STAT: Subtle Typing Around the Thigh for Head-Mounted Displays

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ABSTRACT

In head-mounted display (HMD) interaction, text entry is frequently supported via some form of virtual touch, controller, or ray casting keyboard. While these options effectively support text entry, they often incur costs of additional external hardware, awkward movements, and hand encumbrance. We propose STAT, a low-cost, mobile, touch typing technique that leverages a smartphone screen located at the thigh, to support both tap and word gesture text input for HMDs. Through a controlled laboratory study, we explore the efficacy of our technique – including a comparison of typing in and out of an enclosed pocket – and present design recommendations for the opportunistic use of a personal touchscreen device positioned at a user's thigh for HMD text entry.

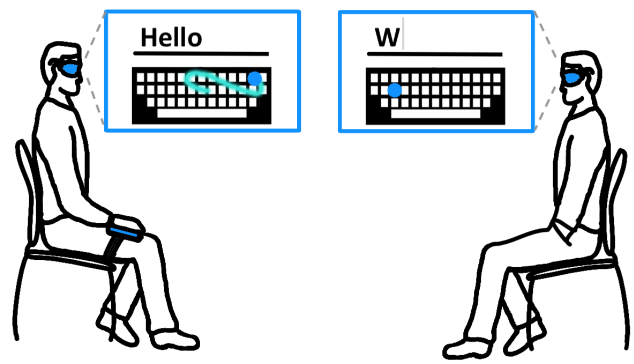

Figure 1: Sample interactions using STAT techniques – *STATSwype* on-thigh (left) and *STATTap* in-pocket (right).

CCS CONCEPTS

• **Human-centered computing** → **Text input**; *User studies*.

KEYWORDS

head-mounted display; HMD; gesture typing

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1 INTRODUCTION

Over the past decade, there has been a surge in popularity of head-mounted displays (HMDs) for presenting an augmented or virtual reality to the wearer. Many HMDs, such as smartglasses, are designed to be ubiquitous displays for providing a personalized, always available, augmented view, without requiring external hardware. A challenge arising from these HMDs, which has subsequently become a roadblock in their widespread adoption (e.g. smartglasses), is the lack of an input mechanism for their control [28].

One primary input mechanism we require for HMDs is some facility for text entry. There is an extensive body of research on techniques for text entry in wearables, including HMDs (e.g. [20, 25, 41, 46]). In general, text entry is a challenge in ubiquitous computing as input either requires a button or key associated with each character, or some form of gesture or chord to describe characters or words. This, in turn, may require specialized devices [25], additional sensors [41], or learning a new input mapping [46] to effectively input text. Gaze eliminates the need for specialized devices, but is perceived to be "complex, strenuous and slow" [2], and both speech and gaze suffer from issues of social acceptability, especially when compared with on-device interaction [35]. While it is possible to type on a virtually displayed keyboard [38], this requires tracking of finger position and, without a physical surface, it is challenging for users to localize keys—potentially reducing the speed and accuracy of such a technique. Thus, a large amount of research has been dedicated to optimizing text input when using a virtual display—resulting in increased performance via novel interaction techniques [1, 12, 38, 45, 46]. Many of these techniques, however, require specialized hardware or physical controllers that often encumber the user's hands during interaction.

In recent work, Akkil et al. [2] note that, for users of smartglasses and other HMDs, mobile phones are considered to "complement" HMDs, particularly for functions where the HMDs are lacking, such as text entry. As users have become proficient in text entry [34] on mobile touchscreens, we propose integrating this existing proficiency with HMDs. Leveraging a state-of-the-art mobile keyboard

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(SwiftKey), we introduce a soft keyboard variant we dub STAT, Subtle Typing Around the Thigh, a low-cost, mobile, touch typing technique. STAT supports both tap and word gesture text entry, leveraging a smartphone screen at a user's front thigh area. This paper describes the implementation of STAT and a controlled within-subjects study of the technique. The results indicate that STAT can reach average speeds of 13.15 words-per-minute (WPM) for word-gesture input and 13.37 WPM for tap-based text entry after minimal training. Our results validate our design choices and argue for the feasibility of leveraging a personal smartphone placed on the users thigh to support text entry for HMDs.

2 RELATED WORK

Based on the context of our work, we begin with a literature review of around thigh and in-pocket interaction, including those with possible applications to HMDs and those specifically applied to HMDs; followed by a review of relevant techniques designed for text entry.

2.1 Around Thigh and In-Pocket Interaction

On-leg and in-pocket interaction is an active area of research. In-pocket techniques such as Tap [36] and Whack [15] leverage the on-device IMU to capture quick, gestural commands. Other in-pocket systems leverage touch-sensing fabric [14, 16] or augment the smartphone to capture touch events through fabric [37]. In contrast to these, alongside the Nintendo Ring Fit's leg strap [30], other researchers have also looked at strap-on controllers to capture at-thigh interactions [22]. On-thigh input is particularly opportunistic because, as Thomas et al. note [39], the front-of-thigh seems an optimal location for high precision input – even in contrast to other on-body locations such as the wrist or forearm – without compromising user comfort. However, care must be taken when supporting interactions near the waist, as these interactions can have low social acceptability ratings [33].

With respect to HMDs, two proposed around-thigh techniques specifically applied to touch interaction are Belt [8] and PocketThumb [9]. In Belt, Dobbelstein et al. [8] added metal divets to a leather belt for touch sensing capabilities, allowing a large horizontal surface for input near a user's waist and found that interaction near the front pocket was preferred for touch input in general (particularly for longer interactions of 10s or more), and interactions near the belt buckle (in the middle) were less desired. Leveraging this idea, PocketThumb employs a dual-sided touch surface, on the inside of a pocket, for the user's thumb and index finger, where the thumb is used as a cursor and the index finger to tap indicating selection (i.e. a pinch gesture). In a target selection task they determined the dual-sided interaction was more efficient than a single-sided touch interaction [9]. One challenge with the systems built for around-thigh and in-pocket interactions is that, while effective, they all require additional hardware for facilitating touch input around the user's thigh. In contrast, a system such as the Nintendo Ring Fit's leg strap makes use of a pre-existing controller that the user already owns (as part of the Nintendo Switch system), and the controller is strapped to the user's thigh [30].

