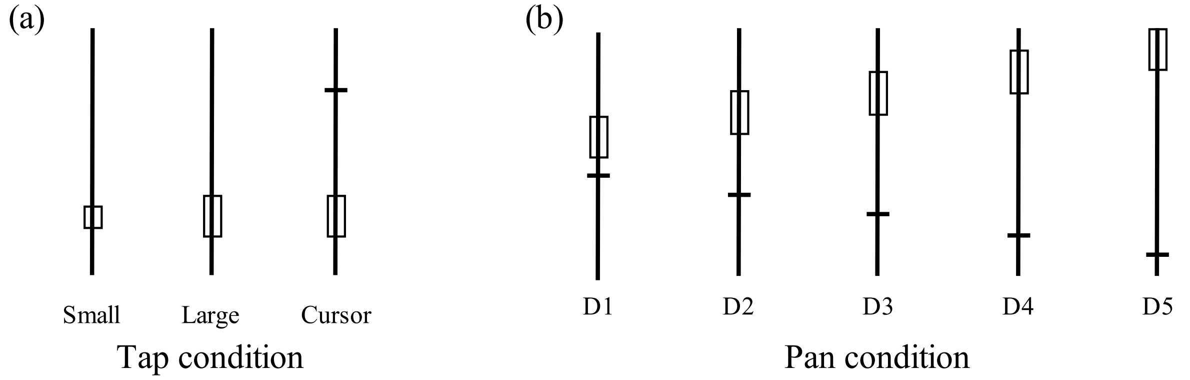

Figure 23: Interface for EarTouch study showing (a) tapping task interface for size and feedback variables and (b) panning tasks interface for shortest (D1) to longest (D5) distances in the upwards direction.

on the stable central period of each touch [131].

5.6.1.1 Performance Study To evaluate performance of this system we used two basic input tasks: tap (selecting a target) and pan (moving a cursor from a start to an end location). For the tap task we studied three variables: *tap-technique* (three levels); target *size* (two levels) and; target *location* (six levels). The three tap-techniques were adapted from work on HMD touch input [226]. They were *landOn*, which triggered a selection event on an initial touch, *liftOff*, which triggered selections on removing a finger and *dwell*, which triggered selections after a participant remained on a target for 400ms (a typical value for touch input [227]). Levels for the target size and location were selected (via pilot tests) to be challenging but achievable. The six target locations were equidistantly spread along the whole ear while the two target sizes were *large*, set at 1/6 of the ear size, and *small*, set as 1/12 of the ear size. The interface for this task is shown in Figure 23.a. A line depicts the ear, with the current target area highlighted. In the liftOff and dwell conditions a cursor showed the location of a touch in this space.

The panning task followed a similar design: three *pan-techniques* by five pan *lengths* by two pan *directions*. The pan-techniques were derived from prior work on hand-to-face input [41, 217]. They were: *drag*, a zero-order control method where the on-screen cursor position changed directly with finger movement on the ear; *joystick*, a first-order control method where finger displacement controlled the rate of cursor movement and; *toggle*, a system that divided the ear into three equal regions, each with a different function. Touching the top third of the ear moved

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the cursor upwards at a fixed speed, the bottom third moved it downwards and a location was selected by a touch to the center. In drag and joystick, a location was selected by releasing the touch. The position/speed mapping for the joystick (twice displacement/second) and fixed speed used in toggle (50% of ear length/second) were set via pilot testing. This task used the six large targets from the tap task, leading to a total of five possible distances between targets in two possible directions. The interface is shown in Figure 23.b. Participants in all conditions were required to touch their ear and then adjust their finger position to move the cursor from its initial location to the displayed target location.

Participants completed tap then pan tasks. Within each task, the study used a fully balanced repeated measures design for the technique variables and a partially balanced design for the binary variables of size and direction. For each combination, all target-position or pan-length trials were shown in a random order to form a single block of trials. For both tasks, each block was repeated four times, with the first presentation discarded as practice. Failed trials were repeated. Measures were task time (from presentation of the instructions until selection), error rate and selected point. To minimize fatigue, participants took a short rest break after each technique condition.

A total of 18 participants were recruited (14 males, mean age 24.7, one left-handed, all UNIST students) and compensated with approximately $10 for the hour long study. Three reported limited prior experience of VR/AR. The procedure for each participant was identical: the study began with instructions and preliminary form filling followed immediately by setup of the equipment. They were then able to practice freely for a maximum of five minutes before beginning the formal study. In this way, we planned to retain 1944 correct tap trials (18 participants by three tap-techniques by two sizes by six positions by three repetitions) and, similarly, 1620 correct pan trials for analysis. A technical error led to the loss of one participant's data in the tap task, leaving 1836 tap trials for analysis.

5.6.1.2 Results and Discussion Time and error data for tap and pan tasks are presented in Figures 24 and 25. All analyses were three-way repeated measure ANOVAs corrected for sphericity violations with Greenhouse-Geisser corrections and followed by *post-hoc* pairwise t-tests adjusted with Bonferroni confidence interval adjustments. For brevity, we report only

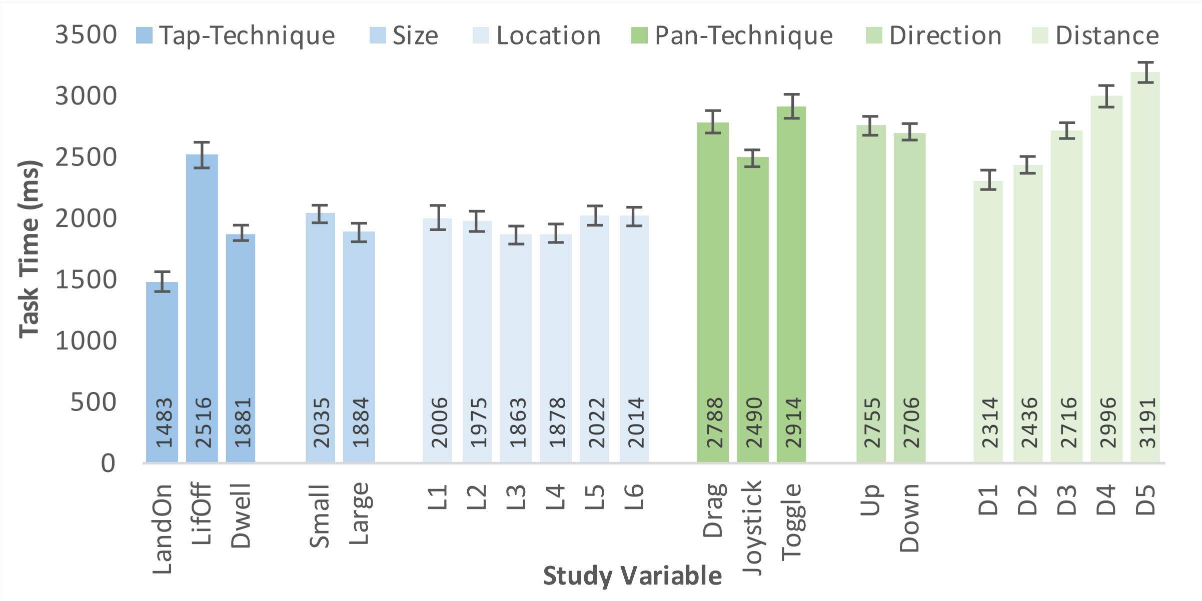

Figure 24: Task times in EarTouch tap & pan tasks. Bars show Std Err.

