Why Is Gesture Typing Promising for Older Adults? Comparing Gesture and Tap Typing Behavior of Older with Young Adults

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ABSTRACT
Gesture typing has been a widely adopted text entry method on touchscreen devices. We have conducted a study to understand whether older adults could gesture type, how they type, what are the strengths and weaknesses of gesture typing, and how to further improve it. By logging stroke-level interaction data and leveraging the existing modeling tools, we compared the gesture and tap typing behavior of older adults with young adults. Our major finding is promising and encouraging. Gesture typing outperformed the typical tap typing for older adults, and was very easy for them to learn. The gesture typing input speed was 15.28% higher than that of tap typing for 14 older adults who had none gesture typing experience in the past. One of the main reasons was that older adults adopted the word-level inputting strategy in gesture typing, while often used the letter-level correction strategy in tap typing. Compared with young adults, older adults exhibited little degradation in gesture accuracy. Our study also led to implications on how to further improve gesture typing for older adults.

Author Keywords
Text Entry; gesture typing; older adults.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation: User Interfaces-Input devices and strategies.

INTRODUCTION

The American population is aging at a rate never seen before. The number of older adults (i.e., ages 65 years or older) is projected to be more than doubled from 46 million (14.5% of population) in 2014 to over 98 million (23.5% of population) by 2060 [27], as the baby boomers – those born between 1946 and 1964 – are aging. In parallel to the rapid expansion of the aging population, older adults are also moving towards more digitally connected lives: around four-in-ten (42%) older adults now report owning smartphones, up from just 18% in 2013 [1].

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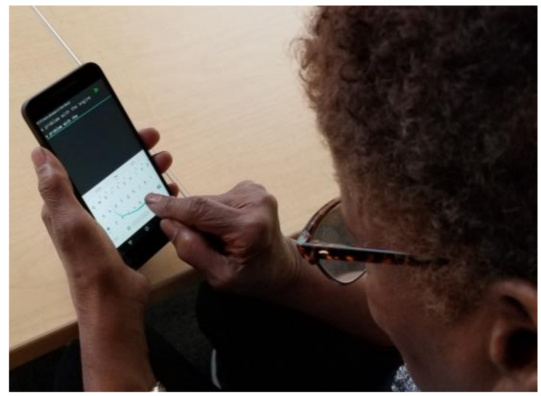

Figure 1. An older adult was gesture typing in the study.

Despite the sharp growth in mobile device adoption, older adults are struggling with using these devices [20]. One of the greatest challenges is to enter text, which is the basic method for communication (e.g., emailing and messaging), and the cornerstone for high level activities such as searching, filling on-line forms, social networking, etc.

Why is entering text challenging for older adults? First, text entry itself is already difficult for the general population regardless of the age: it is difficult to land a relatively large finger on small keys on a phone-sized virtual keyboard. Second, the age-related degradation in motor control ability, visual acuity, and cognitive ability exacerbates the problem for older adults. It is even harder for older adults to search for and acquire small keys.

The difficulty of text entry has prevented older adults from reaping the benefits of mobile computing at the same level as younger adults. Kurniawan et al. 's study [20] showed that some older adults even tend to be panic when dealing with text messages; some also think that it would be impolite not to reply immediately.

The text entry technique has advanced considerably as the smartphones has becoming increasingly popular. One of the breakthroughs was *gesture typing* [19], which supports a user to enter a word by gliding the input finger from letter to letter without lifting it off. Gesture typing has possessed a number of advantages over the typical tap typing: it is immune to a major problem plaguing regular touchscreen typing: the lack of tactile-feedback, and allows users to express intended words with approximate shape and location finger strokes, rather than precisely tapping on the corresponding keys. To date, it is enabled in many large-scale commercial or freely downloadable keyboard products (e.g., Google Gboard, Microsoft SwiftKey, and TouchPal), has been adopted by a number of languages, and has been used by hundreds of millions of users all over the world.

Given the success of gesture typing among the general population, would it work for older adults? The answer is not immediately obvious. Previous research has shown both positive and negative evidence. On the one hand, Kobayashi et al.'s research [17] shows that older adults in general prefer sliding or dragging over tapping, as tapping requires repetitive finger take-off and land-on actions. Nicolau et al.'s [26] research on five text entry methods showed older adults were slightly faster with tracing than with typing. On the other hand, it is known that older adults often undergo age-related degradation in motor control ability[14], which might prevent them from freely drawing gestures. Because of the decline of procedure memory, their ability of learning new skills degraded [13]. It might prevent them from learning gesture typing, which is a new typing paradigm than the typical tap typing.

Facing evidence from both sides, we have carried out a study to compare the gesture and tap typing behavior of older adults with young adults. We aim to answer the following questions. Is gesture typing a promising text entry method for older adults? If so, why? What are its strengths and weaknesses compared with tap typing? How will older adults gesture type differently from young adults? By logging stroke-level events (i.e., key strokes and gesture strokes) in a 28-user lab study, we were able to perform a *model-based*, *stroke-level* analysis between older and young adults for both gesture and tap typing, leading to a number of novel findings.

