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Texting While Walking: Is It Possible With a Smartwatch?

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Abstract

Smartwatches are quickly becoming a popular complement to smartphones for notifications and activity tracking, yet most lack an effective method for text input. Typing on a smartwatch with an onscreen keyboard was originally thought to be impractical due to the small screen size. As a result, alternative keyboards that use "zoom" features to enlarge key size were developed as a potential solution. However, observed typing speeds with alternative keyboards are slow, and they often have a steep learning curve. Recent research, in a lab setting using a more familiar full QWERTY onscreen keyboard, demonstrated that it is possible to type quickly on a smartwatch while seated. Given the ubiquitous and mobile nature of smartwatches, this study examines typing performance using a full QWERTY keyboard while mobile. Participants typed using two different text input methods—trace and tap—with their index finger while standing and while walking. Results show participants typed faster with trace (35 words per minute) than tap (30 words per minute), regardless of whether they were standing or walking or whether they had prior experience with trace input. These typing speeds are among the fastest reported in the smartwatch literature. Typing accuracy was also better for trace than for tap and better when standing than while walking. Subjectively, participants rated trace easier to use, preferred it over tap, and suggested they would use it in the future if available. Recommendations to include a full QWERTY keyboard on all smartwatch designs are discussed.

Keywords

smartwatch, typing, trace, tap, QWERTY

Introduction

In a society that appears to be "always on," personal computers that offer a unique and convenient contribution to consumer lives are of great value. The smartwatch is the latest in a line of personal computers that aim to be the next great step in convenient technology. Smartwatches are billed with the promise of bringing the power of the smartphone to the convenient location of the wrist. However, nearly all smartwatches are lacking one crucial feature—typing capabilities—which is a primary function of smartphones. Pre-defined responses (e.g., "In a meeting," "Call you back later," and "Hello!") and voice input are the typical solutions to this issue, yet these methods lack the versatility and customization that typing on a keyboard allows. If smartwatches are to be the next level of convenient technology, then an efficient method of keyboard typing is essential.

Alternative Typing and Interaction Methods for Smartwatches

When smartwatches made their debut, early thoughts of including a keyboard for typing purposes faced much skepticism for three main reasons. First, the size of the smartwatch screen and resulting size of the keyboard was thought to be too small for effective use (Arefin Shimon et al., 2016; Hong, Heo, Isokoski, & Lee, 2015). Second, users' fingers were assumed to be too large in relation to the keyboard to accurately hit the small keys, also known as the "fat finger issue" or "fat finger problem" (Arefin Shimon et al., 2016; Kim, Sohn, Pak, & Lee, 2006; Oney, Harrison, Ogan, & Wiese, 2013; Siek, Rogers, & Connelly, 2005). Third, the users' input finger was thought to be too large in relation to the size of screen and could occlude the users' view of the screen (Arefin Shimon et al., 2016; Funk, Sahami, Henze, & Schmidt, 2014). In response to these issues alternative forms of input, not limited specifically to typing, for small screen devices were developed. These include gesture recognition systems, wristband input, and skin-based input among others.

The development of gesture recognition systems is an attempt to circumvent the limited screen space of small screen devices, including smartwatches, by expanding interaction to the mid-air space around the watch. Examples of gesture recognition systems include HoverFlow (Kratz & Rohs, 2009), MagiWrite (Ketabdar, Roshandel, & Yüksel, 2010), Gesture Watch (Kim, He, Lyons, & Starner, 2007), zSense (Withana, Peiris, Samarasekara, & Nanayakkara, 2015), WristFlex (Dementyev & Paradiso, 2014), Transture (Han, Ahn, & Lee, 2015), Abracadabra (Harrison & Hudson, 2009), and mid-air gestural input (Katsuragawa, Wallace, & Lank, 2016; Song et al., 2014). Gesture recognition systems paired with finger rings/discs have also been explored, such as eRing (Wilhelm, Krakowczyk, Trollmann, & Albayrak, 2015) and Magic Ring (Jing, Cheng, Zhou, Wang, & Huang, 2013). Darbar, Sen, Dash, and Samanta (2016) introduced a sensor-based mechanism paired with a magnetic disk on the index finger for text input on smartwatches; the authors of the study found that users were able to input four words per minute (WPM).

Attempts have also been made to use the wristband and bezel of smartwatches as a means of input. Designs for wristband input include BandSense (Ahn, Hwang, Yoon, Gim, & Ryu, 2015), Watchit (Perrault, Lecolinet, Eagan, & Guiard, 2013), and CircularSelection (Plaumann, Müller, & Rukzio, 2016). Funk et al. (2014) evaluated a touch-sensitive wristband and found users were able to type three WPM using an on-band linear keyboard and four WPM using the on-band multi-tap keyboard layout. Modified bezel designs use the watch bezel as an interactive input method. TiltType (Partridge, Chatterjee, Sazawal, Borriello, & Want, 2002), 2D panning and twist with binary tilt and click (Xiao, Laput, & Harrison, 2014), WatchMI (Yeo, Lee, Bianchi, & Quigley, 2016), EdgeTouch (Oakley & Lee, 2014), WatchOut (Zhang, Yang, Southern, Starner, & Abowd, 2016), and B2B-Swipe (Kubo, Shizuki, & Tanaka, 2016) are all examples of modified bezel designs. Kerber, Kiefer, and Löchtefeld (2016) compared the input techniques of a digital crown, a rotating bezel, and touch input on a one-dimensional selection task using a smartwatch. Kerber et al. (2016) found both the touch input and digital crown were rated as more usable than the rotating bezel. Other bezel designs extend input to the side of the smartwatch, such as PressTact (Darbar, Sen, & Samanta, 2016).

Additional input methods include the use of the back of the device for interaction (Baudisch & Chu, 2009), a smartwatch camera (WatchMe; Van Vlaenderen, Brulmans, Vermeulen, & Schöning, 2015), a non-smartwatch camera based keyboard (CamK; Yin et al., 2016), thumb slide movement of the watch hand (ThumbSlide; Aoyama, Shizuki, & Tanaka, 2016), blowing air (Blowatch; Chen, 2015), a non-voice acoustic input (Whoosh; Reyes et al., 2016), lightful interaction (Yoon, Park, & Lee, 2016), multi-screened bracelets (Facet; Lyons, Nguyen, Ashbrook, & White, 2012), a finger-mounted fine-tip stylus (NanoStylus; Xia, Grossman, & Fitzmaurice, 2015), single-tap interaction with different areas of finger pads (TouchSense; Huang et al., 2014), and gaze interaction (Akkil et al., 2015).

Even the skin of the user has been utilized as an input area by SkinWatch (Ogata & Imai, 2015), Skin Buttons (Laput, Xiao, Chen, Hudson, & Harrison, 2014), iSkin (Weigel et al., 2015), and Skinput (Harrison, Tan, & Morris, 2010). Knibbe et al. (2014) combined gesture and skin input for a bimanual gesture input system.