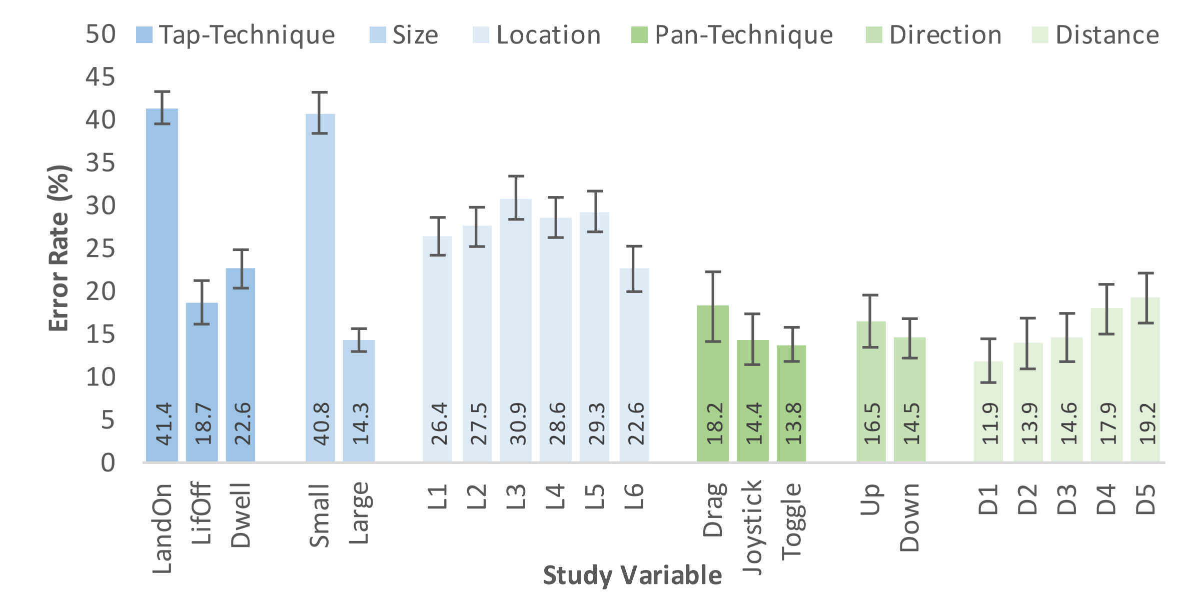

Figure 25: Error rates in EarTouch tap & pan tasks. Bars show Std Err.

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significant ($\alpha < 0.01$) results - see Table 6 for interactions and main effects. *Post-hoc* comparisons are discussed in the following sections.

In the tap task, there was a single weak interaction effect. Accordingly, we opt to interpret the results in terms of the moderate to high power main effects. All three tap-techniques differed significantly in terms of the task time (all p<0.001). Unsurprisingly, the ability to make position adjustments with dwell and liftOff required time and, with liftOff, the need to trigger selection via an explicit finger-up event took yet longer. The benefits of these increased task times are clearly observed in the lower error rates for these conditions: both significantly improve over landOn error rates (p<0.001). In addition, and unsurprisingly, small targets also led to greatly increased error rates, and modestly increased task times, when compared to large targets. Data from the pan task were more uniform. The joystick pan-technique led to faster task times than both drag (p=0.002) and toggle (p=0.001) and task times, and to a lesser extent error rates, predictably increased with distance.

These results provide a window into comparing our system with prior work and deriving appropriate target sizes and techniques for ear based touch interfaces. In terms of the time data, figures for landOn data (1.48s) are relatively similar to those recorded on FaceTouch's [226] head mounted touch screen (1.39s, reported for touches to the side of the head). On the other hand, data from the LiftOff condition (2.5s) are noticeably slower than with FaceTouch (2.07s). This suggests that while initial touches can be readily performed, it may be more challenging to control a cursor via touches to the skin of the ear than via a standard touchscreen. A candidate explanation for this difference is that the skin is not as smooth, low-friction or uniform as a touchscreen - moving along its surface precisely is more difficult. In terms of errors,

Table 6: Significant RM ANOVA results from the EarTouch study.

Task	*Measure*	*Comparison*	*Outcome*		
Tap	Time	Tap-Technique	F(2,32) $=$ 80.6	$p < 0.001$	$\eta_p^2 = 0.85$
		Size	F(1,16) $=$ 17.8	$p = 0.001$	$\eta_p^2 = 0.53$
	Error Rate	Tap-Technique	F(2,32) $=$ 43.3	$p < 0.001$	$\eta_p^2 = 0.73$
		Size	F(1,16) $=$ 173.5	$p < 0.001$	$\eta_p^2 = 0.92$
		Tap-Tech. x Location.	F(10,160) $=$ 3.99	$p < 0.001$	$\eta_p^2 = 0.2$
Pan	Time	Pan-Technique	F(2,34) $=$ 12.54	$p < 0.001$	$\eta_p^2 = 0.42$
		Length	F(4,68) $=$ 121.94	$p < 0.001$	$\eta_p^2 = 0.88$
	Error Rate	Length	F(4,68) $=$ 5.1	$p = 0.001$	$\eta_p^2 = 0.23$

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EarPut's [217] is the most directly comparable work. Its capacitive sensing wrap-around ear sensors logged 42% failures with six targets positioned on the edge of the ear, equivalent to the most error-prone landOn condition in the current study. In contrast, errors on large targets with the liftOff technique drop to a mean of 8.9%, a substantial improvement over this prior work. This suggests that optical tracking may offer considerable advantages over capacitive sensing for ear augmentation.

To better shed light on this issue, we examined the precision of both tap and pan inputs. For this analysis, we extracted the distance between the points selected and the target center in all trials (i.e., including errors) and processed it as follows. We discarded outliers more than three SD from the absolute mean, removing 93 (2.9%) trials from tap and 30 (1%) from pan. We then recalculated mean and SD values and report precision as mean plus/minus three times the SD (in normalized 0-100 units). This should account for 99.7% of the inputs intended to reach a given target location. Results for tap were: dwell (M:4.8, SD:4.8, precision:19.2); landOn (M:7.6, SD:6.0, precision:25.6) and; liftOff (M:4.3, SD:4.4, precision:17.5). This suggests liftOff and dwell will perform optimally with five targets, while landOn is more suited to a four target system. Data for pan are: drag (M:6.6, SD:9.9, precision:36.3); joystick (M:5.7, SD:8.8, precision:32.1) and; toggle (M:7.5, SD:11.6, precision:42.3). These values suggest that pan requires fewer and larger targets than tap for optimal input - three targets in the best performing joystick system. This suggests that pan input tasks for ear based systems may have limited expressivity. However, given the comparatively low error rates observed in the pan tasks (see Table 25), further study of pan input would be needed to confirm this recommendation.

5.6.2 Case Study 2 - ThumbTouch

The second case study explores input via a device mounted on the hand, rather than on the face. Specifically, we developed a capacitive sensing thumbnail, similar to Kao *et al.*'s NailO [14], and applied it to the previously unexamined setting of hand-to-face input – prior work has only considered finger touches to a sensing nail. This design was motivated by outcomes from the elicitation study. Specifically we envisaged nail touches to the cheek and chin, the two most frequently used face regions, and sought to embody three of the design strategies: *screening*, as

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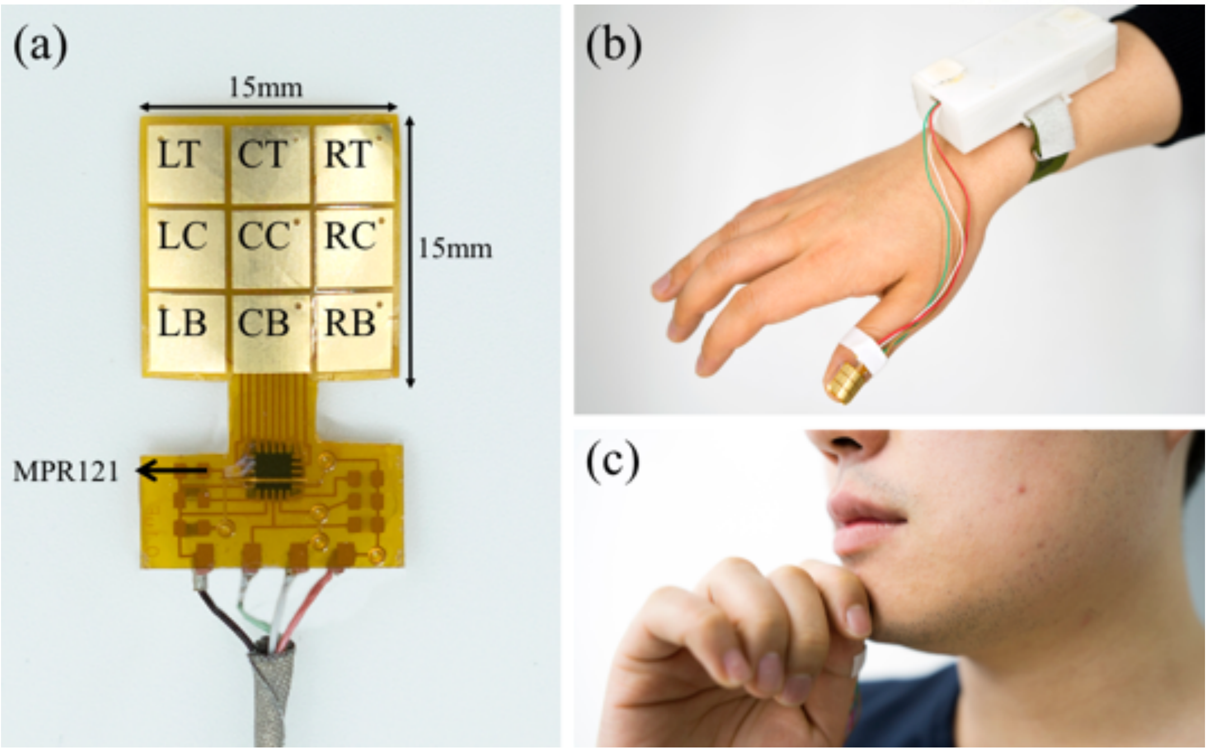

Figure 26: Prototype of the ThumbTouch system. (a) Dimension of the sensor array and labeling of target locations. (b) Wireless wearable design (c) Example use scenario.

touches to the face by the thumbnail could remain hidden behind the fingers; *re-purposing*, as such touches might support co-opting common actions such as scratching the cheek or gripping the chin and; *miniaturizing*, as input under such constraints is inevitably small in scale.