2.2 Text Entry Techniques

As discussed earlier, text entry is one of the primary input requirements of technological devices. In designing STAT, relevant research includes text entry for head-mounted displays (HMD), smartphone-based text entry, and text entry on constrained touch surfaces.

2.2.1 *Text Entry for HMDs Presenting Virtual Content.*

The current work is focused on ubiquitous HMDs, such as smartglasses; however, many virtual reality (VR) scenarios leverage HMDs for their presentation. Physical keyboards have been studied as a text entry technique in VR, and have proven effective, with users performing only slightly slower than with physical keyboards outside VR [17]. However, physical keyboards may be impractical in ubiquitous HMD settings.

Where physical keyboards are impractical, specialized text entry devices can be used to support text-entry. For example, when evaluating text entry techniques in VR, Gonzales et al. [10] found mobile text entry with 12-15 physical buttons particularly effective (reaching 32.75 to 107.39 characters-per-minute, i.e. 6.5 to 20.5WPM). However, physical buttons are rarely present on modern smartphone devices. Without physical buttons, text entry rates tend to be more modest: Speicher et al. [38] conducted a study evaluating common selection based text entry techniques for VR, including head pointing [45], controller pointing (i.e. ray casting at characters), controller tapping, freehand selection, and discrete and continuous cursors. While Yu et al. [45] found that gestural head-pointing reached WPM rates of up to 24.7 WPM after 60 minutes of training, Speicher et al. found more modest rates of text entry for head-pointing (10.2WPM). Speicher et al. also found that controller pointing achieved the highest text entry rate, 15.4 WPM. More subtle forms of text input have also been evaluated; for example, Lu et al. [24] studied various algorithms of decoding thumb-based tap text entry on a blank smartphone screen for use with HMDs and external displays. Their baseline cursor implementation achieved 7.66 WPM, while more complex statistical decoding algorithms boasted rates of up to 17-23 WPM [24], but required a user to hold their phone in their hand.

2.2.2 *Smartphone-Based Text Entry.*

Modern smartphone-based text entry typically leverages a soft keyboard to capture text (i.e. an on-screen keyboard to replace the physical keyboard). On these soft keyboards, users can enter text character-by-character, or, they can take advantage of a series of intelligent typing options, including auto-correct, word-completion, and word-gesture-keyboarding (WGK) [19, 34, 47, 48]. While it seems clear that auto-correct boosts text input speed [31], word-completion and WGKs are more difficult to analyze. In an extensive study of over 37,000 smartphone users, conducted by Palin et al. [31], approximately one quarter of users reported using WGKs versus 3/4 who used tap-based typing. They found that both word-completion and WGKs actually resulted in slower text entry than typing. However, in an earlier in-the-wild study of the Google keyboard, Reyal et al. [34] found that gesture-based text entry resulted in a significantly greater text entry rate than tapping-based text entry, with average WPMs of 33.6 and 30.1, respectively. While there is a significant body of work that leverages WGKs in various forms [13, 27, 44, 45, 50], what is clear from the Palin et al. study [31], is that both character-by-character input on soft keyboard (75% of data) and WGKs (25% of data) are both common mechanisms for text entry.

One advantage of WGKs is that they are tolerant to a degree of imprecision in the gesture input [19], provided the word is in the dictionary and there is sufficient difference between word gestures [3]. Given this tolerance for imprecision, WGKs have been explored for eyes-free text entry. Of particular relation to the current work, Zhu et al. [50] modified the original gestural text entry algorithm to develop an eyes-free gesture typing system using a smartphone's touch screen. In their evaluation they reached an average WPM of 23.27. Similarly, Yang et al. [43] studied gesture typing on a smartphone's touch screen – motivated by first-touch imprecision for indirect touch text entry. Their technique assumes every gesture begins at 'G' and reached an average WPM of 22 in their user study. While restricted to in-dictionary words, this past research highlights the strong desire for eyes-free text input in a variety of contexts.

2.2.3 Text Entry on Constrained Touch Interfaces for HMDs. We define a *constrained touch interface* as a device with limited space for providing input. Previous studies have worked on improving touch typing interactions on constrained touch interfaces such as devices with ultra-small interfaces or small interaction space. Within this space, Ahn et al. [1] explored various techniques that leverage a smartwatch's touch screen. TipText [42] uses small finger-tip gestures to capture text input (but requires augmentation of the fingertips). Researchers have also used the surface of an HMD for text input, e.g. the arm of smartglasses [11, 21, 46]. Typically, these small screen text input techniques reach input speeds of between 8 and 11 WPM. Alongside constraints of screen size, physical restriction can further constrain the use of touch interfaces—e.g. when a user's hand is in their pocket. Zhong et al. [49] presented a subtle pressure-based text input technique that leveraged an off-the-shelf iPhone with (now discontinued) pressure sensing. Users entered text by varying pressure via their finger on a smart phone touch screen. While they note in-pocket interaction as a use-case, they do not explicitly evaluate in-pocket performance.

3 STAT DESIGN

STAT is designed to be a subtle technique to facilitate text entry while wearing an HMD. The subtlety of the technique lies in its positioning [22]: the controller is mounted to the front of the user's thigh, the typical location of a user's hand/arm at rest, when seated or standing. The technique is implemented using two components: the controller and the display.