A mobile typing method must meet three requirements to be acceptable to the mass consumer market (Zhai & Kristensson, 2012). First, the input method must be fast, allowing users to type quickly. Second, it should be intuitive for new users to efficiently use the entry method. Third, the input method should support increasing efficiency through practice in use. Based on these requirements, it is doubtful the alternative input methods discussed in this section may ever be adopted by the mass consumer market for typing on smartwatches as they all fail at least one of these requirements.

Alternative Keyboards for Smartwatches

Despite the original skepticism regarding the feasibility of typing on a smartwatch, several studies have shown keyboard-based typing is feasible and more effective than alternative input methods. In recent years, numerous keyboards have either been designed or adapted for use on smartwatches. In a review of the current existing smartwatch keyboards, Arif and Mazalek (2016) provided a summary table and detailed descriptions and illustrations of these keyboards. In this study, we updated the summary table presented in Arif and Mazalek's (2016) article with the latest research findings, and we added columns for participant mobility (seated, standing, walking) and subjective measures (see Appendix). As alternative keyboards continue to be developed, it is important to know how participant mobility affects performance, perceived workload, user satisfaction, and intent to use. As shown in the Appendix, few studies report detailed subjective ratings for alternative input methods, and the studies focus primarily on performance metrics. The studies that do report subjective ratings tend to be limited to preference ratings and non-standardized questionnaires. We believe solely relying on performance as a measure of keyboard quality is shortsighted; if users do not like the keyboard or use it, typing speed is irrelevant.

Despite all the research done with both non-QWERTY and QWERTY alternative keyboards, they have primarily failed at mass adoption largely due to their steep learning curves (Bi & Zhai, 2016). In addition, several of these alternative keyboards demonstrate very low text entry speeds. According to Arif and Mazalek (2016), most techniques using predictive technology achieved about 20 WPM, and for non-predictive, the range was from 4 to 22 WPM. The fastest typing speeds observed on a smartwatch have been accomplished with the use of a sentence-based decoder: Velocitap (41 WPM; Vertanen, Memmi, Emge, Reyal, & Kristensson, 2015) and trace input (24 WPM and 37 WPM; Gordon, Ouyang, & Zhai, 2016; Turner, Chaparro, & He, 2016, respectively). According to the guidelines of Zhai and Kristensson (2012), an existing smartphone keyboard that users are already familiar with may be best suited for use on a smartwatch, especially if the end goal is mass adoption.

In this paper, keyboards designed specifically for use on small screen devices, or those requiring an extra interaction outside of typing (i.e., zooming or panning), are referred to as *alternative keyboards*. In addition, traditional point-and-tap input is referred to as *tap*, and gesture input is referred to as *trace*. Trace is unique over point-and-tap in that it requires the user to use one continuous on-screen finger motion to type a word (Figure 1).

Figure 1. Examples of standard point-and-tap input (left) and trace input (right).

Walking and Typing

The majority of the aforementioned keyboards have only been studied with the users in a seated position. Yet, typing on a smartphone is rarely static, in fact, typing while standing or walking is quite common (Yatani & Truong, 2009). For example, Turner et al. (2016) observed some of the highest reported typing speeds on a smartwatch in a seated position. The authors went on to state in their limitations and future studies the importance of observing typing performance and garnering user feedback in mobile scenarios to more accurately represent normal user typing behavior. They also mentioned that additional research is needed to determine how users perform with smartwatch keyboards in mobile conditions. Based on the findings of Schildbach and Rukzio (2010), alternative keyboards that utilize zoom or panning functions may not be effective for text input while walking; however, little research has been done to determine what keyboard may be better suited. Not only do smartwatches need an effective typing method, but the method must be versatile and forgiving enough for mobile typing.

Smartphone

Walking and typing on a smartphone is a complex, yet common, task that requires the coordination of multiple cognitive and physical resources. To achieve an accurate text message when walking and typing, visual-motor coordination, finger movements, and cognitive attention must integrate to compensate for hand and body oscillations experienced during walking (Agostini, Fermo, Massazza, & Knaflitz, 2015; Bergstrom-Lehtovirta, Oulasvirta, & Brewster, 2011). Walking while using a smartphone has been shown to negatively affect text legibility (Mustonen, Olkkonen, & Hakkinen, 2004), reading comprehension (Barnard, Yi, Jacko, & Sears, 2007; Schildbach & Rukzio, 2010), working memory (Lamberg & Muratori, 2012), target selection (Kane, Wobbrock, & Smith, 2008), and increase mental workload and stress (Vadas, Patel, Lyons, Starner, & Jacko, 2006). In addition, walking while typing affects user walking behavior, such as walking speed, gait pattern, and situational awareness (Agostini et al., 2015; Bergstrom-Lehtovirta et al., 2011; Hatfield & Murphy, 2007; Lamberg & Muratori, 2012; Licence, Smith, McGuigan, & Earnest, 2015; Lopresti-Goodman, Rivera, & Dressel, 2012; Plummer, Apple, Dowd, & Keith, 2015; Schabrun, van den Hoorn, Moorcroft, Greenland, & Hodges, 2014). Bergstrom-Lehtovirta et al. (2011) showed the preferred walking speed of participants dropped from 2.4 mph while undistracted to 1.8 mph while interacting with a touchscreen device. In addition, accuracy for the target selection task significantly decreased when walking only 20–40% of their preferred walking speed. The decrease in walking speed observed by Bergstrom-Lehtovirta et al. (2011) is not surprising as typing has been shown to affect walking more than either talking or reading (Lamberg & Muratori, 2012; Schabrun et al., 2014).

Most relevant to our review is walking's impact on typing. Several studies have shown typing on a smartphone declines both in speed and accuracy with walking compared to sitting or standing (Clawson, Starner, Kohlsdorf, Quigley, & Gilliland, 2014; Conradi, Busch, & Alexander, 2015; Mizobuchi, Chignell, & Newton, 2005; Nicolau & Jorge, 2012; Schildbach & Rukzio, 2010; Yatani

& Truong, 2009). Attempts have been made to improve typing performance when walking such as the exploration of the following technologies: walking user interfaces (WUIs; Kane et al., 2008), games to improve the typing and walking experience (Rudchenko, Paek, & Badger, 2011), use of a smartphone accelerometer to increase accuracy (Goel, Findlater, & Wobbrock, 2012), and feedback of user surroundings (Arif, Iltisberger, & Stuerzlinger, 2011). Other research has studied optimal key size for mobile text input, recommendations range from 3 to 14 mm depending on the device used (Conradi et al., 2015; Mizobuchi et al., 2005; Parhi, Karlson, & Bederson, 2006). Lin, Goldman, Price, Sears, and Jacko (2007), using Fitts' Law, stated target size should be dynamic and change for the user's mobility: 4.2 mm in diameter when seated, 5.3 mm when walking on a treadmill, and 6.4 mm when walking an obstacle course. Optimal key size for use on a smartwatch is thought to be 5.7 x 5.7mm to 7 x 7mm (Dunlop, Komninos, & Durga, 2014; Shao et al., 2016).