We developed a touch sensitive thumbnail by mounting a 0.3mm thick flexible PCB covered with a three-by-three grid of 4.5mm square electrodes, spaced with 0.4mm gaps, directly on the thumbnail. This device was intentionally designed to be much thinner (0.3mm) than prior systems that integrate all components into the nail (e.g., [14], 4mm). This is likely important in our scenario as the nail is used to touch rather than be touched by another finger. To minimize noise, the electrodes were connected to an MPR121 capacitive sensing micro-controller mounted just behind the nail on the thumb's distal phalanx. The MPR121 was connected to an Arduino Fio mounted on the wrist, which streamed data via a wireless xBee link to a host PC, which then processed this data and transferred it, via OSC, to the same BT-200 HMD used in the EarTouch study. All graphical interfaces were shown on this HMD. Sensor latency and update rate were approximately 7ms and 60Hz. The nail was attached to participants via double sided tape and the MPR121 chip secured with a band-aid. A key goal for this hardware design was to

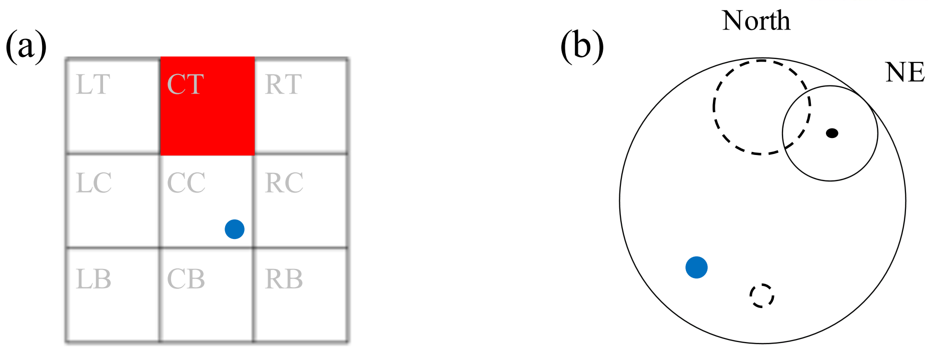

Figure 27: Interface for ThumbTouch study. (a) 3 by 3 grid used in tapping task showing target (red square) and cursor (blue dot). (b) Panning task interface for NE direction. Dotted line indicates another example: a North direction task.

minimize the thickness of the nail sensor as preliminary testing during development indicated that a thicker nail would impede performance. The prototype is shown in Figure 26

We acquired touch position data from this sensor by following Oakley *et al.*'s [129] use of the ratio of baseline to currently measured capacitance on each MPR121 electrode to derive a three by three grid of touch intensities. We then processed this data using a three window median filter to remove noise, performed a bicubic upscale by a factor of three to increase resolution and extracted touch regions via Xiao *et al.*'s [130] method of flood fill to identify individual touches and image moments to calculate properties such as their centroid. As we were interested in a single touch point on the face, we always considered only the largest touch. As with EarTouch, we ignored data from the first and last 100ms of each touch.

5.6.2.1 Performance Study The study broadly followed the format of the EarTouch study, adapted to the nail device format. We highlight key differences below. We again studied both tap and pan tasks. In the tap study, we maintained the three *tap-techniques* of *landOn*, *liftOff* and *dwell* and used nine 4.5mm square targets, arranged in a three-by-three grid that matched the sensor electrodes. These locations are identified by two-letter acronyms such as *LC* for Left-Center (see Figure 26.a). In addition, we studied thumbnail touches to two *face-sites*: the *chin* and *cheek*. This led to a 3 (tap-techniques) by 9 (target-locations) by 2 (face-sites) design. In the pan study, we used just two *pan-techniques*: *drag* and a combined *joystick*-toggle. We combined these techniques to better fit the small nail input device. The unified technique simply varied cursor speed proportionally (at twice displacement/second) to the distance of a touch from the

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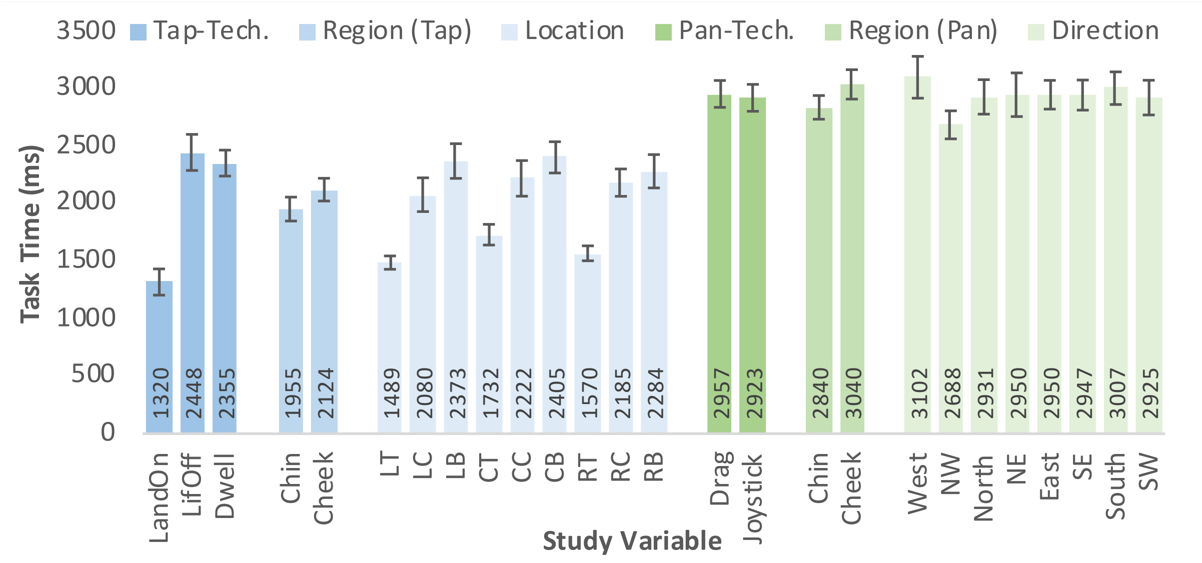

Figure 28: Task times in ThumbTouch tap/pan tasks. Bars show Std Err.

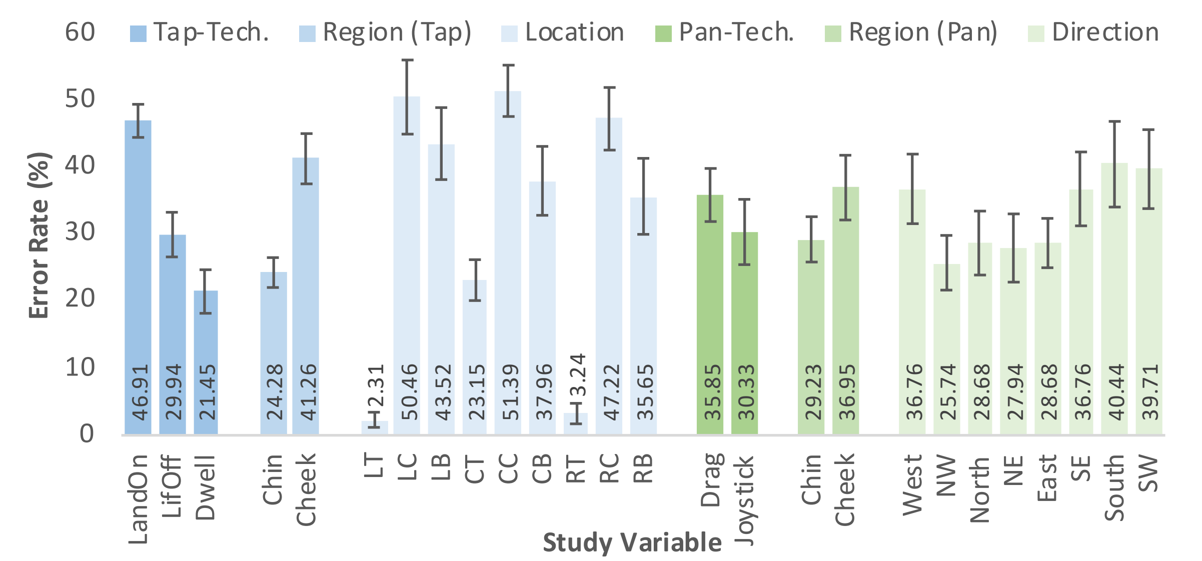

Figure 29: Error rates in ThumbTouch tasks. Bars show Std Err.