To implement STAT, a Huawei Nexus 6P running Android 8.0.0 was used for the display, with screen dimensions 2560×440 (landscape), encased in a MoGo Cinema2Go headset [23]. The headset allows for near-display viewing, i.e. the phone display remains the same but appears as a large screen close to the user's eyes in the HMD. The smartphone for text entry was an LG Nexus 5 running Android 6.0.1, with screen dimensions 1080×1920, mounted to the user's thigh either using a Velcro strap (portrait), as shown in Figure 2a or inside a simulated pocket attached to the user's clothing, Figure 2b. A "simulated" pocket was chosen both for internal validity (to control pocket size for consistent measurement) and to ensure inclusivity of participants (regardless of wardrobe preferences/size). Both the HMD and the smartphone for text entry were connected to a Macbook Pro (OSX 10.11.6) and information was wired through USB between the two devices and sent via tcp/adb forwarding.

3.1 STAT Controller Design and Input

During the design phase, we evaluated a series of potential interactive designs via pilot studies. We explored screen layout mechanisms and input paradigms, including whether a Word-Gesture-Keyboard (WGK) or a Tap-Based-Keyboard should be used.

3.1.1 Two-State versus Three-State Input and Screen Orientation. One challenge with mobile phone touch-screen based input is that mobile phones are a two-state input device (versus a three state model [4]) due to the absence of a tracking state. Furthermore, because of the presence of an HMD, the user's eyes are focused on the HMD. As a result, the user is typing eyes-free relative to the smartphone screen.

In Zhu et al.'s I'sFree [50] developed a shifting QWERTY layout to support eyes-free typing, where they synthesize a deformation model for WGKs that they then apply to infer word gestures. However, one challenge we found in applying an eyes-free technique was the inverted mapping which alters spatial perception. As well, while Zhu et al.'s technique can effectively be used for WGKs, it is unclear how accurate the technique would be for character-by-character entry, and, given that character-by-character entry appears to be the most common smartphone-based text entry paradigm [31], we felt it important to support both character-by-character and WGK-based text entry. Character-by-character text entry was plausible with Lu et al.'s eyes-free technique [24], however, without spatial perception of where your fingers are tapping in relation to the edges of the phone, as possible while holding a phone, this becomes a challenge. While we considered performing additional analysis to explore inverted eyes-free tap typing, in pilot testing, another option presented itself—the use of multi-touch input to support a 3-state input model. We highlight the ability to support text entry without spatial perception – via 3-state input – as an integral difference in our work in comparison to Blindtype [24] and I'sFree [50], which leveraged 2-state input.

To capture 3-state input, STAT takes advantage of the multi-touch nature of the smartphone screen by dividing the screen into a touchpad and a button. Given the position of the smartphone on the thigh, the "top" section (dimensions 1080×608) of the smartphone is used as an absolutely mapped trackpad for a cursor on the HMD. This "top" section is positioned further from the waist (so nearer the user's knee). The bottom section (dimensions 1080×1312) of the smartphone is a button to indicate an action (either being a gesture or tap on a character, Figure 2c) and is positioned nearer the user's waist. To use the smartphone for text input, the user positions their hand on top of the screen; the index, middle or ring finger can be used on the trackpad as a cursor, and the thumb is used to press the button for an action.

Screen separation was chosen for several reasons. First, when mapping the text entry smartphone to HMD, the HMD smartphone was landscape oriented and thigh positioned smartphone portrait; this complicated mapping for our participants, leading us to divide the screen so that mapping was more natural. Second, our pilot studies highlighted an advantage in dedicating the lower section to state-switching. Consider, for example, if the user navigates to the right edge of the thigh-mounted phone with their index finger and attempts to tap with their middle finger they will miss the screen, whereas the thumb will always be placed on the lower portion of the screen (closer to the user's belt) regardless of index finger position. Thus screen separation and mapping ensures the thumb is always ideally positioned to manipulate input state. Finally, the separation of sections allows for navigation with only minimal movements of the navigational (index) finger. In a constrained pant-pocket, the deeper the hand is, the more restricted movement becomes, and in our technique, the navigational finger (placed deeper in the pocket) does not require lifting/tapping at all, while the thumb (placed nearest to the pocket entrance) is at the easiest location for lifting/tapping (to switch states).

3.1.2 Gesture versus Tap-Based Text Entry. Given the above 3-state model, Gesture versus Tap text entry can be supported. Actions differ subtly based on two different implementations of the STAT technique: *STATTap* or *STATSwype*.

- *STATTap*: This implementation utilizes tapping on each individual key to type. Finger position on the track pad in the top section of the controller is depicted as a cursor on the HMD. The user moves the cursor using their finger to the letter they wish to type, and presses the button in the bottom section of the controller using their thumb to select.
- *STATSwype*: This implementation utilizes word gesture typing. Again, finger position on the track pad is depicted as the cursor, and the user presses the button with their thumb to start a word gesture. To end the word gesture, the user can lift their finger that is on the track pad or press the button again in the bottom section with their thumb. In the case a word gesture is not recognized, to type a single letter the user can press the button with their thumb twice in a row (double-tap), or press the button with their thumb once and release the cursor finger (lift-cursor-finger).

Alongside character-by-character and WGK typing, both autocorrection and word-completion are also commonly used techniques to assist users in fast, accurate typing [31]. In order to provide these features, many researchers make use of state-of-the-art keyboards that incorporate language models such as the Google or SwiftKey keyboards for gesture recognition [29]. In our work, we make use of the SwiftKey keyboard [29]. Events were injected using Android NDK [7] to the SwiftKey keyboard on the HMD. The smartphone used for text entry was in incognito mode to prevent confounds introduced by the learning of user input. Participants were permitted to use predictive text and auto-complete during text entry. Corrections were completed by tapping backspace, and participants could only backspace a single character at a time.