Smartwatch

It would appear that walking and typing is quite difficult and demanding for a user, yet it is a common user behavior on a smartphone. Only two studies have evaluated typing on a smartwatch in mobile scenarios: Hong, Heo, Isokoski, and Lee (2016) and Darbar, Dash, and Samanta (2016). This is most likely due to the fact that most smartwatches do not currently include a keyboard for typing.

Hong et al. (2016) compared user performance with SplitBoard, Zoomboard, and a standard QWERTY keyboard using a Samsung Gear 1 smartwatch with the auto-correct feature disabled. Participants in the study completed the study tasks while standing or walking on a treadmill. Participants were allowed to set their own walking speed, walking 2.4 mph on average. Performance decreased for all three keyboards from the standing to walking condition: SplitBoard (15 WPM to 13 WPM), ZoomBoard (10 WPM to 9 WPM), and the standard QWERTY (13 WPM to 12.5 WPM). Declines in performance when walking is to be expected, as seen in the literature on walking and typing on a smartphone. However, declines observed by Hong et al. (2016) on a smartwatch were quite small, refuting the idea that key size has to be increased to avoid degraded performance while mobile (Lin et al., 2007).

Darbar, Dash, et al. (2016) compared their ETAO keyboard prototype to SplitBoard, Zoomboard, and a standard QWERTY keyboard using a LG W100 Watch without an auto-correct feature. Study participants' performance was compared when they used the different keyboards while sitting or walking in the lab. As with Hong et al. (2016), performance worsened with all keyboards from the sitting to walking condition: ETAO (12 WPM to 9 WPM), SplitBoard (12 WPM to 9 WPM), ZoomBoard (9 WPM to 8 WPM), and standard QWERTY (7 WPM to 5 WPM).

Experience

In addition to mobility, prior experience with text input methods may influence typing performance on a smartwatch. Reyal, Zhai, and Kristensson (2015) found that novice trace users were able to increase trace typing speed on a smartphone from 26 WPM to 34 WPM over a 10-day period. Relatively little research has been reported on how prior typing experience affects typing performance on a smartwatch. Kim et al. (2006) found entry speeds increased 18% over 5 days with no difference in error rate when using the One-Key Keyboard. Gupta and Balakrishnan (2016) demonstrated user performance increased over a 10-day span with both the DualKey QWERTY and DualKey SWEQTY keyboards. Turner et al. (2016) showed that self-reported experts with trace input on a smartphone typed 6 WPM faster, when tracing on a smartwatch, than novice trace users. This finding provides evidence that experience with trace input may carry over to smartwatch performance.

Purpose

This study is a follow-up to Turner et al. (2016). In the current study, we investigated participants' typing performance and subjective user ratings while they performed the study tasks on a full QWERTY smartwatch keyboard while standing or walking. This study aims to answer four research questions:

- What impact does mobility (standing vs. walking) have on typing performance using trace and tap input?
- Which input method (trace vs. tap) results in better typing performance when walking?

- Does prior experience with trace input on a smartphone influence typing performance on the smartwatch?
- Which input method (trace vs. tap) results in better subjective ratings when walking?

Methods

The metrics gathered in this study mirror those used in Turner et al. (2016) with the exception that participants typed while standing and while walking rather than sitting. Mobility (standing vs. walking), tracing experience (novice vs. expert on a smartphone), and text input method (trace vs. tap) were the independent variables. Typing performance (WPM), accuracy (word error rate [WER]), and subjective measures of performance were the dependent variables. Multiple hand dimensions were also measured to assess if there was a relationship between hand and finger size and typing performance.

Participants

Thirty-two college age participants (20 female, 12 male), ranging from 18–34 years of age (*M* = 22.53, *SD* = 4.42), participated in this study for course credit. Participants were recruited based on their expertise with trace on a smartphone (all had experience with tap). None had experience typing on a smartwatch. Participants self-reported their experience level with trace on a 1–7 scale (1 = no experience; 7 = expert). Novices were categorized by a 1 or 2 (*M* = 1.25, *SD* = 0.44) and experts by a 6 or 7 (*M* = 6.38, *SD* = 0.5) rating. Participants were not made aware of the expertise criteria prior to their self-evaluation. Those who identified as a 3–5 rating were dismissed from the study and given partial course credit. Two participants were dismissed for not meeting the study criteria. Sixteen novices (11 female, 5 male) and 16 experts (9 female, 7 male) participated; all typed on the smartwatch using their index finger.

All participants were fluent English speakers, had normal or corrected to normal vision, and did not have any physical limitations to their hands that would prevent them from being able to type on a smartwatch. All participants were experienced with sending and receiving text messages on their touchscreen smartphone.

Materials

A Samsung Galaxy Gear 1 (display size of 1.63 inches) with the Swype word-gesture keyboard (version 1.6.5.23769) was used in this study. The keyboard measured 17.5 mm wide x 30 mm high, and each key 4 mm x 3 mm. All 35 keys on the keyboard were fully functioning and the autocorrect feature was enabled.

A subset of phrases were randomly selected from a list of 500 composed by MacKenzie and Soukoreff (2003). Ten practice phrases and 15 experimental phrases were randomly chosen for each condition; there was no overlap between the practice and experimental phrases. The following are some example phrases: "time to go shopping," "a great disturbance in the force," and "all good boys deserve fudge." Novices and experts of the same participant number received the same phrases (i.e., p1 novice received the same phrases as p1 expert, but a different set than p2, p3…novice and expert). The phrases contained lowercase letters only (no numbers, symbols, punctuation, or uppercase letters). Phrases ranged from 16 to 42 characters for all conditions. A JAS Trackmaster (model number: TX425C) treadmill was used to simulate walking conditions (Hong et al., 2016). Participants were allowed to choose their walking speed but instructed to select a comfortable speed they could maintain for the entirety of the walking conditions (Hong et al., 2016). Walking speeds ranged from 1.5 to 2.5 mph (*M* = 2.04, *SD* = 0.30). Figure 2 shows the experimental setup.