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Table 7: Significant RM ANOVA results from the ThumbTouch study.

Task	*Measure*	*Comparison*	*Outcome*		
Tap	Time	Tap-Technique	F(2,34) = 26.8	$p < 0.001$	$\eta_p^2 = 0.63$
		Location	F(4.5,71.9) = 14.1	$p < 0.001$	$\eta_p^2 = 0.47$
		Tap-Tech. x Reg.	F(2,34) = 8.6	$p = 0.001$	$\eta_p^2 = 0.35$
		Tap-Tech. x Loc.	F(6.5,104.2) = 3.5	$p = 0.003$	$\eta_p^2 = 0.18$
	Error Rate	Tap-Technique	F(2,34) = 48.8	$p < 0.001$	$\eta_p^2 = 0.74$
		Region	F(1,17) = 28.1	$p < 0.001$	$\eta_p^2 = 0.62$
		Location.	F(4.6,77.8) = 27.7	$p < 0.001$	$\eta_p^2 = 0.62$
		Tap-Tech x Loc.	F(7.8,133.2) = 3.3	$p = 0.002$	$\eta_p^2 = 0.16$
		Region x Loc.	F(8,136) = 5.2	$p < 0.001$	$\eta_p^2 = 0.23$
Pan	Time	Pan-Tech. x Dir.	F(7,98) = 5.4	$p < 0.001$	$\eta_p^2 = 0.28$
	Error Rate	Pan-Tech. x Dir.	F(7,119) = 3.35	$p = 0.003$	$\eta_p^2 = 0.16$

nail's center point. Additional, we studied eight *pan-directions* (cardinal and semi-cardinal) and the chin and cheek *face-sites*. We used a single *pan-distance* of 10mm, always starting from one edge of the sensor/screen and moving across its center to the opposite side. Graphical feedback in these studies was updated to a 2D setting with targets and cursors shown as squares or circles (see Figure 27).

Procedures followed the EarTouch study: participants were provided with instructions, donned the equipment and practiced freely for up to five minutes. They then completed tap followed by pan tasks in a repeated measures study design. In both tasks, tap/pan–technique and face–region were fully balanced, while target-location/–direction were randomized. A block was one set of directions or locations and participants completed three blocks per condition, with the first block considered practice and not retained for analysis. Pilot tests indicated that some input tasks were extremely challenging, so we opted not to require participants redo trials in which they made an error. In total 18 participants (10 males, mean age 24, all right-handed) completed this study. All were UNIST students, or recent graduates, and compensated with approximately $10 for the one hour experiment. 11 had limited prior experience of VR/AR. In total, we captured 1944 taps (18 participants by 3 tap-techniques by 2 face-sites by 9 target-locations by 2 blocks) and 1152 pans (18 participants by 2 pan-techniques by 2 face-sites by 8 pan-directions by 2 blocks).

5.6.2.2 Results and Discussion We analyzed results using similar methods to the EarTouch study: repeated measures ANOVA following by *post-hoc* testing, with sphericity and confidence interval adjustments applied where appropriate. We report only significant results ($\alpha < 0.01$). Time and error data are depicted in Figures 28 and 29 and ANOVA results are shown in Table 7. Time data includes measurements from both successful and error trials as we observed few differences between the aggregate performance of these sets (overall means and SDs were 38-114ms apart) and, given failed trials were not repeated, the entire set was considerably more complete. Data from timeouts are not shown (38 or 1.95% of tap trials and 31 or 2.7% of pan).

Performance in the tap task varied considerably in both time and accuracy. As in the EarTouch study, landOn was both faster and more error prone than both liftOff and Dwell (all $p<0.001$): without interactive feedback, the tap task can be executed quickly, but not accurately. Touches to the cheek also led to significantly more errors, but not longer times, than touches to the chin. We speculate this is due to differences in compliance between the relatively rigid chin and soft cheek - it was more difficult to make accurate taps on a soft skin surface. Due to the large number of comparisons it involves, we opted not to conduct pairwise tests on the location variable; instead we depict this data in the confusion matrix in Figure 30. The error interaction effects (not plotted) are due to the accurate performance of the TL and TR locations (the left and right tips of the nail) remaining unaffected by the main effects of technique and region: these were readily accessible locations. The interaction of technique by region in the time data suggests dwell is faster on the chin that the cheek, while the relatively weak technique by location effect had no clear interpretation. Performance in the more challenging pan task was more uniform and the two weak interaction effects suggest that the joystick technique performed better than the drag technique for upward directions (NW, north and NE). This again reflects the increased accessibility of these regions - it is easier to touch the top of the nail.

The tap confusion matrix sheds more light on this issue. While the strong performance of the TL and TR tip locations is inarguable, we also note that nail edges may be reliably detectable using a more advanced algorithm - touches to the LC, TC and RC are correctly associated with the left, top and right of the nail in a mean of 96.9% of cases. This indicates participants were able to select the correct side of the nail, but had difficulty selecting specific locations on that side. This is likely due the whole edge of the nail making contact with the face. We speculate

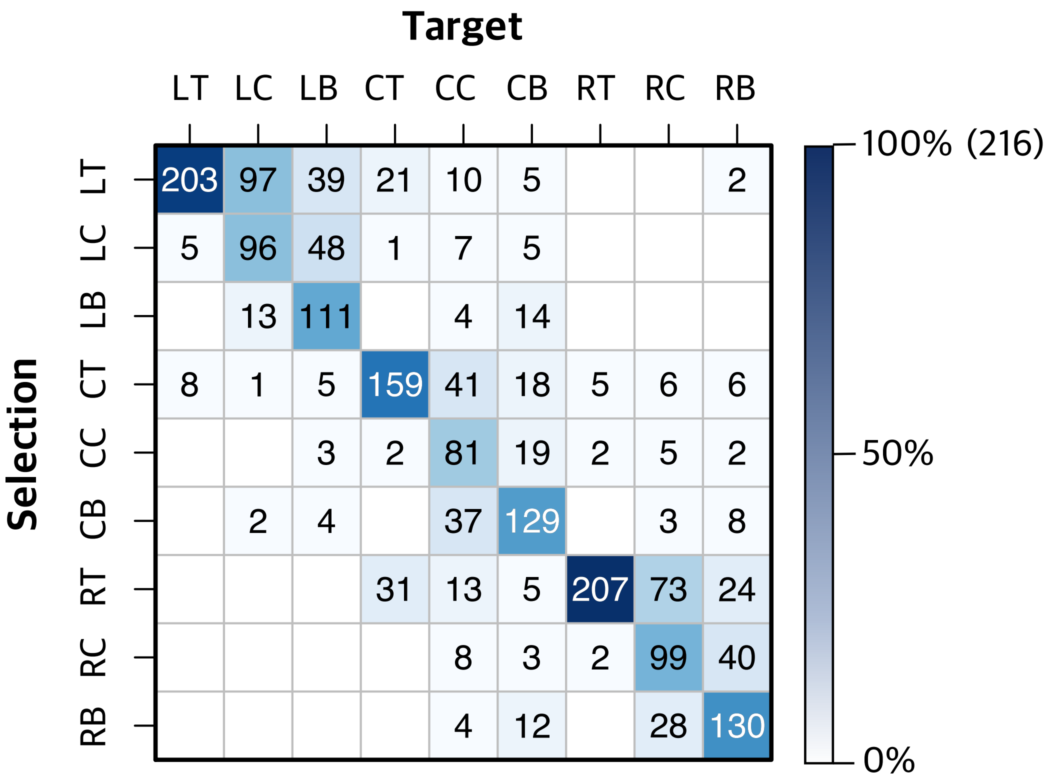

Figure 30: Confusion matrix for ThumbTouch tap task.

that side touches could be accurately performed and easily disambiguated from tip touches by examining the size of the contact area. Similarly, we note that the CC and CB touches are the only two locations with errors distributed over all other locations. This suggests that the input action was akin to simply pressing the whole nail against the face, an action that could also likely be distinguished from edge contacts by examining touch region sizes [129]. Adding this functionality and capturing data on these inputs is a clear next step for this work.