3.1.3 Finger Movement Mapping. One primary design decision that must be made in STAT is how best to map finger motion on the display to cursor motion in the HMD. Consider Figure 2b, where the participant is standing with the controller smartphone in the simulated pocket. The keyboard could either be mapped such that gestures toward the waist, gestures that are "up" relative to the ground, map to "up" in the HMD display (upright mapping), or gestures that move toward the waist, away from the ground, could

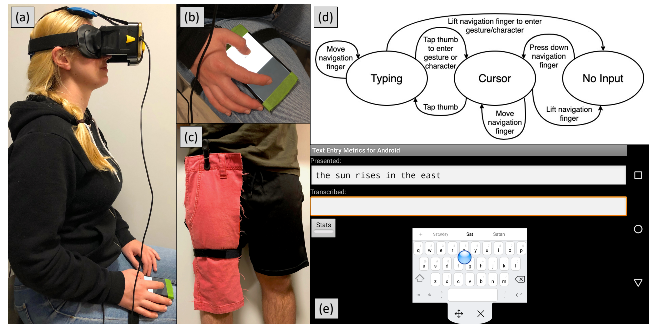


Figure 2: (a) A participant using STAT for text entry on the HMD; (b) A closeup of the STAT controller on a user's thigh, with the index finger being used on the top section trackpad as a cursor, and the thumb on the bottom section to press the button for an action; (c) The simulated pocket used for in-pocket interaction; (d) State diagram for user input using STAT; (e) The experimental interface used for performing text entry.

be mapped "down" from the perspective of the user in the HMD (inverted mapping).

We performed a series of pilot studies, and in all cases, participants preferred inverted mapping, where gestures toward the waist map as down. Because this perspective was the most natural for end users, we adopted it for our STAT evaluation/implementation.

4 EXPERIMENTAL PROTOCOL

In this section, we describe an evaluation of STAT. The purpose of the user evaluation was two-fold: first, to assess the validity of typing on the thigh, where the user's hand naturally rests when seated, and where the user's front pocket on the side of their dominant hand would be; and second, to compare implementations for interacting in this location, using either gestural text entry (*STATSwype*), or tapping text entry (*STATTap*).

Aside from these two primary questions, we wished to investigate whether or not users were capable of using the aforementioned techniques, once they had learned to type on their thigh, while carrying their phone in a more constrained environment (in a pocket or bag, where these devices are typically carried). To provide a preliminary investigation of the in-pocket interaction use-case (i.e. as suggested by Zhong et al. [49]), a pocket (taken from a pair of trousers so as to keep pocket size and tightness the same for every participant) was clipped to the participant's waistband and held in place with an adjustable elastic strap (Figure 2b). The study followed a within-subjects design, counter-balancing ordering of conditions. The apparatus was as-described in the previous section: i.e. a Huawei Nexus 6P in a MoGo Cinema2Go headset [23] for the display and an LG Nexus 5 at the user's thigh (either externally or encased in the strap-on pocket) for text entry.

4.1 Participants

12 participants were recruited for the study and paid $15 for the session. Average age was 24.92 (SD=2.27). Two participants identified as women and the remaining ten identified as men. All participants were post-secondary students from a technically-focused university.

Each participant signed an informed consent form before starting the experiment. Participants were screened for motion sickness and whether or not glasses were required for normal vision, to reduce possible discomfort while wearing the HMD.

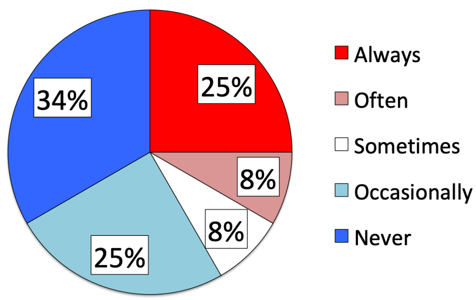


Figure 3: Distribution of participants' self-reported usage of word-gesture typing.

4.2 Procedure

Prior to the study, participants were asked to self-report expertise with the QWERTY keyboard and word gesture typing (depicted in Figure 3), as well as general demographics (e.g. gender, age, occupation, and handedness). Thereafter, participants were fitted with an adjustable elastic strap around their thigh on the leg on the side of their dominant hand, with a Velcro section facing the front. They sat on a chair for the duration of the study—between 1 and 1.5 hours. In order to get a baseline of participants' mobile typing speed, before being given instruction on the upcoming typing technique to be used, participants were asked to type five phrases with either tap or word gesture typing, without the HMD and holding the device in their preferred manner, i.e. not attached to their thigh. Following this, the controller phone was mounted to the Velcro section of the strap on the participant's thigh and the display phone fastened to the headset which was then placed on the participant's head. Depending on the ordering of the conditions, participants were instructed to perform a series of text entry tasks (described in more detail in the next section) using either the *STATSwype* or *STATTap* implementation. To assess for potential learning of word-gesture text entry, upon completion of the *STATSwype* technique, participants were asked to do a second block of gestural text entry on the mobile device, holding it in their preferred manner without the HMD.

In the *STATSwype* condition, participants were told that they could 'double-tap' or 'lift-cursor-finger' on each individual character, if they were unable to type the correct word or phrase after the first attempt with gesture typing. This was made possible because, first, it is common for users to employ both tapping on individual keys and gesture writing in the same phrase (as mentioned in [12]) and second, to ensure that participants attempted gestural text entry at least once before abandoning the input method in preference for tap.

4.2.1 Task. We assessed the STAT technique using Castellucci and Mackenzie's TEMA application [6], used for assessing text entry on android devices. The TEMA application presented random text phrases from the Mackenzie corpus [26] and participants were asked to transcribe these phrases. Each participant completed 5 trials (1 trial = 1 phrase) per block, with a total of 4 blocks for each condition. Upon completing each phrase, participants selected the enter button on the keyboard to continue. At the end of each block they were given the opportunity to take a break. Participants were told to focus on accuracy and speed while completing the task. If participants had an uncorrected error rate (UER) of 15% after a trial, they were required to re-do the trial. After completing the 4 blocks of one condition, participants were asked to complete the NASA Task Load Index (NASA-TLX) to measure perceived workload.