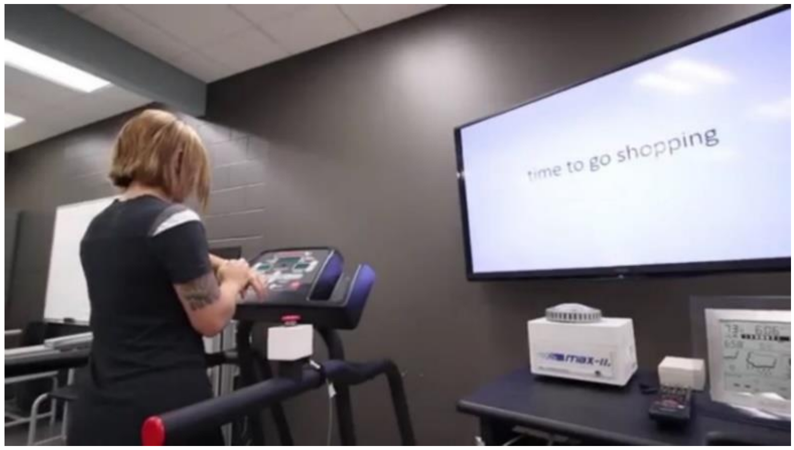

Figure 2. Experimental setup.

Procedure

After providing consent, participants were given a brief demographic survey assessing smartphone texting behavior and text input method usage. Based on their experience with trace input on a smartphone, participants were placed in either the novice or expert group. Participants were then introduced to the first condition, either tap or trace and walking or standing, and given a brief tutorial by the experimenter. Next they were given 10 practice phrases to type before the experimental trials began. For the walking conditions, participants started off at a speed of 1.0 mph and allowed to increase walking speed after each practice phrase until a comfortable speed was selected. The order of input method and mobility condition was partially counterbalanced across all participants to prevent participants from doing two consecutive walking conditions.

For the experimental trials, 15 phrases were presented one at a time on a computer screen in front of the participants. They were instructed to read each phrase aloud to ensure that they understood the phrase and to verbally indicate when they started and stopped typing (Arif et al., 2011; MacKenzie & Read, 2007). Time was recorded by a researcher using a digital stop watch. Participants were instructed to type the phrases as quickly and accurately as possible. They were allowed to correct mistakes but not required to do so. Phrases were saved as a text file on the watch and later scored manually by an experimenter.

Once participants had completed the 15 phrases of the condition, they completed a perceived usability survey and a mental workload assessment. After finishing the mental workload assessment, participants were introduced to the second condition and the steps were repeated.

After all four conditions were completed, participants were asked to rate the four conditions on perceived performance and preference scales and an intent to use scale. Finally, the participants' typing hand and finger dimensions were measured. They were then debriefed and thanked for their time.

Design

A 2 x 2 x 2 mixed design was used for this study. The independent variables were input method, mobility, and experience. Input method (trace vs. tap) and mobility (standing vs. walking) were the within-subjects factors. Experience (novice vs. expert) was the between-subjects factor. Dependent variables included typing speed, typing accuracy, subjective perceptions of usability, workload, performance, and intent to use.

Performance

Performance was measured by typing speed, words per minute (WPM), and typing accuracy as reflected by the word error rate (WER). Typing speed was calculated using $WPM = 12*(T-1)/S$ where T is the number of transcribed characters, S is the number of seconds, and one word is assumed to be 5 characters (MacKenzie & Tanaka-Ishii, 2010). Typing accuracy, or WER, was calculated using the number of word errors per phrase divided by the total number of words per phrase.

Typing accuracy was investigated by the WER and the type of errors: substitution, insertion, and omission error rate. Substitution errors occurred when a word was transcribed other than what was intended. Insertion errors occurred when an extra word was transcribed. Omission errors occurred when an intended word was omitted from the transcription.

Subjective Measures

The subjective measures were determined by measuring the workload, perceived usability, perceived performance and preference, and intent to use.

Subjective workload

The raw NASA Task Load Index (NASA TLX - R; Hart & Staveland, 1988) was used to measure participants' perceived workload and performance after each condition. Participants provided ratings on a 21-point scale for perceived mental, physical, and temporal effort; performance; overall effort; and frustration. A higher score indicates a more demanding experience or worse perceived performance.

Perceived usability

An adapted System Usability Scale (SUS) was used to measure participants' perceived usability of each input method with the mobility condition. The SUS is an industry-standard 10-item questionnaire with 5 response options (Strongly Disagree to Strongly Agree) that is summarized as a single score between 0–100 (Brooke, 2013). Higher scores indicate higher perceived usability. The scale was adapted by replacing "system" with "input method."

Perceived performance and preference

Perceived accuracy, perceived speed, and overall preference with each input method and mobility condition was measured using a 50-point scale with higher scores reflecting more preferred or better in terms of accuracy or speed.

Intent to use

Participants rated the likelihood they would use each input method with each mobility condition on a 0–10 scale with a 10 being very likely.

Anthropometric Measurements

A sliding digital caliper was used to measure the typing hand of each participant. Hand measurements included the length and width of hand, length, width, and circumference of the index finger and thumb in millimeters. Thumb dimensions were later excluded from analysis because no participants used their thumb to type.

Results

All dependent measures were analyzed using a 2 x 2 x 2 mixed model ANOVA. Partial eta squared (η_p^2) was used to estimate effect size for all ANOVA tests. Analyses of simple main effects were conducted to follow-up on all significant interactions. Bonferroni correction was used to control for family-wise Type I error across multiple comparisons.

Typing Speed

Significant main effects of input method and mobility were found for typing speed (WPM), with participants typing faster with trace (M = 35.33, SD = 9.01) than tap (M = 29.88, SD = 6.86) and when standing (M = 32.25, SD = 7.76) than walking (M = 29.88, SD = 8.21): $F(1, 30)$ = 77.42, $p < .001$, $\eta_p^2 = .72$; $F(1, 30)$ = 19.69, $p < .001$, $\eta_p^2 = .40$, respectively. No other main effects or interactions were found for WPM, $p > .05$. Figure 3 shows typing speed by input method, mobility, and experience.

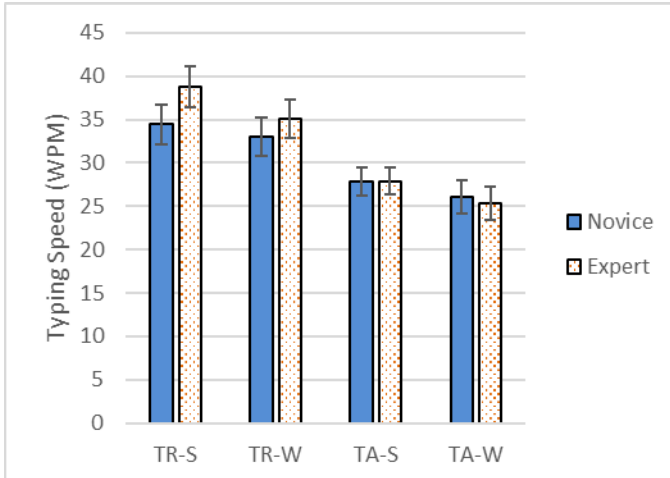

Figure 3. Typing speed. Error bars represent ± 1 standard error.
TR = Trace, TA = Tap, S = Stand, W = Walk.