Our main finding is that gesture typing is a very promising text entry method for older adults. It outperformed the typical tap typing for the 14 older adults, who had none gesture typing experience at all (13 of them had not even heard of it before the study). The average input speed of gesture typing was 15.28% faster than that of tap typing. One reason was that gesture typing prompts older adults to adopt a word-level inputting strategy: waiting until the end of a gesture to correct errors, while they often used a letter-level strategy for tap typing: correcting any letter errors immediately as they appear, which prevented them from benefiting from the word-level correction power of the modern statistical decoding technology. Our study showed that the accuracy of gestures of older adults did not degrade compared with young adults, although they were slower at gesturing, especially with long gestures. Our research also revealed the behavior patterns of gesture typing in both temporal and spatial dimensions for older adults, and leading to implication on how to design text entry technology for older adults.

RELATED WORK

Our research is built upon the prior work in text entry techniques for general population, text entry techniques for older adults, and age-related ability degradation.

Text Entry Techniques for General Population

Text entry techniques have advanced a great deal in the past decades. Our research is particularly related to the following two breakthroughs: gesture typing and statistical decoding.

Since introduced in 2004 by Kristensson and Zhai[19], gesture typing has gained large adoption worldwide. It has been extended to accommodate a variety of input modalities and support various scenarios. Bi et al. created a bimanual gesture keyboard [4], which allowed one word to be entered by multiple strokes using both hands. Markussen et al. investigated gesture typing in mid-air [23], Yu [36] explored using head movement to perform gesture typing, while Yeo et al. [34] explored using device tilt angle for gesture typing.

On the tap typing front, one breakthrough is the wide adoption of the statistical decoding algorithm [11, 32]: instead of mapping a touch point to the corresponding key based on whether it falls within the key boundary, this algorithm infers a probability distribution over multiple keys based on its spatial relation to keys (i.e., spatial model) and language context (i.e., language model). To date, the statistical decoding algorithm has been adopted by almost all the commercially available keyboards. Previous research has shown that the statistical decoder could reduce the input errors more than 70% [3], and its performance could be further improved by adapting the spatial model to postures[2, 6, 7], activities, and individuals [10, 36], or personalizing language models [9].

Text Entry Techniques for Older Adults

It has also long been recognized that text entry is challenging for older adults. Nicolau and Jorge [26] investigated older adults' typing behavior on a simplistic touchscreen keyboard without any correction or prediction ability. Their research showed that the error rates of older adults were higher, and the most common types of errors were omission, followed by substitutions and insertions. They further suggested using language models to correction errors, which was one of the topics investigated in this paper (i.e., effect of a statistical decoder for older adults). Smith and Chaparro [31] compared the performance of five smartphone text entry methods, voice, physical keyboard, virtual keyboard, tracing, and handwriting, between older and young adults. Their research showed that voice and physical keyboard were the most effective methods, while handwriting was the least effective. Interestingly, their study showed tracing (a.k.a gesture typing) slightly outperformed tap typing. This finding motivated us to carry out the current study focusing on the stroke-level behavior of gesture and tap typing, to understand why gesture typing could be more suitable for older adults, and why the existing tap typing did not work well for older adults.

A number of methods have also been proposed to improve text entry performance for older adults. Hagiya et al. developed Typing Tutor [12], an individualized tutoring system for older adults; Rodrigues et al. [30] explored highlighting the most probable next letter, or enlarging its size, to ease the typing for older adults; Komninos et al. proposed the MaxieKeyboard[18], which highlighted errors, auto-corrections and suggestion bar usage, for older adults. The understanding gained from our study would in turn guide the design of appropriate text entry methods for older adults.

Age-related Ability Degradation

Older adults undergo age-related degradation in various abilities. Motor control ability declines as adults are aging: the execution of movement becomes slower and more variable [15, 33]. In Fitts law tasks (i.e., aimed rapid pointing tasks) [8], older adults tend to move slower than young adults at all levels of difficulty [16], and demonstrate higher variability in the trajectory and end-point position, compared with young adults. Visual acuity also declines as adults age [13, 25]. Presbyopia, or the inability to change the eyes focal length, is so common during the last half of life that most people over age 40 have experienced it [28]. Additionally, the cognitive processing ability also deteriorates as adults age [13, 29]. More specifically, procedural memory – knowledge about how to perform activities, declines. Although the well-learned behaviors (i.e., automatized procedures prior to senescence) remain intact, older adults have difficulty developing new automatic processes (conceptually like developing new habits) [29].

The research on age-related degradation shows that gesture typing could be challenging to older adults, because it is a new input method which might require learning, and it might be challenging for older adults to draw gesture strokes due to the degraded motor ability. These disadvantages could offset the potential benefits shown in other research. It serves as another motivation of the current work: to understand overall how well older adults perform in gesture typing considering all the advantages and disadvantages.

GESTURE AND TAP TYPING BEHAVIOR OF OLDER ADULTS

We have conducted a control experiment to compare the performance and behavior of gesture and tap typing between older and young adults.