After the TLX, participants performed one block (transcribing 5 phrases) with the controller in the simulated pocket (Figure 2b). Then, participants were asked to comment on the experience interacting in-pocket in comparison to out-of-pocket (mounted on the thigh). Once this was complete, participants repeated these steps in the second condition (either *STATTap* or *STATSwype*). At the end of the session, participants were asked which text entry method, tapping or swyping, they preferred in-pocket, and which out-of-pocket. Finally, participants were debriefed, asked for additional commentary and paid for their participation.

4.3 Measures

At a high level, our study reports on the following: *Performance* (measured with text entry and error rates), *Perceived Workload* (measured using the NASA-TLX), and *Subjective Preference* (measured through survey questions at the end of each condition and session). Text entry rate was measured using WPM, where a word is five characters (including spaces). Text entry duration for each trial began when the participant's finger tapped the bottom section of the controller, and ended when the participant ends the final word (either by releasing their finger on the upper section of the controller or by tapping the bottom section of the controller). The error rates calculated were corrected error rate (CER), which considers rectified errors made during transcription, and uncorrected error rate (UER), i.e. errors left uncorrected.

The study employed a within-subjects design with the following factors and levels: condition (gestural text entry out-of-pocket, gestural text entry in-pocket, tap text entry out-of-pocket, and tap text entry in-pocket) and block (1-4).

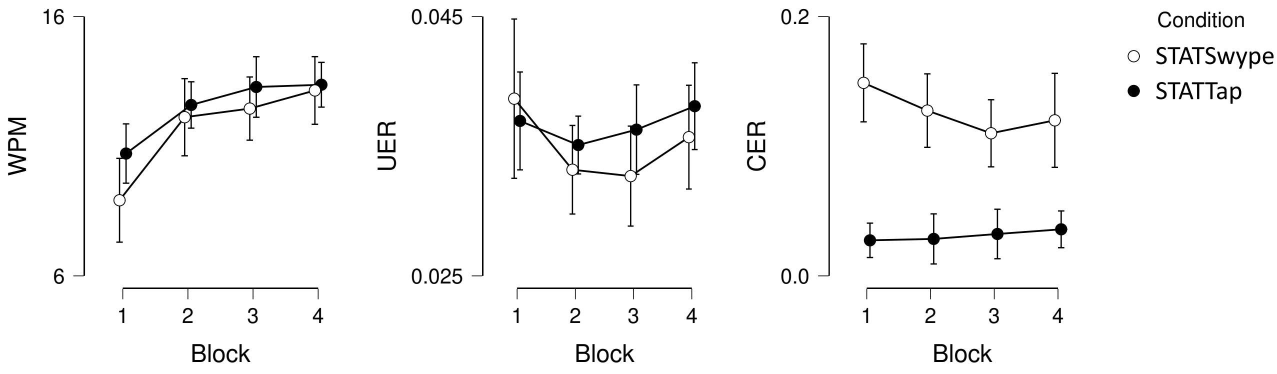
In total, we collected:
12 participants $\times$ ((5 phrases $\times$ 4 blocks $\times$ 2 conditions)
+ (5 phrases $\times$ 2 conditions))
= 600 phrase data points

5 RESULTS

5.1 Gesture vs. Tapping - Out of Pocket

A repeated measures Analysis of Variance (RM-ANOVA) was conducted for text entry rate (WPM), uncorrected error rate (UER) and corrected error rate (CER) with two factors: condition (levels: gesture and tap), and block (1-4).

5.1.1 Text Entry Rate (WPM). Figure 4 (a) shows the text entry rate in WPM across the 4 blocks, for both *STATTap* and *STATSwype*. There is no significant effect of condition on text entry rate, nor an interaction effect of condition and block. However, block does have a significant effect ($F_{3,33}$ = 25.662, p < .001). Bonferroni post hoc



(a) Out of Pocket WPM. (b) Out of Pocket UER. (c) Out of Pocket CER.

Figure 4: Each dependent measure across blocks and conditions (out of pocket). Error bars indicate a 95% confidence interval.

tests indicate significant differences between block 1 and 2 (mean difference = -2.537, $p < .001$), block 1 and 3 (mean difference = 3.051, $p < .001$), and block 1 and 4 (mean difference = -3.443, $p < .001$). Growth in WPM appears to slow from block 2 onward for both conditions—for *STATTap* performance seems to plateau, but continues slight growth in *STATSwype* from block 2 to 4. Mean WPM scores are depicted in Table 1.

Table 1: Summary of means by block and condition. (SS = *STATSwype*; ST = *STATTap*; in = in-pocket; out = out-of-pocket); HH = hand-held (T = tap, S = gesture). Note: Block 2 for regular on phone gestures is reported to control for those who were word-gesture typing novices.

Condition	Block	WPM	UER	CER
SS out	1	8.92	0.04	0.15
SS out	2	12.12	0.03	0.13
SS out	3	12.45	0.03	0.11
SS out	4	13.15	0.04	0.12
SS out (mean)	-	11.66	0.035	0.1275
ST out	1	10.72	0.04	0.03
ST out	2	12.59	0.04	0.03
ST out	3	13.28	0.04	0.03
ST out	4	13.37	0.04	0.04
ST out (mean)	-	12.49	0.04	0.0325
ST in	1	12.25	0.04	0.03
SS in	1	12.31	0.04	0.11
HH T	1	36.30	0.04	0.02
HH S	1	22.68	0.04	0.09
HH S	2	26.14	0.04	0.08

5.1.2 Uncorrected Error Rate (UER). Figure 4 (b) depicts the UERs over the 4 blocks. There is no significant effect of condition nor block; although we note a near significant effect on block ($F_{3,33}$ = 2.423, $p < 0.1$). It may have been the case that some uncorrected errors were due to certain words not being present in the Swiftkey dictionary (as was found in prior work that used the same task setup [13]).