We also calculated precision data. After discarding outliers (tap: 64 or 2.1%, pan: 72 or 4%), the values (in mm) were: dwell (M:1.94, SD:1.26, precision:5.72); landOn (M:3.15, SD:1.62, precision:8.01); liftOff (M:2.45, SD:1.53, precision:7.04); drag (M:2.16, SD:1.62, precision:7.02) and; joystick (M:2.88, SD:2.95, precision:11.73). These relatively large figures, relative to sensor size, confirm the difficulty of tasks studied and the need to consider alternative approaches.

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5.7 Validation Study

While the lab studies of the Ear– and ThumbTouch extend prior work and contribute practical assessments of performance in hand-to-face input tasks, they do not address our core goal of improving our understanding of socially acceptable hand-to-face input. Accordingly, we conducted a final study to assess the input techniques, and the design guidance they instantiate, from the perspectives of social acceptability and subtle or non-obvious/unobtrusive input. In this study participants operated or observed the HMD and Ear/Thumb prototypes in representative input tasks in the same coffee shop used in the original elicitation study. In total, 12 new participants (4 males, mean age 23.7, all right-handed, all UNIST students) were compensated with \$10 to complete the study. As in the elicitation study, they worked in six pairs (all strangers).

One participant in each pair took the role of the *user*, wearing and operating the devices, while the other acted as an *observer*, watching these activities, but not briefed in advance that input actions were taking place. The study presented three input tasks on both devices. On EarTouch, participants experienced the liftOff (tap), drag and joystick (both pan) tasks, while on ThumbTouch they experienced dwell (tap), drag and joystick (both pan). These techniques were selected to ensure a diverse set of techniques and/or due to their comparatively strong performance in the lab studies. The order the prototypes were experienced was balanced between participant pairs, while the order of three techniques on each prototype was varied using a Latin square design. For each task/device pair, the user participants performed the training tasks from the original studies, experiencing the input and feedback (but not performing any sustained, repetitive input tasks) while the observer watched. Between each task, both participants filled out the social acceptability/obviousness questionnaires from the elicitation study. At the end of the study, we conducted a semi-structured interview with the pair of participants capturing opinions and reactions to the input techniques. Participants were asked to reflect on and contrast the techniques in terms of general opinions and how comfortable and unobtrusive (or uncomfortable and obvious) they felt they were. Finally, we note that due to problems with the lighting conditions in the coffee shop, the EarTouch system performed poorly for three participants. These participants received an explanation of the system and were able to partially experience it, but the reliability of the input was low. This may have influenced performed actions, opinions and ratings.

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5.7.1 Experiment Results

The data from the questionnaires are summarized, in the form of the compound acceptability scores we used in the elicitation study, in Table 8. The data show that *users* tended to rate tap tasks (liftOff/Dwell) as socially acceptable and unobtrusive in more locations and situations than pan tasks (drag/joystick). No such clear cut effect was observed in the the data from the *observers*. Furthermore, they tended to score lower than the *users*. The likely reflects the fact that the *observers* were naïve. The input actions, without being situated in the context of controlling an interactive system, may have appeared less acceptable than to the fully-aware *users* operating them. To shed further light on these issues, we turned to the diverse set of comments and opinions captured in the interviews, which we processed by transcribing them and then organizing them via an iterative affinity process. In this description, quotes are marked with *U* for device *Users* and an *O* for *Observers*.

We first focused on comments with respect to the five design strategies from the elicitation study. All participants commented on the value of the *camouflaging* strategy. Eight participants viewed the ear as a suitable site for masking input actions as it was commonly touched. It was "OK because it is similar to touching an earring" (U1), or things "people already wear in their ear like Bluetooth earphones" (O4). Two participants (U6, O1) also referenced sweeping back their hair over their ears. O4 suggested that "even if there was a stranger passing by they would never know" the touches were controlling a device and O2 remarked that, if s/he had not been participating in a study, s/he "would not have thought of assessing or paying attention to [the ear touches] at all". Five participants felt touches to the chin were also "natural" (U1) or "habitual" (O4) and touching it resembles common behavior such as "thinking or when they scratch it" (O2, O6) or that it was simply a region where people usually touch their faces (O5). Participants also offered contrasting opinions: the ear "stands out too much" compared to the

Table 8: Mean acceptability scores (0-1) in the validation study.

Role	*Prototype*	*Overall*	*LiftOff/Dwell*	*Drag*	*Joystick*
User	EarTouch	0.74	0.85	0.67	0.70
	NailTouch	0.70	0.81	0.70	0.60
Observer	EarTouch	0.58	0.57	0.65	0.51
	NailTouch	0.69	0.68	0.75	0.64

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chin (O2) or that people "do not normally touch their chins" (O3) – it is an "[un]common form" of touch (U3). Ultimately, the diversity in this assessment reflects what O3 referred to as the "gestures that we normally do as habit" – to be successful, camouflage needs to adapt an existing user behavior, a "daily gesture like touching or putting" (U1). It thus varies from user to user.

The *miniaturizing* strategy was highlighted as valuable by nine participants. Two felt the control actions were not "big, [so] they were mostly OK" (O1) or were simply "too small to notice" (U4), while one emphasized the importance of touches to a "small region" (O3). Others appreciated ThumbTouch as its "small movements won't be weird" (U2) or favored it over EarTouch as "the gesture for the ear was too big up and down" (O5) and you have to raise "your arm higher to reach the ear" (O6). The value of *miniaturizing* also came across in an assessment of the input techniques – the larger or prolonged movements in the pan tasks were "weird" and would "gather the attention" (U1) and actions that involved larger physical movements such as "taking the finger off the ear" in liftOff (O2) stood out. Although EarTouch involved larger movements, it benefited from the *obfuscating* strategy of using the head to obscure input. O1 remarked on the "difference between front and side" and touches to the ear being less "intrusive" that those on the chin, while O4 acknowledged that "the active range was much bigger for ear gestures, but since the ear is on the side, it didn't matter". Participants also suggested this strategy for new designs: under the chin, on the neck or behind the ear would "hide the gesture well" (O6). The *screening* strategy was mentioned by a single participant who noted that in ThumbTouch they "could hide my thumb so I can make others not notice this" (U1), while the *re-purposing* strategy did not emerge in the interviews, possibly due to its relatively weak embodiment in the two prototypes.

Beyond these comments on the strategies, participants brought up a range of other issues. U6 was concerned about hand-to-face touches and makeup, an issue that has cropped up in prior work [41], while U5 appreciated that neither input technique required a hand-held controller and also the proprioceptive aspects of the tasks: it was convenient that s/he "could know where the hand is touching now". In general, participants, and particularly four from the six observers, were positive about performing the input actions in the coffee shop setting. O3 remarked that s/he "didn't think people would care about the gestures in a cafe", O4 that they "certainly didn't bother me" and O6 that the input actions "are fine to do" as a cafe as it is "a place where

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people move around and talk". In addition, O6 felt they would be suitable "on the street or on the bus", while O5 was more cautious: in a cafe, "it was ok", but somewhere "quiet and static it would have stuck out".

The results from this study generally validate the design strategies identified in the elicitation study and instantiated in the prototypes. In particular, the interview data reveal that both users and observers, who respectively conducted and naïvely viewed input tasks on the prototypes, frequently highlighted aspects of the strategies as important qualities or mechanisms to achieve socially acceptable and non-obvious or unobtrusive hand-to-face input. For both prototypes, strategies such as camouflaging and miniaturizing were viewed as critical, whereas both obfuscating and screening were viewed as effective aspects of the techniques by smaller numbers of participants. A key topic for future work on this topic would be to tackle issues of how unobtrusiveness could be sustained for prolonged or frequent use. One way to achieve this might be to provide multiple input mechanisms [220], so that users would be able to vary how they performed input depending on the situation they were in, rather than engage in sequences of repetitive motions.

5.8 Conclusions

This paper describes a multi-stage research process that identifies and validates design strategies for making subtle, unobtrusive and socially acceptable hand-to-face input. Specifically, from an elicitation study focused on social acceptability we derive, and contribute, five strategies for the design of socially acceptable hand-to-face input techniques. We instantiate these strategies in two novel prototype input systems and contribute empirical characterizations of their use, extending knowledge about human performance in hand-to-face interaction. Finally, we validate the design strategies in a study that has user and observer participants experience the prototypes in a public setting. We reflect on the importance of the different strategies in achieving socially acceptable hand-to-face input.