Typing Accuracy

Significant main effects of input method and mobility were found for typing accuracy (WER), with participants typing more accurately with trace (M = .10, SD = .07) than tap (M = .14, SD = .12) and when standing (M = .10, SD = .08) than walking (M = .15, SD = .11): $F(1, 30) = 5.82$, $p = .02$, $\eta_p^2 = .16$; $F(1, 30) = 20.57$, $p < .001$, $\eta_p^2 = .41$, respectively.

A significant main effect of mobility was found for substitution error rate with participants typing fewer substitution errors when standing (M = .07, SD = .06) than walking (M = .11, SD = .08); $F(1, 30) = 14.65$, $p = .001$, $\eta_p^2 = .33$.

Significant main effects of experience, input method, and mobility were found for insertion error rate, with experts (M = .02, SD = .03) committing fewer insertion errors than novices (M = .04, SD = .05); $F(1, 30) = 4.86$, $p = .04$, $\eta_p^2 = .14$. Participants typed fewer insertion errors with trace (M = .01, SD = .01) than tap (M = .05, SD = .05) and when standing (M = .02, SD = .04) than walking (M = .03, SD = .05): $F(1, 30) = 20.45$, $p < .001$, $\eta_p^2 = .41$; $F(1,30) = 6.66$, $p = .02$, $\eta_p^2 = .18$, respectively. A significant interaction of input method and experience for insertion errors was found; $F(1,30) = 4.52$, $p = .04$, $\eta_p^2 = .13$. Follow-up analysis revealed novice participants made more insertion errors with tap than trace, and novices made more insertion errors than experts, $p < .05$. No other significant main effects or interactions were found, $p > .05$. Figure 4 shows typing accuracy by input method, mobility, and experience.

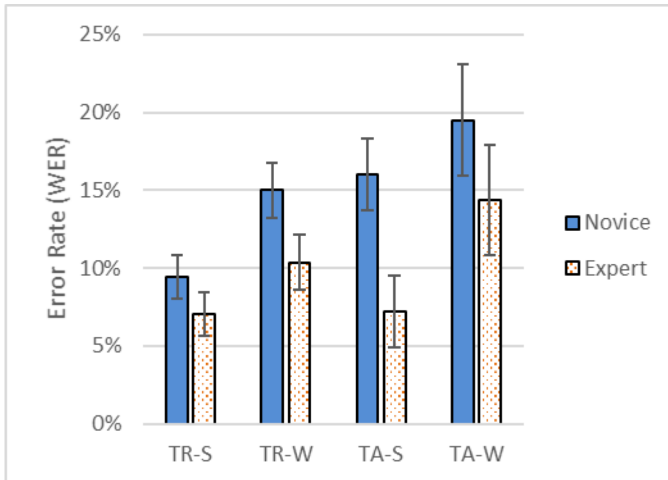

Figure 4. Typing accuracy. Error bars represent ± 1 standard error.
TR = Trace, TA = Tap, S = Stand, W = Walk.

Subjective Workload

A significant main effect of input method was found for frustration with trace (*M* = 6.73, *SD* = 4.79) being rated as less frustrating than tap (*M* = 10.30, *SD* = 5.25); $F(1, 30) = 16.38$, $p < .001$, $\eta_p^2 = .35$. A significant main effect of mobility was found for mental, physical, temporal, performance, effort, and frustration with standing being rated as less demanding than walking: $F(1, 30) = 31.30$, $p < .001$, $\eta_p^2 = .51$; $F(1, 30) = 54.49$, $p < .001$, $\eta_p^2 = .65$; $F(1,30) = 19.09$, $p <. 001$, $\eta_p^2 = .39$; $F(1,30) = 11.24$, $p = .002$, $\eta_p^2 = .27$; $F(1,30) = 21.40$, $p < .001$, $\eta_p^2 = .42$; $F(1,30) = 22.00$, $p < .001$, $\eta_p^2 = .42$, respectively. No other main effects or interactions were found for subjective workload, $p > .05$. Figure 5 shows perceived workload by mobility.

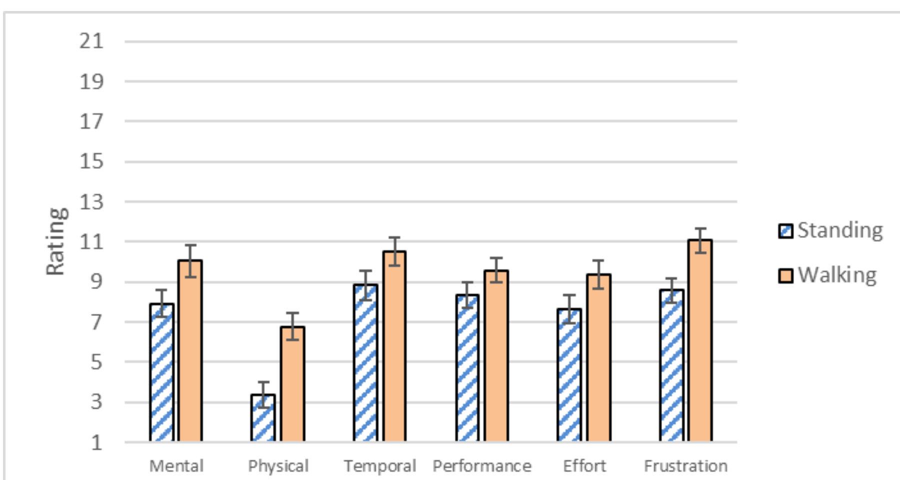

Figure 5. Perceived workload by mobility (1 = least). Error bars represent ± 1 standard error.

Perceived Usability

Significant main effects of experience, input method, and mobility were found for perceived usability, with experts (*M* =75.39, *SD* = 15.98) reporting higher scores than novices (*M* = 57.50, *SD* = 17.68); $F(1,30) = 22.43$, $p < .001$, $\eta_p^2 = .43$. Trace (*M* = 74.10, *SD* = 16.80) was perceived as more usable than tap (*M* = 58.79, *SD* = 18.15), and standing (*M* = 67.77, *SD* = 19.48) was perceived as more usable than walking (*M* = 65.12, *SD* = 18.64): $F(1, 30) = 22.53$, $p < .001$, $\eta_p^2 = .43$; $F(1, 30) = 5.25$, $p = .03$, $\eta_p^2 = .15$. No other main effects or interactions were found for perceived usability, $p > .05$. Figure 6 shows perceived usability score by input method, mobility, and experience.