5.1.3 Corrected Error Rate (CER). Figure 4 (c) presents the CERs, showing a clear contrast between the two conditions. In fact, condition has a significant effect on CER ($F_{1,11}$ = 64.129, $p < .001$), with a mean difference = 0.096. There is no effect of block or condition*block. Mean CERs are depicted in Table 1.

5.1.4 NASA Task Load Index. We found no significant effects across conditions via the NASA TLX. Results are summarized in Figure 5.

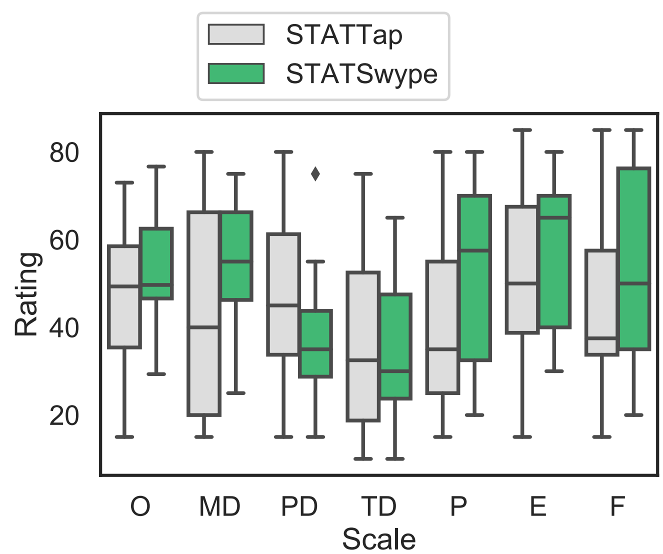


Figure 5: Categorical NASA TLX scores across conditions out of pocket. (O = Overall, PD = Physical Demand, TD = Temporal Demand, P = Performance, E = Effort, F = Frustration)

5.2 In-Pocket vs. Out-of-Pocket

A one-way RM-ANOVA was conducted for text entry rate, UER, and CER, with one factor: condition, with four levels (Block 4 of *STATSwype* out-of-pocket, Block 4 of *STATTap* out-of-pocket, *STATSwype* in-pocket, and *STATTap* in-pocket).

There was no significant effect of condition on text entry rate or uncorrected error rate (UER). Mauchly's test of sphericity indicated the assumption of sphericity was violated for CER ($p < .05$). Using Greenhouse-Geisser correction, there was a significant effect of condition on CER ($F_{1.681,18.493} = 18.408$ $p < .001$). Bonferroni post-hoc tests (summarized in Table 2) indicate a significant difference between *STATSwype* in-pocket and *STATTap* in-pocket (mean difference = 0.080, $p < .001$); *STATSwype* in-pocket and *STATTap* out-of-pocket (mean difference = 0.079, $p < .001$); *STATSwype* out-of-pocket and *STATTap* in-pocket (mean difference = 0.085, $p < 0.01$); *STATSwype* out-of-pocket and *STATTap* out-of-pocket (mean difference = 0.084, $p < 0.005$). No significant difference was found between *STATSwype* in-pocket and *STATSwype* out-of-pocket; and between *STATTap* in-pocket and *STATTap* out-of-pocket. This indicates that once users had learned to type on their thigh, they were able to transfer this knowledge to a more constrained environment, with little loss in accuracy; further depicted in Table 1.

Table 2: Results of Bonferroni Post-hoc comparisons of CER for in-pocket vs. out-of-pocket. Mean differences (standard error) shown. ** indicates significance at the 0.01 level, and * at 0.001. (Naming conventions follow Table 1).**

	SS in	SS out	ST in	ST out
SS in	1	−0.005	*** 0.080	*** 0.079
SS out		1	** 0.085	** 0.084
ST in			1	$-8.69e^{-4}$
ST out				1

5.3 Subjective Preferences

Preference for either STAT implementation did not seem to exhibit any strong trend. However, for out-of-pocket interaction, participants seemed to lean more toward word-gesture typing, with 7 participants preferring *STATSwype*, 3 preferring *STATTap* and 2 had no preference either way. For in-pocket, 5 participants preferred *STATTap* and 7 preferred *STATSwype*.

6 DISCUSSION

This work demonstrates and evaluates the STAT technique for HMDs. Two implementations of STAT were tested: *STATTap* and *STATSwype*, and two levels of constraint: in and out of an enclosed pocket. At a high level, our results indicate: (1) STAT is comparable to prior work in text entry for HMDs, (2) *STATSwype* and *STATTap* exhibit similar performance and combining their usages would likely improve the technique, and (3) while out-of-pocket is usually preferred, in-pocket text entry is feasible under certain circumstances (unrestrictive pockets).

6.1 Comparison of Performance with Prior Work

Since our study measured 4 blocks of 5 phrase trials, we focus on the novice stages of top performing related techniques of each category (findings outlined in Table 3) at the closest reported WPM measure to 20 phrase trials. Surprisingly, our technique was able to substantially outperform prior cursor based techniques that had an average rate of 7.66 WPM vs. the current techniques' average rates of 12.49 and 11.66 WPM.

The techniques that out-perform STAT are head pointing [45], controller pointing [38], and techniques optimizing hand-held smartphone typing [24, 43, 50]. Considering head and controller pointing, we note that, while speed is high, gaze is perceived to be strenuous [2], and may suffer from issues of social acceptability [35]; in contrast, while specialized handheld controllers may exhibit stronger overall performance, they are yet another device to locate, and, as Akkil et al. note [2], mobile phones are considered a natural complement to HMDs for functions such as text entry.