Experimental Setup

Design

We adopted a 2 × 2 mixed factorial design. The between-subject independent variable was *user group* (older and young adults), and the within-subject independent variable was *keyboard type* (gesture and tap keyboards). The dependent variables included input speed, error rates, backspace used per word. Each participant was asked to complete phrase transcription tasks on two keyboards. The order of keyboard type was counter balanced within each user group. Each task consisted of 4 blocks, each block containing 5 phrases. The order of the phrases in each block was randomized.

Task and apparatus

A Nexus 5X smartphone running Android 6.0.1 with a 5.2 inch 1080 × 1920 display was used in this study. A customized Google keyboard with logging feature was used.

Figure 2. shows the screen shots of the text entry app used in this study. The app prompted target phrases on top of the screen. A subject repeated the phrases by typing on the keyboard. The subjects were instructed to type naturally as fast as possible also as accurate as possible. When the subject finished repeating the phrase, she pressed the green arrow button to submit, then the app prompted next phrase to be entered. Every touch event was recorded during the study session. The phrases were randomly selected from a subset of Mackenzie and Soukoreff phrase set [22, 35]. The same set of phrases were used in the study. Each participant spent around 40 minutes to complete the study.

Procedure and participants

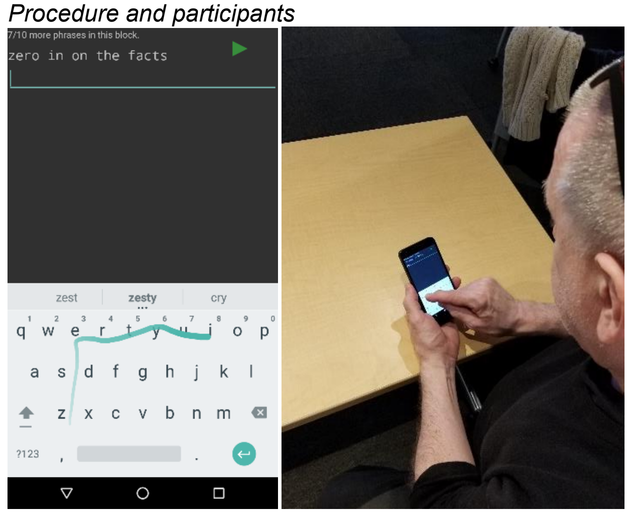

Figure 2. Experimental Setup.

14 young adults (1 female) aged from 24 to 34 were recruited with the help of university mailing list and bulletin boards. As for older adults, they were recruited in Senior Planet Center in New York City via emails and posters. Their ages ranged from 65 to 81, and they were all in good health conditions and had no vision or motor deficit. We used the default settings in Google keyboard, with suggestion, prediction and vibration enabled. Each subject practiced prior to each condition, and they chose their preferred posture. All the subjects typed using one hand to hold the phone. The orders of the conditions were counterbalanced.

The self-reported familiarity with tap typing and gesture typing were based on a five-level Likert scale (1: Never heard of it, 5: expert). The medians of the young adults' familiarity were both 4 in tap typing and gesture typing, and the medians of the older adults' familiarity were 5 and 1 in tap typing and gesture typing, respectively.

We asked participants to come to our lab for the study. We then gave a briefing of the tasks and asked the participants to sign the consent forms. If the user agreed to do the study, we then gave a 5 minutes tutorial on how to use the keyboards. Participants were also given a warm up session that required them to type 5 phrases before going to the formal session.

In total, our study included:

14 subjects × 2 groups × 4 blocks × 5 phrases = 560 phrases

Results

We first analyzed the performance metrics such as speed and error rates, and then analyzed the detailed typing behavior.

Speed

The input speed was calculated following [21]:

$$WPM = \frac{|S-1|}{T} \times \frac{1}{5}$$

where S is the length of the presented string in character, T is the time elapsed in minutes from the start of the first touch down event of the first gesture stroke to the moment pressing the next button. On average each English word has 5 letters (including space). 1/5 was used to convert "character per minute" into "word per minute", as explained in [22].

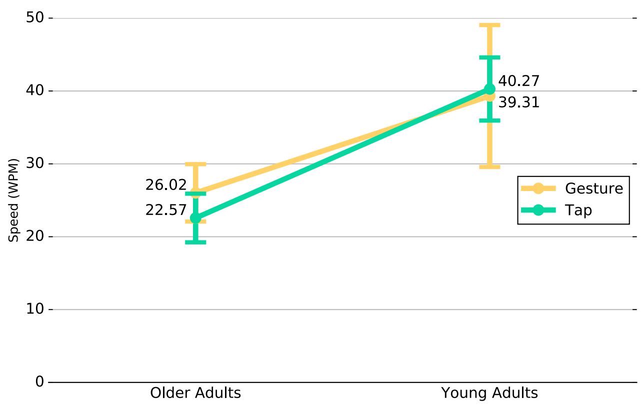

Figure 3. Mean (95% CI) Input Speed.

Figure 3 showed the means (95% confidence interval) of input speed of gesture typing and tap typing across all the participants for both older and young groups. The mean speed (SD) in WPM for older adults were 26.02 (6.82) for gesture typing, and 22.57 (5.78) for tap typing. For young adults, the average speed (SD) were 39.31 (16.88) for gesture typing, and 40.27 (7.50) for tap typing. ANOVA showed a main effect of keyboard type on the input speed within older adults group ($F_{1,13}$ =4.901, p<.05), but not within young adults group ($F_{1,13}$ =0.089, p=.77). There was also a significant main effect of user group on input speed ($F_{1,26}$ =20.29, p<.001). No significant interaction was observed between user group and keyboard type either ($F_{1,26}$ =1.50, p=0.229).