Limitations of this work include a reliance on participants from a single culture and age range; more diverse participants would improve its validity. The current study could also have been subject to experimenter effects [228] and follow up work should seek to isolate their impact by, for

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example, objectively logging bystander reactions in response to hand-to-face input. Additionally, we note the current prototypes do not represent a comprehensive exploration of the design space outlined by the design strategies; additional cases should be developed to better showcase the value of the strategies. The immaturity of the prototypes (e.g., exposed wires, visible cameras) may also have impacted the results, although we expect this would only have lowered perceptions of social acceptability and that more mature devices would only boost these ratings. Indeed, the prototypes could be improved in many ways. Next steps for EarTouch involve integrating machine learning algorithms to detect a greater number of hand actions, such as bends, pushes or deformations of the ear. For ThumbTouch, a clear follow-up is to create a system focused on capturing performance using edges of the nail rather than 2D positions and on enhancing performance in directional input tasks. One possibility here would be to focus on open-loop tasks such as swipe. Finally, longer term field studies of hand-to-face input will be required to move beyond some of the reservations advanced by our participants: the techniques described in this paper were deemed appropriate for short term use in public settings such as coffee shops, but over more prolonged periods, the input techniques they feature, and strategies they represent, may not hold up to scrutiny. Future work should look into deploying hand-to-face input systems to participants for sustained use to better understand these long-term, real-world, effects.

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VI Conclusion

6.1 Summary

This dissertation sought to address the current limited input space of wearables by exploring the design space of intra-hand input. To this end, three separate scenarios were investigated to verify the general claim, that intra-hand input can be an expressive and effective modality for interaction with wearable devices such as HMDs. For an in-depth discussion, I assessed each scenario considering four design factors: manipulation, accessibility, space, and social.

The first scenario begins with the exploration of the intra-hand input space for wearable devices via a touch-sensitive fingernail system. Through an ideation workshop, a large set of 144 input actions was derived and subsequently complemented with a subjective comfort and objective performance (task time and accuracy) to refine it into a set of 29 viable inputs. The final study verified that these small-scale inputs are expressive, accessible, can be comfortably and efficiently performed, and can be readily recognized using simple criteria.

Next, to better understand the accessibility of intra-hand input for the mobility condition, the second scenario focused on text entry in a mobile setting with the same touch-sensitive fingernail system. Through a comparative empirical study on both sitting and mobile conditions, the result confirms that such a nail-based intra-hand input is robust to the physical disturbances inherent while mobile. The results of the final study on the word repetition task revealed that intra-hand input can achieve up to 33.1 WPM when key layouts were appropriately optimized, which demonstrates that intra-hand input can support rapid, accurate, and comfortable typing within a mobile context.

The last scenario examined an alternative form of input that rely on small-scale hand touches on the face via the lens of social acceptability. The result of an elicitation study on unobtrusive and socially acceptable hand-to-face actions was refined to five design strategies to achieve socially acceptable input. The final study on a prototype that instantiates these strategies validated the effectiveness of these strategies and yielded a characterization of the speed and accuracy achieved by the user with each system.

By analyzing three different scenarios, these verifications produced a range of data on objective performances (speed and accuracy) and subjective experiences (comfort and social acceptability) that can support the general claim in common wearable use scenarios, such as in mobile settings and in public.

6.2 Design Factors in the Three Scenarios

These three scenarios provided a broad spectrum of data on objective performance and subjective experience in common wearable use scenarios. These records over a diverse set of scenarios verify that intra-hand input can support quick, accurate, expressive, and always-accessible interactions with wearables in diverse contexts, such as when mobile and in public. In the following subsections, I review these records and discuss them in terms of design factors.

6.2.1 Manipulation

Chapter3: The touch-sensitive nail prototype was able to perform a set of 29 inputs with an accuracy of up to 94.3% and a mean speed of 1.61s.

Chapter4: The touch-sensitive nail prototype with an optimized keyboard layout showed a text entry speed of up to 31.3 WPM and a 3.3 WER in a study on word repetition (assuming the expert level of speed).

Chapter5: The two prototypes (ear touch/chin and cheek touch) presented the speed and accuracy of (2.5s, 91.1%) and (2.4s, 78.5%), respectively, for the tasks (selecting one of the six targets along the ear and selecting one of the nine targets of a three-by-three grid). For the chin and cheek touch, regarding edge detection design (selecting one of three edges except for root edge), the mean accuracy increased to 96.9%.

These intra-hand inputs show quick performances. In terms of input speed, these actions can occur within three seconds (microinteraction [27]). Likewise, as for accuracy, these inputs provide results comparable to similar sensing configurations [14] (92.3

6.2.2 Accessibility

Chapter3: The study confirmed that the final set of 29 viable inputs was easily accessible without discomfort, pain, or fatigue.

Chapter4: The comparative empirical study on both sitting and mobile conditions confirmed that the nail-based touches are robust to physical disturbance while mobile.

The intra-hand inputs were highly accessible for diverse situational impairments, such as attention-demanding tasks, mobile use, and hands-occupied tasks in eyes-free and one-handed situations. In addition, intra-hand inputs are comfortable—the 144 touches were rated with a mean of 3.41/5 (mean of 4.2/5 for the final 29-input set) and are fairly comparable to the mean of 3.34/5 for 12 touches to the inner fingers in Huang et al. [49]).

6.2.3 Space

Chapter3: The ideation workshop generated various intra-hand input primitives (taps, flicks, and swipes on multiple nail regions) and derived a large set of 144 input actions from these input primitives. Finally, this led to the set of 29 viable nail inputs.

Chapter5: The elicitation study explored diverse face regions and touch input techniques, and among them, tap and drag inputs on three face regions (chin, cheek, and ears) were examined.

The most comparable study was conducted by Soliman et al. [80]. They explored 50 different gestures with eight finger action classes (including taps, tap-and-flap, slides, and drawing) with diverse variations (e.g., different tap locations). In particular, these actions included six swipe actions on the fingernails (horizontal swipes on index, middle, and ring with two directions). Likewise, Kao et al. Kao15 presented a touch-sensitive nail prototype and a basic five-action set (four directional swipes and one tap). Compared to these works, this study explored more diverse intra-hand input actions within a fingernail by examining multiple actions (taps, swipes, and flicks), nail combinations (single and multiple nails), nail regions (tip, center, root, and both sides), and input spaces (thumb-to-fingers, fingers-to-thumb, and hand-to-face). The combinations of these input primitives can complement the design space of intra-hand input that have not yet been explored by prior works.

More practical comparisons should consider real-world complex applications, such as 3D modeling, sculpting, multi-objects controlling, and gaming. In most current VR devices, these are typically manipulated by hand controllers including two joysticks, six to eight buttons, and two touchpads with 3D motion tracking. To address this issue, our intra-hand input system can provide several buttons, swipes, pan, and flick actions with the vision system for 3D freehand motion. The thumb pad can be used for joystick, while other fingers can be used for buttons. These wide input spaces will be useful for various frequently used shortcuts. For example, flicks can be used for frequently used system functions (e.g., copy, paste, and undo) and finger tapping (on single or multiple nails), while arm rotation can be used for diverse bar input controls (e.g., brush weight, volume, or size). In comparison with other AR devices, such as Hololens2 (freehand motions with a pinching gesture) and GoogleGlass (tap and swipe gestures on the glass temple), our system can provide much wider input spaces by adding more functionalities to the fingers and hand motions.

6.2.4 Social

Chapter 5: The elicitation study considering the public and social contexts provided five design strategies to achieve social acceptability and the follow-up study on two prototypes that instantiate these strategies validated the effectiveness of each strategy.

Regarding the social factor, while intra-hand input enables unobtrusive microinteraction, the main concern was on hand-to-face input because the face is one of the most prominent regions that can easily cause social problems when used as input surface. The results of the studies conducted here generally validate the effectiveness of the design strategies identified in the elicitation study and instantiated in the prototypes.

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6.3 Considerations

The discussions in this section span diverse considerations, such as suitable tracking technologies, appropriate body regions, viable input types, and effective design processes. This section aims is to provide design issues that should be considered by researchers, designers, and developers who seek to implement these types of input.