This, then, leads to smartphone-based techniques for HMD text entry. While blind tapping [24] and eyes-free gesturing [43, 50] have higher reported input rates, it is important, first, to note that Lu et al.'s evaluation was performed on a touchpad oriented with the screen and Yang et al.'s [43] and Zhu et al.'s [50] techniques are restricted to gesture-typing. As well, all were evaluated such that user's can monitor the position of the touchpad/smartphone via interhand proprioception and peripheral vision (both of which simplify spatial correspondence targeting [32]). In our pilot evaluations, the inverted and strapped nature of the device increased the complexity of the targeting problem. We highlight these phenomena as a trade off revealed when introducing the usage of a truly eyes-free technique, such as STAT, where users have more limited proprioception and peripheral vision of the touch screen input device (than prior approaches discussed [24, 43, 50]). Finally, in contrast to these prior approaches [24, 43, 50], positional correction for eyes-free taptyping and gestural typing both depend on dictionaries; *STATTap* can handle out-of-dictionary words due to its ability to select characters deterministically.

This is not to say that past work in blind-tapping and eyes-free gesture typing are flawed in any way; we believe that there is a second trade-off between hands-encumbered techniques such as those of Lu et al., Yang et al., and Zhu et al., and techniques that use more subtle forms of input via specialized controllers or restricted input spaces [1, 13, 42, 45, 46] as highlighted in Table 3. After minimal training, and considering Table 3, STAT's performance recommends it as a useful addition to the suite of techniques for text-based input on HMDs. Though a useful comparison, we do acknowledge limitations due to the varying number of phrases in each study.

6.2 Design Implications

We conclude this discussion section by addressing issues of gesture versus tap text entry and in- vs. out-of-pocket use.

6.2.1 Gesture vs. Tap Text Entry. Our results indicate comparable performance for our two technique variations in terms of speed, with *STATSwype* reaching 13.15 WPM on average in block 4 and *STATTap* reaching 13.37 WPM on average in block 4. Both conditions exhibited learning over time, as depicted in Figure 4 (a). *STATSwype*

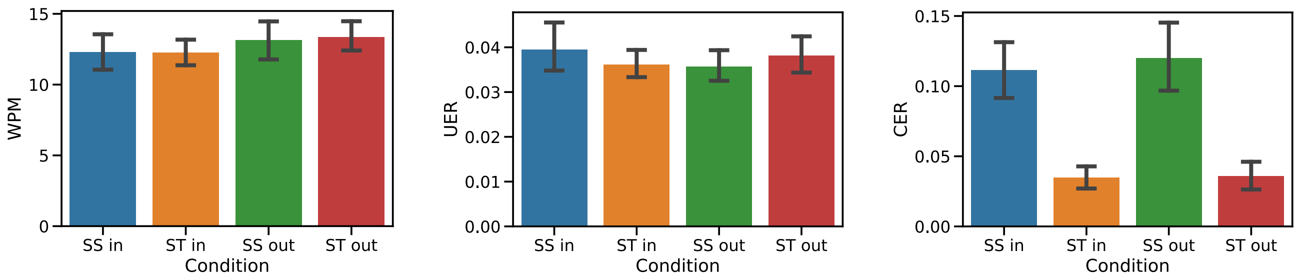


Figure 6: Each dependent measure for block 4 of out-of-pocket (SS out, ST out) and in-pocket conditions (SS in, ST in). Error bars indicate a 95% confidence interval.

Table 3: Text entry speed of related techniques (WPM) in comparable (novice) learning stages. We note a challenge in this direct comparison with differing # of phrases. (WGK = Word Gesture Keyboards).

Technique	# of phrases	WPM
STATTap	20	12.49
STATSwype	20	11.66
Eyes-free WGK [50]	10	22.44
Indirect Touch WGK [43]	10	19.40
Eyes-free Tapping [24]	30	17-23
Head Pointing WGK [45]	8	17.04
Controller Pointing [38]	5	15.40
Index + thumb tapping [42]	40	11.90
Smartwatch [1]	60	10.24
Wrist Rotation (via ring, WGK) [13]	20	9.20
Arm of SmartGlasses [46]	18	8.84
Eyes-free Cursor [24]	15	7.66

may have a slightly steeper learning curve than *STATTap*, and, while both converge on a similar speed, *STATTap* appears to be plateauing sooner than *STATSwype*, so results for *STATSwype* could be pessimistic. One participant noted this, stating: "I think that gesture could be better in both scenarios if I had more time to practice more and become more comfortable with this method of typing" [P9].

A notable difference between techniques is the CER—while *STATSwype* exhibits comparable speed to *STATTap*, a significantly higher amount of corrections, thus increased usage of the backspace key, were required to input the same phrase. This highlights an important trade-off in comparing the techniques: small deviations, gesture collision between similar words, and out-of-dictionary words in gestural text entry will be more detrimental to recognition of the intended word or phrase, but in-dictionary words that do not collide will require less effort (not having to tap for each individual character), a higher risk, higher reward input scenario. However, since we restricted correction to deleting each character (as opposed to word-deletion), optimizing of correction/backspacing is likely to increase speed of the *STATSwype* variation and increase its external validity – particularly since users tend to spend more time on correction in real-world mobile-typing than in laboratory studies [18].

Considering real-world gestural text entry on smartphones, while we restricted participants to at least try the gesture first before employing the secondary tap technique in *STATSwype*, a combination of the two (as on modern smartphones) would likely exhibit better performance, giving the user the choice to tap or gesture if they think a word will not be correctly recognized. [P9] observed that "smaller words are much more difficult than larger words in the gesture method"—thus for words they believed would not be recognized, they would prefer tapping. One advantage of STAT in real-world use is that, as with modern smartphone-based WGKs, both tap and gesture typing can elegantly co-exist. While our chosen task for evaluation was transcription, due to ease of comparison with related works, a composition task [40] would assist in assessing these real-world scenarios in future work, and has the potential to reveal additional benefits of incorporating out of dictionary text in tapping conditions.