We also compared the input speed by block for each keyboard condition, as shown in Figure 4. For older adults, as shown the average speed within each block for the gesture typing was lower than tap typing for the first 2 blocks, but higher in the last 2 blocks. For young adults it was not the case. The speed of gesture typing was slower than tap typing on any block number. ANOVA showed a significant main effect of the block number on the input speed within older adults group ($F_{3,78}$= 8.854, p<.001), but not within young adults group ($F_{3,78}$=0.883, p=.453). There was also a significant keyboard × block interaction effect observed ($F_{3,162}$= 3.968, p<.001).

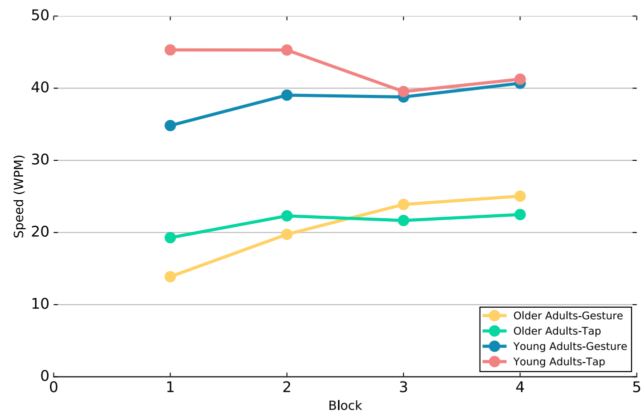

Figure 4. Mean Input Speed by Block

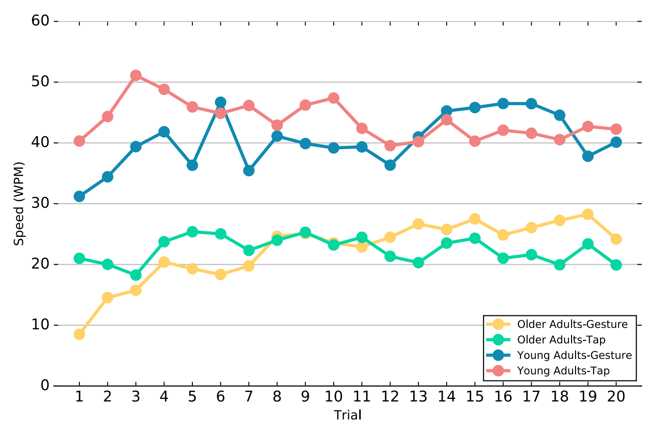

Figure 5. Mean Input Speed by Phrase Order

Figure 5. showed the input speed by each trial, indicating a trend of growing of speed by trail number when using gesture typing.

To understand why older adults typed slower than young adults, especially for tap typing. We analyzed the number of keystrokes per word, and the average time of entering a keystroke in tap typing. As shown in Table 1, older adults tended to use keystrokes per word, and their speed was slower for each keystroke, compared with young adults. The average length of a word in the tested data set was 5.3

(including space). The extra keystrokes were likely caused by the usage of backspace, which was analyzed later.

	Keystrokes used per word	Seconds per keystroke
Older Adults	6.6	0.56
Young Adults	5.27	0.36

Table 1. Number of keystrokes per word, and average time of entering a keystroke in tap typing.

Error rate

Since both gesture and tap typing keyboards performed word-level corrections, we measured error rate with word error rate. The word error rate [3] is based on minimum word distance (MWD), which is the smallest number of word deletions, insertions, or replacements needed to transform the transcribed string into the expected string. The word error rate is defined as:

$$r = \frac{MWD(S,P)}{WordCount(P)} \times 100\% \qquad \text{(Eq. 1)}$$

where MWD(S, P) is the minimum word edit distance between transcribed phrase S and the target phrase P, and WordCount(P) is the number of words in P.

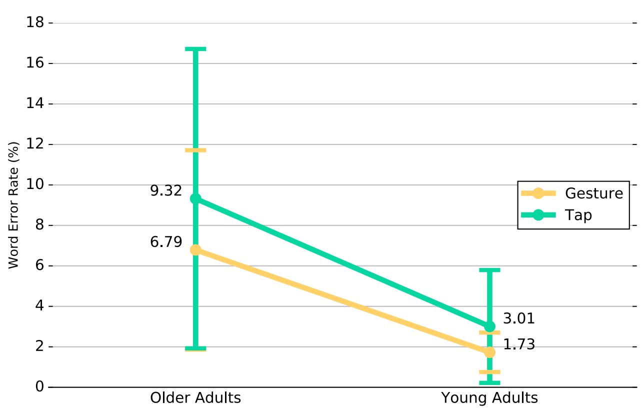

Figure 6. Mean (95% CI) Word Error Rate

Figure 6. shows the means (SD) of word error rate of gesture typing and tap typing across all the participants for both older and young groups. The mean WER for older adults were 6.79% (SD=8.53%) for gesture typing, and 9.32% (SD=12.81%) for tap typing. For young adults, the average WER was 1.73% (SD=1.69%) for gesture typing, and 3.00% (SD=4.82%) for tap typing. ANOVA did not show a main effect of keyboard type on the WER ($F_{1,26}$=0.846, p=0.366). There was a significant main effect of user group on WER ($F_{1,26}$=6.33, p<.05). No significant interaction was observed between user group and keyboard type ($F_{1,26}$=0.092, p=0.764).