6.3.1 Tracking Technologies

Touch: Unlike other input modalities that utilize vision, IMU, or acoustics, the touch input can directly track the hand articulation from a touch. This dissertation leverages this precise and explicit input to build touch-sensitive nails for intra-hand input. Nails are not only a suitable place to adhere to the touchpad, but also a place where diverse actions, such as tap, swipe, and flick, can be performed and easily detected. The results in each scenario indicate that the touch interface on the nail enables accurate and quick inputs.

Motion: The motion input was utilized in Chapter 3 to track hand gestures and motion inputs, including flick and wrist rotation. Particularly, the flick, which is a difficult action to detect by touch input, could be easily detected by measuring the wrist acceleration. Further, by being combined with the touch input, flick detection became more robust without a dynamic pattern matching algorithm such as DTW – it just requires checking the 100ms of a window right after the release of the touch.

6.3.2 Body Regions

Nail regions: Chapter3 designed an initial set of nail inputs based on key variations observed in the workshop. The set contained five nail regions (tip, center, root, inner side, and outer side) on each of the five single nails or six nail combinations. These input locations show quite different performance and comfort parameters depending on the nail and nail region. In short, the results indicate that, in general, the tip and inner side of the nail were quick and comfortable to make an input. In addition, for single nails and combination of nails, if a little nail was used,

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there was a significant drop in both comfort and objective performance (time).

Face regions: Chapter 5 explored input positions on the face based on data from user elicitation studies. Since the experiment asked users to create a socially acceptable input, the frequency of the use of each face region was expected to reflect a good face region to make socially acceptable diverse inputs. The results show that the cheek (27.2%), chin(18.2%), and ear(10.3%) were the most used regions. In terms of the acceptability score presented in Chapter 5, the highest scores were on the ear, neck, and temple, which suggests that input areas away from the center of the face may be appropriate for hand-to-face designs. The lowest scores were reserved for areas such as the hair, the whole face, or nose, regions where input actions were either large or front-and-center.

6.3.3 Input Types

intra-hand: Based on the actions proposed in the workshop, we included taps of the nail, flicks of the finger, and swipes over the nail(s) either horizontally (HSwipe) or vertically (VSwipe) in both directions. In short, regarding comfort and objective performance(time), the tap and flick actions were better than swipes, while the HSwipes were the worst.

Hand-to-face: Hand actions tended to be swipe-like strokes (27.9%) or various forms of the tap (e.g. tap, push, long- tap: 29.9%) over more unusual types of input. In terms of acceptability score, tap, a small discreet movement, rated best, while spread, a large action involving moving all five fingers out from a central pinch, scored poorly. Similarly, actions such as fold, universally applied to the out-of-the-way ear, scored highly.

6.3.4 Design Processes

Ideation workshop: The ideation workshop aimed to better understand the input and interaction space enabled by a set of touch-sensitive nails. To this end, five semi-experts went through the process of generating useful services for the wearable device, input actions for that service, nail input actions, and the interaction concept between tasks for the service and nail

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input actions. The results provided intra-hand input primitives (taps, flicks, and swipes on the multiple nail regions) from which a large set of 144 input actions were derived.

Elicitation study: Chapter 5 examined hand-to-face input through an user elicitation study via the lens of social acceptability. To this end, several settings were considered. First, to improve the ecological validity of the proposed actions, the study was conducted in a busy public place (a coffee shop). In addition, participants were asked to generate unobtrusive or subtle actions, suitable for use in the public setting, and both they and their partners rated the input proposals for social acceptability and how obvious the input action was. Through this process, with the think-aloud notes and their rates, five strategies to achieve socially acceptable inputs were derived, namely miniaturizing, obfuscating, screening, camouflaging, and re-purposing.

6.4 Lesson Learned, Limitation and Future Work

The following subsections the lessons learned while designing intra-hand input, the limitations of this dissertation, and the scope for future works from these discussions.

6.4.1 Multimodal Input

In the dissertation, the two input modalities, touch and motion, provided several benefits by being combined with each other as a multimodal input. First, they provided a much wider input space. For example, Chapter 3 leveraged this in the demo (Fig 11) to provide music player controls, as users can control the volume with the combination of index finger tap and wrist rotation and change the music position with the combination of middle finger tap and wrist rotation. In this manner, various inputs can be made as much as the number of motion actions multiplied by the number of touch actions. Likewise, they complement each other so that the touch input can utilize the user's posture, which cannot be recognized only by the touch input. For example, as mentioned in Chapter 5, intra-hand input can be used to manipulate smartglass by raising the hand to the face (proximate space to the smartglass) while it can control the smart-watches with watch-seeing posture. Lastly, this can improve the detection algorithm. For example, in Chapter 3, the flick used wrist motion data of a 100ms window right after the end of

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touch. This idea was from the observation that every flick was preceded by the touch. Through this implementation, the prototype can prevent the mistake by wrist motion inputs and provide easier implementation without computation and power-consuming algorithms [229].

In this manner, many other input modalities such as acoustic, camera, and electrical signals can also be combined with each other which will result in an enormous number of combinations. The well-known combinations are the speech + hand gesture, eye tracking + hand gesture, and head gesture + controller [32]. Although current implementations have been typically used as a means for the two inputs to complement each other for simple pointing tasks, as mentioned above, various inputs provided by multimodal input will be particularly effective for complex tasks such as 3D modeling, which require diverse functions to be run with shortcuts. In this dissertation, only a limited number of multimodal inputs were examined in this regard. Therefore, future studies, should examine in depth the input space of each combination and various types of combinations.

6.4.2 Interface Design

Although the dissertation mainly focused on the input for wearables, the design of output display is also an important issue [98]. This became a particularly difficult problem by spatial separation between the input space and the output space (e.g., hands down eyes-free inputs) [42]. In such an environment, conventional UI designs such as pointer-based WIMP interface or touch interface will not be effective [7] for diverse forms for inputs (e.g., vision, speech, touch, and motion) that the wearable devices provide. Instead, this new form of interface arise further questions such as how to map various input actions to each function and how to make the user aware of such a mapping. For example, some of the mapping examples presented in the demo of Chapter 3 showcase how the input actions could be used to control a wearable device, but these did not consider its appropriateness in terms of the cognitive model of the users. Likewise in chapter 4, it was difficult to create a mapping between the 2D graphic (on-nail keyboard) on the smartglass screen with on-nail touch input because the direction, angle, and position of the hand can be changed continuously. The solution that provides the fixed nail-shaped keyboard (palm facing toward face shape) on the screen showed reasonable performance for the word entry input among the users, but still, there were some initial difficulties in recognizing each button or finger. For this reason, it is important to understand the cognitive model of the users for such a system to provide an easily understandable mapping between intra-hand inputs and application functions. Thus, future work should consider the mental model of the user to support better design of output interface to elicit proper intra-hand input actions.

6.4.3 Customization and Bespoke Design

To satisfy the needs of diverse users, it is necessary to customize input devices to their various body sizes (e.g., finger length or nail size) and input behavior (e.g., speed or force). In particular, the bespoke design of the input device can affect comfort and input performance [7, 38]. For example, in the performance study of Chapter 3, some participants with smaller nails than the nail touchpad prototype often encountered false touches due to the “slipped” touches by the adjacent fingers. To address this issue, future designs of the nail touch prototype may require the user to cut the touchpad to fit into their nail as done for cosmetic artificial nails.

Regarding the software, customization of the detection algorithm is also crucial. For example, in Chapter 3, an observation showed that input behavior for each action between users is different. For example, there was a variation of movement length for swipe between users due to their physical differences in hand (e.g., size, finger length, or dexterity). Unlike conventional touchscreen on a smartphone, nail touchpads are small; accordingly, such differences in input behavior can greatly impact the input performance. Therefore, in the final experiment of Chapter 3, a customized threshold for each user was applied and, as a result, the accuracy improved from 89.7% to 94.3%. Taking this into account, future designs should consider an algorithm that learns from user data to improve input performances.

6.4.4 In the Wild: Midas Touch

Inputs on wearable devices require immediate and always-available input in any context. Users frequently check their messages, e-mails and calls, and they may even control music or navigation within situational impairment environments, such as running or driving. However always-on

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input functionality in such a situation may cause Midas touch problems produced by unintended false input. In this case, this can be embarrassing or even dangerous when playing a music during a meeting or playing a video on the HMD while driving. To prevent these undesirable or even safety-critical situations, the input of the wearable device should be carefully designed. In terms of intra-hand input, there is a high possibility of accident touches while performing other daily activities. However, it is difficult for the system to check the intention of the user. To tackle this issue, it is worth considering the following approaches. First, the bespoke design of the input device can prevent such accident touches as mentioned above. Second, activation input can make it easier to identify the user's intention to perform a gesture. For example, unusual inputs such as long-tapping on the entire nails before the intentional gesture will significantly reduce the false inputs. However, this one added step will decrease the input speed and accessibility with more burden. Lastly, the software can help to ignore these unintended inputs. For example, the device can use a customized touch threshold (e.g., regarding small touch signals as unintentional input) or multimodal input to confirm each action (e.g., use touch input as an activation input to confirm the flick action). As this issue is important or even safety-critical for always-worn wearable devices, future work should consider these points in more depth with longitudinal field studies.