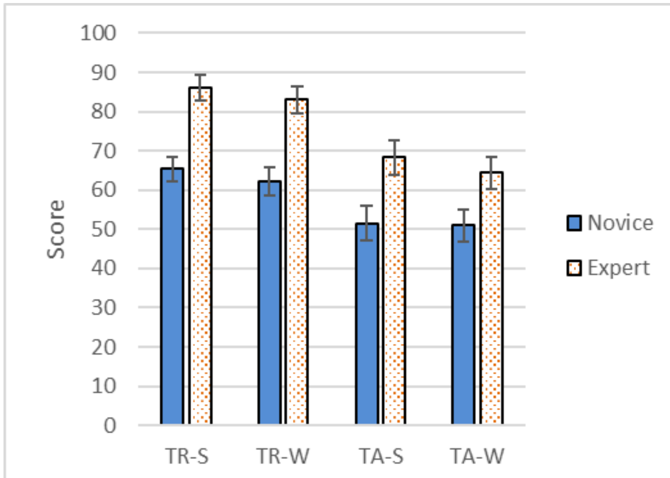

Figure 6. Perceived usability score (100 = highest). Error bars represent ± 1 standard error. TR = Trace, TA = Tap, S = Stand, W = Walk.

Perceived Accuracy, Speed, and Preference

Significant main effects of experience, input method, and mobility were found for perceived accuracy, with experts ($M = 37.45$, $SD = 7.63$) having higher perceived accuracy ratings than novices ($M = 29.22$, $SD = 11.50$); $F(1, 30) = 11.57$, $p = .002$, $\eta_p^2 = .28$. Trace ($M = 36.42$, $SD = 9.65$) was perceived as more accurate overall than tap ($M = 30.25$, $SD = 10.61$) and standing ($M = 35.75$, $SD = 10.34$) more than walking ($M = 30.92$, $SD = 10.31$): $F(1, 30) = 11.90$, $p = .002$, $\eta_p^2 = .28$; $F(1,30) = 24.65$, $p < .001$, $\eta_p^2 = .45$. No other main effects or interactions were found for perceived accuracy, $p > .008$.

Significant main effects of input method and mobility were found for perceived speed, with trace ($M = 40.08$, $SD = 6.57$) having higher perceived speed ratings than tap ($M = 29.38$, $SD = 9.12$) and standing ($M = 36.89$, $SD = 8.84$) higher than walking ($M = 32.56$, $SD = 9.84$): $F(1,30) = 45.77$, $p < .001$, $\eta_p^2 = .60$; $F(1,30) = 19.48$, $p < .001$, $\eta_p^2 = .39$. No other main effects or interactions were found for perceived speed, $p > .008$.

Significant main effects of experience, input method, and mobility were found for overall preference, with experts ($M = 34.70$, $SD = 12.29$) having higher overall preference ratings than novices ($M = 30.02$, $SD = 11.80$); $F(1, 30) = 4.32$, $p = .05$, $\eta_p^2 = .13$. Trace ($M = 38.59$, $SD = 9.01$) was preferred more overall than tap ($M = 26.13$, $SD = 11.89$) and standing ($M = 34.52$, $SD = 11.53$) more than walking ($M = 30.20$, $SD = 12.62$): $F(1, 30) = 27.13$, $p < .001$, $\eta_p^2 = .48$; $F(1, 30) = 11.51$, $p = .002$, $\eta_p^2 = .28$. No other main effects or interactions were found for overall preference, $p > .008$. Figure 7 shows overall preference by input method, mobility, and experience.

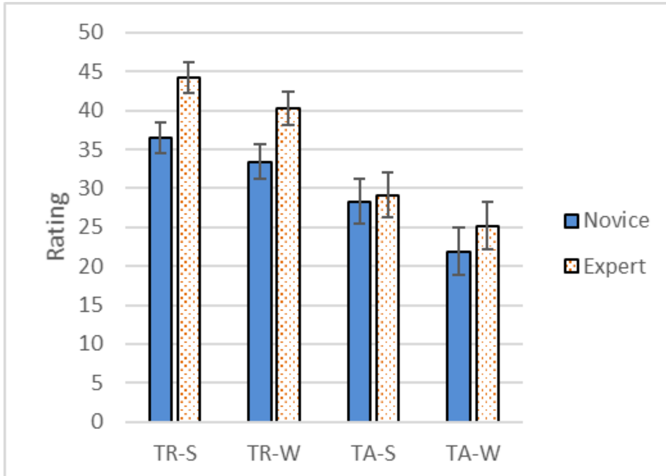

Figure 7. Overall preference (50 = best). Error bars represent ± 1 standard error.
TR = Trace, TA = Tap, S = Stand, W = Walk**.**

Intent to Use

Significant main effects of input method and mobility were found for intent to use, with trace (M = 7.95, SD = 2.48) having a higher intent to use rating than tap (M = 4.30, SD = 2.88) and standing (M = 6.67, SD = 2.95) higher than walking (M = 5.58, SD = 3.45): $F(1,30) = 30.29$, $p < .001$, $\eta_p^2 = .50$; $F(1,30) = 22.33$, $p < .001$, $\eta_p^2 = .43$, respectively. A significant interaction of input method and mobility also was found; $F(1,30) = 9.02$, p = .01, $\eta_p^2 = .23$. Follow-up analysis revealed participants rated standing and walking with trace higher on intent to use than standing and walking with tap, and they rated tap standing higher than tap walking, $p < .05$. No other main effects or interactions were found, $p > .05$. Figure 8 shows intent to use by input method, mobility, and experience.

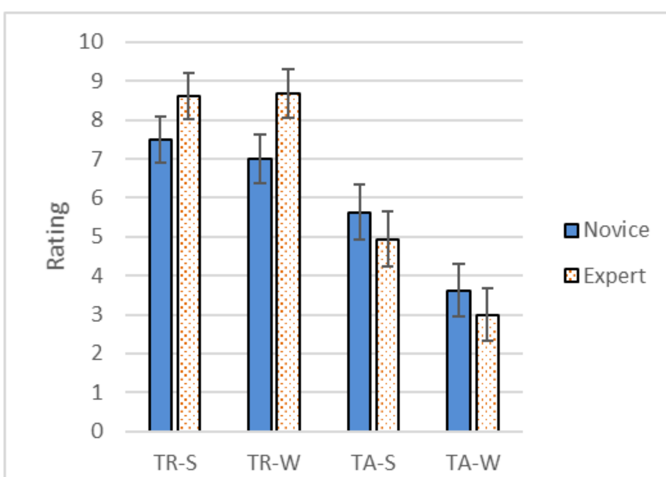

Figure 8. Intent to use (10 = best). Error bars represent ± 1 standard error.
TR = Trace, TA = Tap, S = Stand, W = Walk.

Hand Measurements

To determine whether there was any evidence of the "fat finger" issue, a series of correlations were conducted between performance, hand width, index finger width, and index finger length in both mobile conditions and both input methods. The range of participants' hand widths was representative of the first to 75th percentile of adult men and women (White, 1980). No significant correlations were found, $p > .05$ (r values ranged from –.27. to +.23).