Backspace usage

To understand how users corrected their mistakes, we measured the backspace key usage. We defined backspace to words ratio as:

$$d = \frac{N_d}{WordCount(P)} \qquad \text{(Eq. 2)}$$

where N_d was the number of backspace key presses in one trial, P was the target phrase in this trial, and $WordCount(P)$ was the total number of words in P. For older adults, the backspace usages were 0.41 (SD=0.38) for tap typing, and 0.15 (SD=0.12) for gesture typing, while for young adults, the backspace usages were 0.33 (SD=0.32) for tap typing, and 0.13 (SD=0.09) for gesture typing.

Furthermore, in tap typing we divided the backspace usage into two situations: intermediate backspace and non-intermediate backspace. In the former the user pressed the backspace key before they reached the end of a word; in the latter, backspace was pressed after the user reached the end of a word. The former reflected that a user tried to correct letter-level errors before the end of the word.

The intermediate backspace usage was 0.17 (SD=0.19) for older adults and the intermediate backspace usages for young adults were 0.18 (SD=0.16). Besides, ANOVA showed a main effect of keyboard type on the intermediate backspace within older adults group ($F_{1,13}$ =6.869, p<.05), and within young adults group ($F_{1,13}$ = 6.537, p<.05) and also for keyboard type ($F_{1,26}$ = 13.029, p<.05). ANOVA did not show significant main effect of user group (F1,26 = 0.499, p = 0.486). No significant interaction was observed between user group and keyboard type ($F_{1,26}$ = 0.495, p=0.48817).

For non-intermediate backspace, the usage was usage was 0.24 (SD=0.25) for older adults and 0.15 (SD=0.19) for young adults. ANOVA show a main effect of keyboard type within young adults group ($F_{1,13}$ = 13.59, p<.05) and also for keyboard type ($F_{1,26}$ = 8.176, p < .05), but no significant main effect in older adults group ($F_{1,13}$ = 0.024, p=0.879) or between user group ($F_{1,26}$ = 0.784, p = 0.384). There was a significant interaction between user group and keyboard type ($F_{1,26}$ = 7.036, p < .05).

Subjective preferences

At the end of study, each subject was asked to provide a continuous numerical rating of the overall impression of the keyboard (1-least like, 5-most like). As shown in Figure 7, the ratings of gesture keyboard were higher than tap typing keyboard in both user groups.

Since subjective preferences were provided as continuous numerical values, we performed ANOVA on it. It did not show a significant main effect of keyboard type ($F_{1,26}$ = 0.237, p = 0.630), or user group ($F_{1,26}$ = 0.415, p = 0.525) on preferences. No interaction effect between user group and keyboard was observed ($F_{1,26}$ = 2.824, p < .105). No significant main effect of keyboard type was observed within older adults ($F_{1,13}$ = 0.16, p = 0.696) or young adults ($F_{1,13}$ = 3.37, p = 0.0893) either.

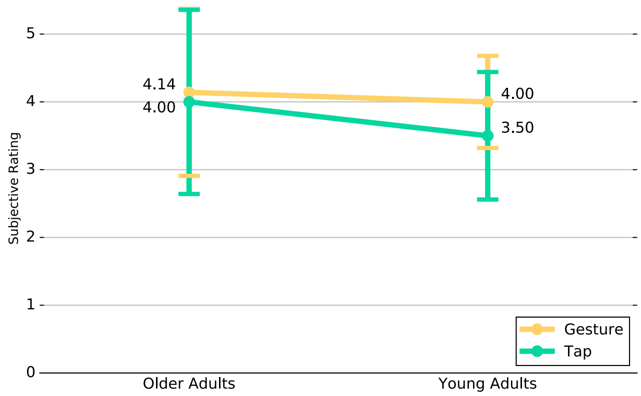

Figure 7. Mean(SD) of subjective rating of keyboards by group.

Touch point distribution

In this section we analyze the distributions of touch points based on keystrokes for older adults and compare them with young adults. The size of the keyboard used in this study was the input area size of the default Google keyboard on a Nexus 5X device (1080 × 825 pixels), each key occupies a rectangular area of 108 × 165 pixels.

Figure 8 showed the distributions of the touch points for each key for tap typing keyboard in both user groups. The mean offsets from key centers were 0.92, 10.06 pixels in x,y-axis for older adults, -1.34, 6.82 pixels in x,y-axis for young adults. The mean standard deviation of all distributions were 87.61 ,46.06 pixels in x,y-axis for older adults , 73.33, 42.82 pixels in x,y-axis for young adults. As shown, the touch points tended to spread wider for older adults than young adults.