6.4.5 Aesthetic

For this type of hand-mounted devices (including nail extension, ring, watch, and glove form factors), as a body extension, aesthetic (or a fashion) is one of the most important factors for the successful diffusion of a wearable device [230]. While the scenarios in this dissertation only focused on the interaction aspect of nail mounted prototype, but the nail extension is also highly appropriate for decorations [14, 58]. In this regard, future work should consider the aesthetic factor for designing intra-hand input prototypes, and this will add desirability and social acceptability of such a system. Specifically, the work may test a diverse form of nail art sticker [14], tattoo on the nail [53, 75], or transparent touch pad [231].

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6.5 Practical Guidance

Based on the various considerations, knowledge, and lessons from the dissertation, this section seeks to provide practical guidance that can support and accelerate further research efforts to achieve real-world systems that realize the potential of intra-hand input for wearables. This section achieves this by revisiting the design factors in the introduction and add more considerations for intra-hand input design.

6.5.1 Manipulation

The input should be quick and accurate. As an always-worn device, many applications such as notification, payment, or music will be used more frequently within a short period of time [30], and this requires seamless use of wearables to do not disturb the user. Thus, These inputs should seek to achieve microinteraction inputs to ensure that interaction duration is short and users were not distracted from their main task. For example, as Ashbrook [32] stated, the time between the first intention of the interaction to input should have a short life span (less than 4 seconds). Regarding this, the intra-hand input can be done quickly without a traveling time to the distant touch surface. In figure 10, most of the nail input was done within 3 seconds.

Moreover, there are several ways to enhance the input for wearables regards the manipulation factor. In terms of hardware, multimodal input or multi-sensor system can increase the input accuracy. By combining the multiple sensor data, they can complement each other to provide a better gesture detection algorithm. Otherwise, the bespoke design of the input device can also be one consideration to make the input system fit to diverse users' profiles to reduce the wrong or unintentional touches. However, these solutions can be costly or limited, so rather the software approach can also provide another solution to improve the manipulation aspect. For example, software calibration and customization must be considered to meet the variation of users in age, motion pattern, experience, and other physical properties to better reflect the user's intention. The optimization (e.g., keyboard layout) also can be an option to increase the user's performance within the same input platform.

6.5.2 Accessibility

The input should be easily and comfortably accessible in diverse usage contexts. In particular, it is necessary to have a highly accessible system for situational impairments such as for attention-demanding tasks [9], mobile use [4], and hands-occupied tasks [3]. The intra-hand input is inherently robust to many of these situational impairments by supporting eyes-free, one-handed, and stable input.

In addition to this, the stand-alone input device should consider the scenario for use multi-wearable devices that are scattered over the body. This requires the way to easily select the target of the input to control each device respectively. One approach is to use the posture of the body. For example, as shown in chapter 5, the intra-hand input sensor can be used for hand-to-face touch for HMDs while it can also be used for a smartwatch with a watch holding posture. In this manner, the input from the device's proximate body surface provides an easy-to-understand interface mapping and allows the user to easily control each device respectively.

6.5.3 Space

The input space should be expressive for more complex tasks in various applications. In particular, it is important to provide a wide set of inputs for both discrete and continuous input [34]. For example, text entry will require a large number of keys to tap, while the map navigation will require precise movement tracking. Generally, this can be achieved by physically larger space (e.g., wider touch surface), various forms of actions (e.g., touch, movement, and deformation of skin), or higher tracking fidelity of sensors (e.g., higher sampling rates in IMU sensor can detect more motion gestures). In addition to this, multimodal input can also increase the input space in much range. For example, hand movement can be combined with a touch on one of each five single nails to provide 5 different hand motion input.

In fact, an appropriate design process should be adopted to better explore the input space. For example, an expert involvement workshop is suitable for getting structured ideas. In chapter 3, through the structured process – generating useful services or tasks, generated input action of each task, and devising interaction concepts based on on-nail touch input, experts generated

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input primitives which provided wide input space with diverse combinations. Likewise, a user elicitation study is suitable for obtaining insights on the user's mental models through techniques such as think aloud. Through this process, chapter 5 explored five strategies, input spaces on the face, and input actions to achieve socially acceptable input. These experts or user involved design processes enable much wider design space and also provides input ideas that reflect the diverse mental model of users.

6.5.4 Social

The input should seek to reflect and fit the public contexts in which wearable device use frequently takes place. The interactions should ensure that control movements required can be performed without attracting undue attention. By and large, the unobtrusive design [25] or natural gestures [36] are considered to be a key strategy to achieve this social acceptability [37]. Chapter 5 also supports this by presenting that among 5 design strategies to achieve socially acceptable input, miniaturizing, keeping movements as small as possible, and camouflaging, creating input actions based on unconscious or non-communicative facial touches such as scratching the face, were viewed as critical. Adopting these strategies on the designing stage of input for wearables will be an important step for the successful diffusion of wearables [38].

6.6 Conclusion

This dissertation explored intra-hand input for wearable devices considering four design factors. First, it explored the design space of intra-hand input by investigating the specific case of touches to a set of five touch-sensitive five nails. This work began with an exploratory design process in which a large set of 144 input actions were generated and was followed by two empirical studies on comfort and performance that refined such large set to 29 viable inputs. The results of this work indicate that nail touches are an accessible, expressive, and comfortable form of input. Based on these results, this dissertation focused on the accessibility aspect of intra-hand input in the text entry task in a mobile setting with the same nail form factor system. Through a comparative empirical study addressing both sitting and mobile conditions, the nail-based touches were confirmed to be robust to physical disturbance while mobile. A follow-up study on

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word repetition indicated that text entry studies of up to 33.1 WPM could be achieved when key layouts were appropriately optimized for the nail form factor. These results reveal that intra-hand inputs are suitable for complex input tasks in mobile situations. Finally, this work examined an alternative form of input in the form of hand-to-face inputs that rely on small scale hand touches, and via the lens of social acceptability. The design stage of this work involved elicitation of diverse unobtrusive and socially acceptable hand-to-face actions from users, outcomes that were then refined into five design strategies that can achieve socially acceptable input in this setting. Follow-up studies on a prototype that instantiates these strategies validate their effectiveness and provide a characterization of the speed and accuracy the user achieved with each system.

Through this series of works, the spectrum of data, conclusions, and discussions present contributions in a range of forms. First, this dissertation provided a range of knowledge obtained in developments, and the design guidelines or strategies (e.g., design strategies to achieve social acceptability). The methods used in each scenario are also a contribution to this dissertation. For example, unknown input spaces can be explored by extracting common touch input primitives with ideas from ideation workshops and exploring diverse combinations of these input primitives. Similarly, as suggested in chapter 5, designing input on the face where social acceptance is important can be explored by modified elicitation study via a lens of social acceptability. These methods can be used to explore such a novel system or an input space. The third contribution is novel artifacts and designs, which include the specific prototypes (e.g., touch-sensitive nails) and the interface designs (e.g., nail touch interface and text entry interface). Lastly, this dissertation makes substantial contributions in terms of data on objective performance and subjective experience with one-handed input system in the various form (e.g., intra-hand or on-face) and situations (e.g., texting, while walking, or in public). The objective data characterizes human performance (e.g., time and accuracy) during input and the subjective data (e.g., comfort and social acceptability) describes user experiences in such settings. These user data can provide clear guidelines to future designers, researchers, and developers to create similar systems more effectively.

I argue this spectrum of metrics, record over a dissertation, supports the general claim that intra-hand inputs for the wearable device can be expressively and effectively operated in

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terms of objective performance (e.g., time, errors, accuracy) and subjective experience (e.g., comfort or social acceptability) in common wearable use scenarios such as when mobile and in public. Further, the additional discussions on the contributions of this work, design factors in intra-hand input, diverse considerations, lessons learned, and practical guidance will be helpful to researchers, designers, and developers who seek to implement these types of input. This dissertation also seeks to support and accelerate further research efforts to achieve real-world systems that realize the potential of intra-hand input for wearables.

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