Discussion

This study is the first to explore trace input on a smartwatch while walking. Our results show both trace and tap are efficient means of typing on a smartwatch while walking and standing. Users were able to achieve 35 WPM with trace and 30 WPM with tap, regardless of mobility or experience. These observed trace and tap typing speeds are among the fastest observed on a smartwatch even though users were standing or walking (see Appendix). The observed superiority of trace over tap is consistent with previous findings (Gordon et al., 2016; Turner et al., 2016). Surprisingly, experience with trace input on a smartphone had no significant impact on entry speed, an effect previously observed by Turner et al. (2016). It is possible the lack of difference between experts and novices is due to the increased variability in performance in the walking condition (participants were seated for Turner et al., 2016). Regardless, this suggests that users completely unfamiliar to trace input are able to quickly reach the performance level of trace experts when typing on a smartwatch after very little practice. In addition, users typed 32 WPM when standing and 30 WPM when walking; these speeds are nearly three times faster than other reported typing speeds on alternative smartwatch keyboards in stationary and mobile scenarios (Darbar, Dash, et al., 2016; Hong et al., 2016).

Prior experience with trace on a smartphone did not seem to have an effect on accuracy. Users typed more accurately with trace (10% WER) than tap (14% WER) and more accurately when standing (10% WER) than when walking (15% WER). These word error rates are consistent with other observed error rates on smartwatches (see Appendix). The increased error rate from standing to walking is consistent with the literature (Bergstrom-Lehtovirta et al., 2011; Darbar, Dash, et al., 2016; Hong et al., 2016). It is possible the higher error between trace and tap when walking is because tap input requires users to lift their finger before and after each keystroke. When walking, this task is even more difficult due to the constant motion of the body with each step. In contrast, trace requires the user to use one continuous motion to type, so the finger is always in contact with the screen. This is likely the reason why tap was rated as more frustrating than trace; however, future research should examine the biomechanics of each interaction method to investigate further.

Performance with both input methods and mobility conditions remained high despite key sizes, 4 mm x 3 mm, being significantly smaller than the recommended key size range for use with a smartwatch, 5.7 to 7 mm (Dunlop et al., 2014; Shao et al., 2016). In addition, no evidence of the "fat finger" issue or screen occlusion was found as performance was not related to hand or finger size.

We believe the observed superiority of trace over the alternative keyboards shown in the Appendix is attributable to three factors. First, users are already familiar with the QWERTY keyboard layout, resulting in a shorter learning curve than alternative keyboard layouts. Second, the small screen size required less distance for the user's finger to travel while typing, resulting in faster input. Third, the keyboard used in this study included an effective auto-correct feature.

Results of this study also add to the limited subjective data typically reported in smartwatch typing studies. Subjectively, trace was rated more favorably than tap across all measures. The perceived usability scores of both input methods fell within the marginally acceptable to acceptable ranges: *Good* for trace and *OK* for tap (Bangor, Kortum, & Miller, 2009). With the exception of perceived frustration, users reported no difference in perceived workload, a finding supported by Sonaike, Bewaji, Ritchey, and Peres (2016). Users also perceived their performance as better when using trace and indicated they would prefer to use trace over tap if given the choice when typing on a smartwatch. Standing was consistently rated more favorably than walking, as expected. Thumb size has been shown to be correlated with user satisfaction when typing on smartphone keyboards (Balakrishnan & Yeow, 2008). Interestingly, no significant correlations between hand size, or finger size, and any of the subjective measures gathered were found in our study. One potential reason for this is that in Balakrishnan and Yeow (2008) all participants typed using a 3 x 4 key keypad and not a full QWERTY keyboard. It is likely the 3 x 4 key keyboard layout yielded more cumbersome typing behavior for users with larger thumbs.

Conclusion

This study expands upon the limited research on smartwatch typing and is the first to explore trace input on a smartwatch while walking. We demonstrated both tap and trace are efficient methods of typing on a smartwatch QWERTY keyboard in a mobile scenario. Users completely naïve to typing on a smartwatch were able to achieve high typing speeds with little practice. Trace input appears to be especially well suited for typing on a smartwatch as users were able to type 30–35 WPM depending on the mobility condition, regardless of prior experience with trace. In addition, users subjectively rated trace easier to use, preferred it over tap, and suggested they would use it in the future. Pulvirent (2015) notes, “To make smartwatches a long-term device and not simply a quick hit, manufacturers and developers are going to need to make them relevant and necessary for daily activities” (para. 6). We believe the addition of a familiar, easy-to-use keyboard that yields accurate typing is both relevant and necessary. Smartwatch manufacturers should include QWERTY keyboards with trace input as a standard feature.

Limitations

While this study investigated more realistic smartwatch usage than sitting at a desk, it was still conducted as a controlled study in a laboratory setting. A treadmill was used to simulate normal walking behavior so we could investigate typing performance in a steady, walking condition. Treadmills have been used to simulate walking environments in other studies; one benefit of treadmill use is that the participant must maintain a steady walking pace. Walking in more natural environments, while more ecologically valid, results in inconsistent gait, as well as starting and stopping. More research should be done to examine typing performance in such environments where distractions are more likely to occur. In addition, this study evaluated college aged individuals who are most likely to be interested in using smartwatch technology. It is unknown how the results from this study would transfer to older age groups less familiar with the technology. Future research should include a wider range of ages, experience, and education levels to test the generalizability of these results.

Recommendations

The following are recommendations for the development of smartwatch keyboard technology and for future smartwatch studies:

- Smartwatch manufacturers should incorporate a trace based QWERTY keyboard in all smartwatch designs.
- Developers of novel keyboards should emphasize the importance of gathering subjective measures to inform design improvements from the user’s point of view.
- Future studies should compare trace input against alternative keyboards, such as WatchWriter and Swipeboard, in different mobile scenarios on different smartwatch designs to see if the superiority of trace generalizes to different mobile scenarios and smartwatch designs.
- Future studies should seek to explore different user age groups, experience, and education levels.

Tips for Usability Practitioners

The following are suggestions for usability practitioners:

- Familiarity with keyboard layout may help new users learn new typing techniques quickly.
- Subjective ratings in addition to performance ratings should be collected when studying mobile device text input to provide the maximal insight to user satisfaction and acceptance.

- Treadmills can be used in lieu of more natural walking tasks to provide a controlled simulation of walking.
- Partial counterbalancing of experimental conditions should be used to minimize participant fatigue in mobile conditions.