If we divide the Qwerty layout into two halves according to [24], the mean offsets from key centers in x-axis were 5.46 pixels for keys on the left, and -5.26 pixels for keys on the right (for older adults). For young adults, the mean offsets in x-axis were 9.92 pixels for keys on the left, and -16.69 pixels for keys on the right. This indicated a tendency of typing towards the center of the keyboard. However, the difference was significant for young adults ($F_{1,24} = 29.02$, $p < .05$), but not for older adults ($F_{1,24} = 2.192$, $p = 0.152$).

We also observed variances in the offsets in the y-axis for touch points on different rows of the keyboard. From the top row to the bottom row, the mean offsets were 17.41, 9.56, and 0.21 pixels for older adults, and 16.88, 6.17, and -6.73 pixels for young adults. There was a main effect of row number on the offsets within older adults group ($F_{2,23} = 6.683$, $p < .05$) and within young adults group ($F_{2,23} = 34.65$, $p < .05$).

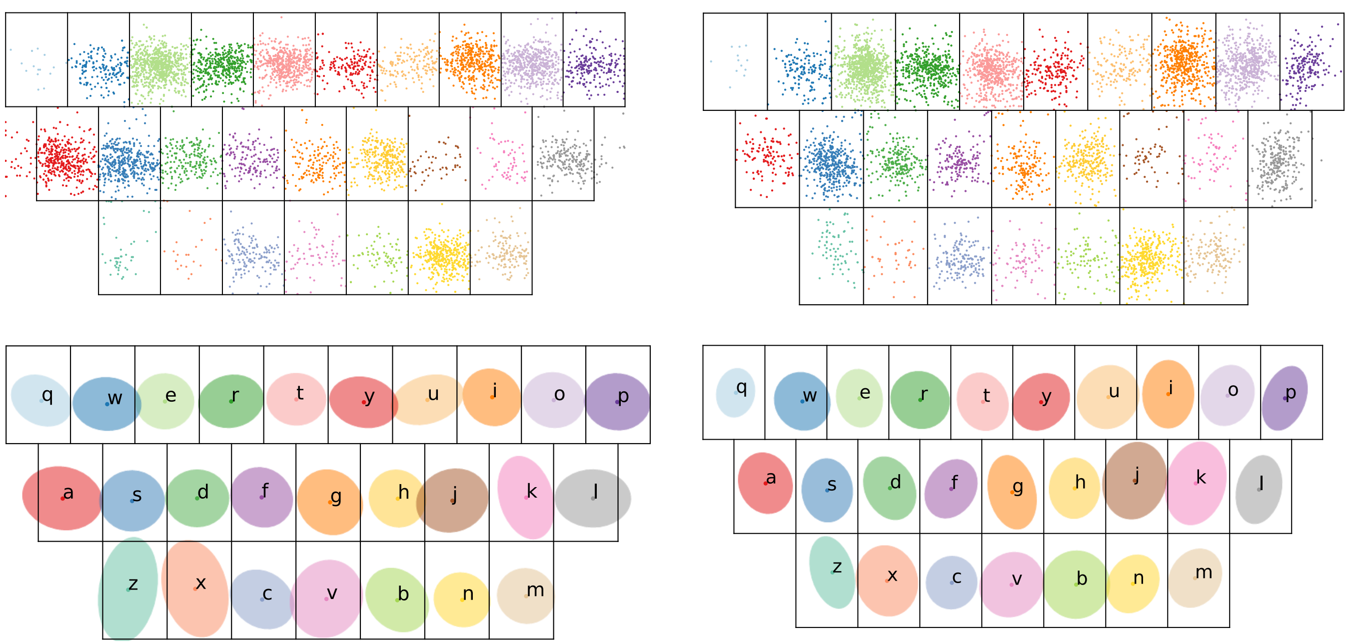

Figure 8. Touch point distribution for tap typing (scatter plots and 95% confidence ellipses). Left: Older adults. Right: Young adults.

MODELING GESTURE TYPING SPEED WITH CLC MODEL

To further understand how fast older adults could gesture type, we use the CLC model [5] which stands for "curves, line segments, and corners" to model the production time of the gestures for both older and young adults. The model partitions the gesture into segments, where each segment is a curve (with a constant radius of curvature), a straight line, or a corner (whose interior angle does not need to be 90°). The time that it takes for a person to gesture each type of segment is modeled with a different function. For line segments, the time is modeled with a power function that echoes how people tend to gesture faster with longer lines:

$$T(line) = mL^n \qquad \text{(Eq. 3)}$$

in which L is the length of the line in pixel, m,n are empirically determined parameters.

Since a gesture template is composed of multiple straight lines, the gesture typing tasks could be modeled using the polyline model as described in the work of [5]. As shown in Cao and Zhai's work [5], the corner time was negligible compared with stroke time and could be accounted for in the line model, the gesture typing time could be modeled as:

$$T = \sum T(line) \qquad \text{(Eq.4)}$$

Which was the sum of time of drawing line segments in the polyline template. Figure 9 showed the gesture typing time per gesture length, and the modeling results.