6.2.2 In vs. Out of Pocket. Our results for in vs. out of an enclosed front pants pocket exhibited similar performance (see Figure 6), but typing out-of-pocket was approximately 1 WPM faster in comparing each condition to their in-pocket counterpart. As anticipated, some participants noted pitfalls of typing in-pocket: the hand posture was more challenging [P5, P7], the cloth made dragging difficult [P3], and there were instances of accidental activation/tapping [P5, P7]. Additionally, some participants noted that in-pocket interaction may be difficult to do if wearing pants with tighter pockets [P4, P8]. While we controlled pocket size/flexibility, the interaction would not be plausible if pockets were too restrictive to contain both the user's hand and phone, while allowing for small motions of the hand; an issue likely to arise for stiff, "skinny" pants – which clothing companies have begun to combat with increasingly more flexible fabric.

We expected that users would prefer STAT outside of an enclosed pocket rather than inside for two reasons. First, prior literature notes that social acceptability increases when it is obvious that the user is interacting with computation [35]; we assumed an explicit controller near the thigh would be perceived as more socially appropriate than subtle touches on one's body near the waist or movement of fingers within one's pocket. As well, the physical constraints of the pocket on the user's hand might make input more challenging. However, surprisingly, multiple participants indicated a preference for in-pocket interaction: i.e. "inside felt better because I was getting some additional support from the pocket walls which made me feel less fatigued" [P3]; "[it] felt almost the same, but [a] bit easier, since I felt that the phone was more stable [in-pocket]" [P9]; the edges of the pocket were effective boundaries [P8, P11]; and "inside the pocket seemed more practical [...] I would use it if it was available" [P11]. Others noted there was "no difference" [P4] or it was "the same" [P6] as out-of-pocket, and that it was "trickier but not as much as I expected it to be" [P5]. These comments by participants suggest that on-body interaction near the user's waist may not always be perceived as less socially acceptable [33]. Further, these results indicate that physical restriction may not necessarily be a limiting factor to the usability of STAT in constrained spaces.

6.3 Limitations

First, considering study design, we evaluated participants primarily in a seated position. This decision was driven by two aspects of our study configuration: the specific HMD used and study length. Considering our HMD, as noted in the Experimental Protocol, we used a MoGo Cinema2Go headset with a Nexus 6P smartphone. This headset, while allowing a headlocked (egocentric) display solution for mobile device screens, lacks the comfort of other common VR HMDs, such as HTC's Vive or Oculus Rift. Thus, for participant comfort, in an extended time frame wearing the headset (1-1.5 hours), our research ethics protocol was restricted to a seated position. While we initially piloted interaction in a standing position using *STATSwype*, we found the technique exhibited comparable performance to a seated position; thus, we determined tap (*STATTap*) vs. gestural text entry (*STATSwype*) to be a more useful contribution of the experiment. While standing in a stationary position in lab may exhibit similar performance, in mobile situations we would undoubtedly anticipate a degradation in performance. It becomes a challenge to compare how walking and/or running would impact performance across text input techniques, primarily because past at-side text input techniques such as Twiddler [25] and "eyes-free" input techniques [1, 12, 24, 38, 43, 45] were also evaluated in fixed, stationary contexts. However, an exploration of text input while moving serves as an interesting avenue for future work of the current technique, as well as others cited.

Next, while our method of strapping a capture device to a user's leg echoes past work on subtle input [22], we acknowledge that this is somewhat unrealistic. We replicate prior evaluations [22] by strapping an input device to the thigh as a mechanism to evaluate the potential of forthcoming input mechanisms, such as pants pockets that allow transmission of touch input through fabric or interactive and touch-sensitive fabrics that transmit input to personal devices. Considering our use of a simulated pocket, it is the case that, unless users choose to wear pockets that have sufficient space or flexibility, in pocket text entry (or even carrying a smartphone in pocket) may not be desired. Past research [12, 22, 25, 39] addressed this by simply wearing the input device at belt or side, as in our strap-on condition. In the end, we chose to include a comparison of in- and out-of-pocket, as improving touch typing interactions on constrained touch interfaces is an area of ongoing research [1, 8, 9, 12, 20, 42, 49] with applications that include in-pocket text entry [49]. Given that many people do carry phones in their pants pockets (21 out of 23 of our survey respondents), we felt both in- and out-of-pocket had merit for exploration, but – while out-of-pocket text entry could be achieved through a strap on a users leg (e.g. Nintendo's Ring Fit [30]), a belt clip [25] or, through fabric that permits text entry atop pants pockets – in-pocket text entry requires small hand movements [49]. While screen separation (see Section 3.1.1) does permit touch input in restricted spaces, both the use of a strap-on sensor and the use of a simulated pocket is one factor that may impact generalizability of our evaluation to real-world contexts.

Finally, we recognize a critique of the work may be the chosen sample size or number of repetitions. Our selection of sample size was initially motivated by prior text entry work [19, 24, 25, 50], and HCI literature, in which 12 participants was the most common sample size reported [5]. As recommended by Caine [5], to ensure that sample size limitations were considered, we performed a power analysis on the 95% confidence interval of sample size 12 for moderate effect size (0.3), means of 12.5 and 11.7 (WPM), S.D. of between 3.0 and 3.1, which yielded power estimates above 0.95 for repeated measures analysis due to highly correlated speed and error across conditions (note that the results of power analysis – while not reported in past work – may be one reason for sample size selection in past work). Also, while we show that both *STATTap* and *STATSwype* are effective implementations for text entry, with only 20 repetitions of phrase entry it may be that our results are pessimistic estimates of the potential of STAT. A longitudinal study may provide more accurate final performance estimates.

7 CONCLUSION

This paper presents and validates two variations of Subtle Typing Around the Thigh (STAT), a text entry technique that allows for subtle, low-cost, unencumbered text entry for head-mounted displays (HMDs). Through a controlled laboratory evaluation of the technique, we validate the efficacy of both the word-gesture variation *STATSwype* and the tap-based text entry variation *STATTap* when in, and outside of, a user's front pocket. We present design implications for further development and usage of mobile devices—placed where they are typically worn—for HMD text entry.

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