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Appendix: Observed Typing Performance and Subjective Measures on Smartwatch Sized Keyboards

Keyboard	Reference	Participants	Participant Mobility	Entry Speed (WPM)	Error Rate %	Subjective Measures
Callout	Leiva, Sahami, Catalá, Henze, & Schmidt, 2015	20	Seated	4.3[1]	2.6[CER]	NASA-TLX, SUS
				7.1[1]	0.8 [CER]	
				8.3[1]	0.7 [CER]	
DriftBoard	Shibata et al., 2016	10	*	9.7[2]	0.6 [ER]	-
DualKey[QWERTY]	Gupta & Balakrishnan, 2016	10	*	19.6[3]	5.3[TER]	Q & A
DualKey[SWEQTY]	Gupta & Balakrishnan, 2016	8	*	7.1[1]	0.8 [CER]	Q & A
ETAO	Darbar, Dash, & Samanta, 2016	10	Seated	8.3[1]	0.7 [CER]	Perceived Learning Time
			Walking	9.4[3]	7.1[TER]	
Fleksy	Chaparro, He, Turner, & Turner, 2015	18	Seated	20.3[3]	16.0[TER]	NASA-TLX, SUS, Perceived Performance & Preference
ForceBoard	Hsiu et al., 2016	12	*	12.4[1]	9..2[TER]	User Preference
Invisiboard	Mottelson, Larsen, Lyderik, Strohmeier, & Knibbe, 2016	12	*	9.5[2]	3.2[MWD]	-
Optimized Alphabetic Layout (OAL)[4]	Komninos & Dunlop, 2014	20	*	8.1[3]	-	NASA-TLX, Qualitative Feedback
QWERTY-like Keypad (QLKP)	Hong et al., 2015	12	*	9.2[3]	4.3[TER]	Questionnaire, Preference Ratings
SlideBoard	Hong et al., 2015	12	*	12.1[3]	7.9[TER]	Questionnaire, Preference Ratings
SplitBoard	Hong, Heo, Isokoski, & Lee, 2016	12	Seated	14.8[3]	9.0 [TER]	Questionnaire, Preference Ratings
		18		10.5[3]	14.0 [TER]	
		12	Standing	11.5[3]	11.0 [TER]	
				15.0[3]	8.0 [TER]	
				14.5[3]	7.0 [TER]	
			Walking	13.0[3]	12.0 [TER]	
	Hong et al., 2015	24	*	14.8[3]	7.5 [TER]	Questionnaire, Preference Ratings
	Hsiu et al., 2016	12	*	11.9[3]	10.1[TER]	User Preference
	Darbar, Dash, & Samanta, 2016	10	Seated	12.2[3]	10.5 [TER]	Perceived Learning Time
			Walking	9.3[3]	12.8 [TER]	
Standard QWERTY	Hong et al., 2016	12	Seated	13.7[3]	21.0 [TER]	Questionnaire, Preference Ratings
		18		10.0[3]	28.0 [TER]	
				12.0[3]	20.0 [TER]	
				14.5[3]	20.0 [TER]	
		12	Standing	13.0[3]	23.0[TER]	
			Walking	13.0[3]	23.0[TER]	
	Hong et al., 2015	12	*	12.9[3]	21.4 [TER]	Questionnaire, Preference Ratings
		10	Seated	7.1[3]	22.1 [TER]	Perceived Learning Time

Keyboard	Reference	Participants	Participant Mobility	Entry Speed (WPM)	Error Rate %	Subjective Measures
	Darbar, Dash, & Samanta, 2016		Walking	5.2[3]	28.5 [TER]	
Swipeboard Alphabetical	Shao et al., 2016	12	*	7.3[3]	9.0 [CER]	Questionnaire, Interview
Swipeboard QWERTY	Chen, Grossman, & Fitzmaurice, 2014	8	*	19.6[2]	17.5 [TER]	-
	Shao et al., 2016	12	*	7.2[3]	10.0[CER]	Questionnaire, Interview, Preference
SwipeKey4	Shao et al., 2016	12	*	11.0[3]	4.4 [CER]	Questionnaire, Interview, Preference
SwipeKey5	Shao et al., 2016	12	*	10.9[3]	7.4 [CER]	Questionnaire, Interview, Preference
Swype Tap	Turner, Chaparro, & He, 2016	16	Seated	27.0[3]	8.0 [TER]	NASA-TLX, SUS, Intent to Use, Perceived Performance & Preference
		16		26.0[3]	5.0 [TER]	
Swype Trace	Chaparro et al., 2015	18	Seated	29.3[3]	9.0 [TER]	NASA-TLX, SUS, Perceived Performance & Preference
	Turner et al., 2016	16		31.0[3]	6.0 [TER]	NASA-TLX, SUS, Intent to Use, Perceived Performance & Preference
		16		37.0[3]	5.0 [TER]	
UniWatch[4]	Poirier & Belatar, 2016	5	Seated	9.8[3]	-	-
Virtual Sliding QWERTY (VSQ)	Cha, Choi, & Lim, 2015	20	Seated	10.8[2]	-	Preference, Ease of Use
				11.7[2]	-	
				11.3[2]	-	
				10.6[2]	-	
				10.0[2]	-	
WatchWriter Gesture	Gordon, Ouyang, & Zhai, 2016	18	Seated	24.0[3]	3.7 [CER]	-
WatchWriter Tap	Gordon et al., 2016	18	Seated	22.0[3]	1.5 [CER]	-
ZoomBoard	Oney et al., 2013	6	*	9.3[2]	-	Qualitative Survey
	Chen et al., 2014	8	*	17.1[2]	19.6[TER]	-
	Mottelson et al., 2016	12	*	9.3[1]	2.1[MWD]	-
	Hong et al., 2015	12	*	9.2[3]	7.1 [TER]	Questionnaire, Preference Ratings
	Leiva et al., 2015	20	Seated	6.0[2]	1.1 [CER]	NASA-TLX, SUS
				7.8[2]	1.2 [CER]	
				8.2[2]	1.4 [CER]	
	Hong et al., 2016	12	Seated	9.8[3]	7.0[TER]	Questionnaire, Preference Ratings
		18		8.0[3]	10.0 [TER]	
				9.0[3]	6.0 [TER]	
				9.0[3]	7.0 [TER]	
		12	Standing	9.0[3]	5.0 [TER]	
			Walking	8.5[3]	8.0 [TER]	

Keyboard	Reference	Participants	Participant Mobility	Entry Speed (WPM)	Error Rate %	Subjective Measures
	Hsiu et al., 2016	12	*	9.5[3]	6.1[TER]	User Preference
	Darbar, Dash, et al., 2016	10	Seated	8.7[3]	8.6[TER]	Perceived Learning Time
			Walking	8.0[3]	9.8[TER]	
ZShift	Leiva et al., 2015	20	Seated	5.4[1]	1.3[CER]	NASA-TLX, SUS
				7.2[1]	1.3[CER]	
				9.1[1]	0.9[CER]	

[*] Mobility not specifically stated, [1] Observed on a smartphone, [2] Observed on a tablet, [3] Observed on smartwatch,
[4] Did not use phrase set from MacKenzie and Soukoreff (2003)

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