Results

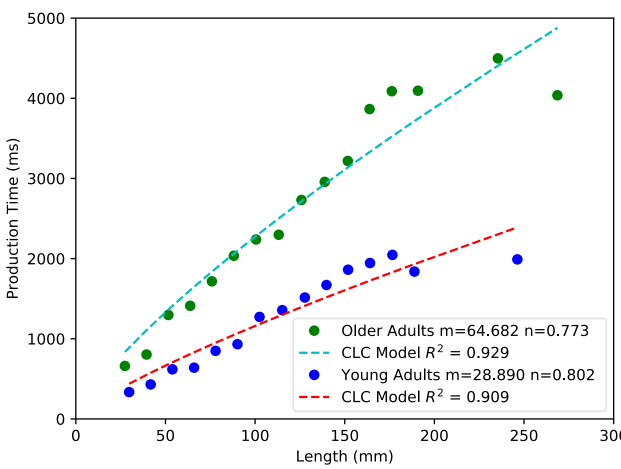

Figure 9. Gesture production time by length for older and young adults separately.

The fitted model T_o, T_y for older adults, young adults respectively were:

$$T_o = 64.68L^{0.773} \qquad \text{(Eq. 5)}$$

$$T_y = 28.89L^{0.802} \qquad \text{(Eq. 6)}$$

The R^2 value were 0.929, 0.908 for T_o and T_y respectively. As shown in Figure 9, both older and young adults' gesture typing speed were well modeled by the CLC model. The modeling results showed that young adults in general were faster than older adults. As the gesture got longer, the gap between older and young adults increase drastically.

Shape error and location error

To understand to what degree the gesture traces deviate from the word template on a virtual keyboard (i.e., connecting centers of letters with straight lines), we compared the *location error* and *shape error* between the actual gesture traces and word templates. Location error and shape error originated from the seminal SHARK2 gesture recognition algorithm [19]. The former reflects the absolute location distance, while the latter reflects the normalized shape difference, between gesture traces and the word templates. Since these two error terms were well defined and explained in [19], we skipped the detailed explanation in this paper. Greater errors indicate that the actual gesture deviates more from the word template.

The mean shape and location error were 0.0668(SD=0.04), 53.697 pixels (SD=28.3). For young adults, the mean shape and location error were 0.0725(SD=0.052), 53.65 pixels (SD=35.09), suggesting that the accuracy of gestures made by older adults did not degrade from the young adults. Figure 10 showed the sample gestures from older and young adults.

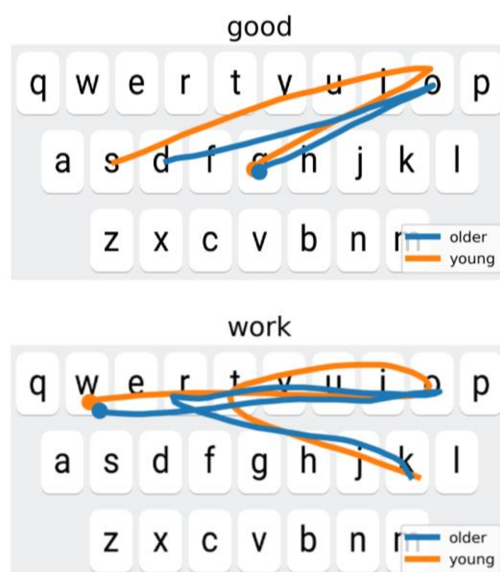

Figure 10. Gesture Samples for Older and Young Adults. The dot indicates the starting position and is for illustration only

DISCUSSION

Gesture typing outperformed tap typing for older adults

Our study showed that older adults performed better in gesture typing than in tap typing. Their average input speed in gesture typing was 26.02 WPM, 15.3% higher than the speed in tap typing (22.57 WPM). The error rates were 6.79%, 27.1% lower than that of tap typing (9.32%). The subjective ratings were also in favor of the gesture typing. In contrast, young adults showed similar performance between gesture and tap typing.

Surprisingly, although all of the 14 older adults had no prior gesture typing experience at all (13 of them had not even heard of gesture typing), they could quickly learn gesture typing. As shown in Figure 5, their average input speed was above 25 WPM after 10 phrases. Some participant commented gesture typing was natural to use, because the underlying action, sliding finger from one place to another was commonly seen in touchscreen interaction.

Why gesture typing is promising for older adults?

Our stroke-level analysis showed why gesture typing outperformed tap typing for older adults.

First, older adults often adopted a word-level inputting strategy in gesture typing: drawing a gesture and checking the outcome only after the finger was lifted off. In contrast, they often used a letter-level inputting strategy in tap typing: correcting errors with backspaces as soon as they appeared. The intermediate backspace usage was 41% among all the backspace usage for older adults, indicating that they often corrected intermediate letters before inputting the last letter of this word. As the existing statistical decoder works at the word level: correcting the errors after the word delimiter (e.g., space) was entered, the letter-level inputting strategy prevented older adults from enjoying the correction power.

Second, although older adults were slow at drawing gestures, they could draw them with high accuracy. Our analysis showed the shape errors of the gesture traces of older adults were even slightly smaller to that of young adults, and the location errors were similar. It showed the degraded motor ability had only minor effect on the accuracy of the gesture traces, which may contribute to the ease of gesture typing.

How to improve gesture typing for older adults?

Our study also revealed potential problems for gesture typing, providing implications for designing more efficient gesture typing technique for older adults.

First, it is considerably challenging for older adults to enter words with long gestures. Figure 9 showed that as the gesture becomes longer, it takes considerably longer time for older adults to draw, compared with young adults. Some older adults commented that it was hard for them to glide the finger over such a long distance. They wished they could stop, and enter the rest of the word with tapping.

It implied that older adults may benefit from mixing gestures and tapping for entering a word: entering some letters with gestures, and some with tapping. It would allow them to enjoy the best of both worlds. Entering a word with mixed gestures and tapping has been shown possible in Bi et al.'s work [4], and the corresponding algorithm has been developed too. It is worth testing it with older adults in the future.

How to improve tap typing for older adults?

Although the focus of our research was on gesture typing, our study also revealed the problems of the tap typing for older adults, implying how to further improve it.

First, a major reason that older adults performed poorly with tap typing was that they tended to correct every error they made along the way. In part, it was because they were unaware of, did not trust the auto-correction ability of the statistical decoder, or were reluctant to learn the expert typing mode: typing ahead and relying on auto-correction. Their text entry performance could be drastically improved if the keyboard UI design could encourage them to further take advantage of its auto-correction ability.

Second, our analysis of touch point distributions showed that the touch points of older adults tend to spread much wider than young adults, indicating that the spatial model of the decoder should be further modified to account for their typing behavior.

Third, the tap typing speed of older adults was drastically slower than that of the young adults. One reason is that older adults typed more strokes per word than young adults. The average number keystrokes per word of older adults was 6.6, 1.33 keystroke more than young adults. The average time needed to enter a key stroke was 55.6% longer than young adults. It suggested that older adults may benefit from technique that can save keystrokes (e.g., predicting the word based on partial input).

CONCLUSION

Our main finding is very promising and encouraging: gesture typing is well-suited for older adults. For 14 older adults who had zero experience of gesture typing in the past, their gesture typing speed was 15.3% faster than tap typing, and error rate was 27.1% lower. Gesture typing was also easy to learn for older adults, who achieved such performance within 20 minutes. The stroke-level behavior analysis showed that older adults adopted a word-level inputting strategy for gesture typing, opposed to the letter-level strategy for tap typing. Our study also revealed that older adults could draw gestures as accurately as young adults, despite the degradation of motor control ability. Overall, our research showed that gesture typing was very promising for older adults and provided implication on how to further improve it in the future.

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APPENDIX

Table 2 shows the touch point distribution for both older adults and young adults in tap typing.

Key	Older adults				Young adults			
	μ_x	σ_x	μ_y	σ_y	μ_x	σ_x	μ_y	σ_y
A	136.86	149.63	271.78	40.19	117.42	127.13	260.01	39.71
B	430.76	48.35	432.73	53.93	440.71	83.38	413.56	77.45
C	645.29	96.69	430.56	46.15	643.49	65.44	424.19	60.77
D	285.06	101.38	116.41	45.96	281.84	70.83	116.52	44.95
E	327.07	54.77	272.90	30.54	337.29	82.21	267.22	31.75
F	536.03	102.44	272.25	49.86	531.51	75.52	280.96	38.81
G	436.18	126.95	268.87	39.86	444.39	88.98	273.37	32.00
H	801.42	100.59	108.33	49.64	788.83	105.30	109.92	50.09
I	650.77	110.51	270.61	49.20	636.64	79.88	266.34	43.70
J	870.73	24.59	276.08	26.95	824.59	103.67	268.94	38.64
K	778.74	10.58	271.00	20.46	745.51	21.28	262.49	17.68
L	851.98	113.76	431.11	50.70	842.37	77.56	420.46	49.84
M	964.69	108.61	270.88	35.16	957.42	66.49	268.63	44.34
N	890.23	125.66	116.25	48.69	891.15	110.75	112.85	49.83
O	762.51	81.41	428.77	75.96	735.78	78.25	420.35	66.52
P	59.00	24.88	107.20	22.15	66.14	26.08	105.64	27.44
Q	968.74	206.23	116.26	47.32	1,003.71	63.02	115.10	44.23
R	233.37	102.69	274.19	42.18	225.86	82.66	270.12	36.51
S	383.85	81.17	115.03	39.18	386.24	42.32	113.10	29.19
T	710.45	64.84	112.27	43.49	702.32	48.49	116.48	58.25
U	486.85	98.42	112.68	39.34	492.41	71.27	120.07	41.07
V	203.01	137.83	128.61	56.73	203.93	136.63	116.92	30.13
W	540.09	87.69	424.55	70.24	529.94	35.07	433.92	21.07
X	601.93	64.90	116.05	33.24	598.16	44.75	117.18	36.82
Y	308.00	39.59	394.32	123.65	347.21	88.95	420.76	50.86
Z	200.41	13.62	451.91	16.88	230.42	30.60	412.14	51.62

Table 2. Touch point distribution (in pixels) of both older adults and young adults in tap typing. μ_x and μ_y are the mean of the touch points. σ_x and σ_y are the standard deviations of the touch points. The origin (x, y) = (0, 0) is on the top of the screen.

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