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Learning to type with mobile keyboards: Findings with a randomized keyboard

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A R T I C L E I N F O

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A B S T R A C T

This paper demonstrates the learning process of typing by tracing the development of eye and finger movement strategies over time. We conducted a controlled experiment in which users typed with Qwerty and randomized keyboards on a smartphone, allowing us to induce and analyze users' behavioral strategies with different amounts of accumulated typing experience. We demonstrate how strategies, such as speed-accuracy trade-offs and gaze deployment between different regions of the typing interface depend on the amount of experience. The results suggest that, in addition to motor learning, the development of performance in mobile typing is attributable to the adaptation of visual attention and eye-hand coordination, in particular, the development of better location memory for the keyboard layout shapes the strategies. The findings shed light on how visuomotor control strategies develop during learning to type.

1. Introduction

A long-standing objective of research in Human-Computer Interaction (HCI) is to improve our understanding of how skill impacts behavior, and how users learn new skills. In this paper, our focus is on the learning of typing, which is a complicated visuomotor task widely influencing the quality and efficiency of interactive behavior. One of the things that make this an interesting problem is the prevalence of the standard Qwerty layout, which persists today, even though multiple optimized soft keyboard layouts have been proposed. The major problem encountered by users of new layouts – even when these are optimized for usability – is the initial productivity decrement and the learning cost against existing motor patterns of typing (Gopher & Raij, 1988). Even switching two key locations on a Qwerty keyboard can lead to an increase in the key-searching time of an experienced typist; changes more drastic than this result in hours of re-learning, during which performance suffers (Jokinen et al., 2017).

When learning to type, users gradually transfer from a "hunt-and-peck" style to a more skilled one, by accumulating experience with repeated practice. As pointed out by (Sono & Hasegawa, 2019), learning and skill improvement in typing is concerned with three aspects: remembering key placement, proper fingering, and touch typing. Developments of the latter two aspects are closely related to the first one. Memorization of keyboard layouts helps to minimize the time needed for visual search (Jokinen et al., 2017), while at the same time, increases the certainty of finger touch operations on the flat screen of software keyboards. Via practice, users can further build internal mappings between the keyboard layout and finger movement control (Crump & Logan, 2010a). In this learning process, strategies for allocating attention and controlling finger movement are adapted to the improvement of the general typing performance. Understanding how users develop their skills with new keyboard layouts, and how the visuomotor control correlates with typing performance can help researchers and designers discover more effective ways of improving the interfaces of text input applications.

In this study, we focused on typing with software keyboards on touchscreen devices, and captured the details of eye and finger movements throughout the typing process with experimental control over the participants' level of skill. By dynamically randomizing the layout of a software keyboard, we artificially manipulated the participants' knowledge of the keyboard they were using, thus impacting their typing skills and performance. Firstly, skilled performance was analyzed with

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experimental data on a conventional keyboard with a Qwerty layout. Secondly, we assigned each participant a statically randomized (SR) keyboard, in which the keys were randomly shuffled before being assigned and kept unchanged during typing. We were able to observe the learning process and adaptations made throughout the trials of sentence typing, during which the participants started to become more familiar with the new layout. Finally, we applied a dynamically randomized (DR) keyboard, on which key locations were re-shuffled after each keypress. In this way, we were able to keep the participants' knowledge of the layout at a complete novice level throughout the trials of typing. In general, we not only compared the user behavior with different levels of typing skills but also observed the learning process of a new keyboard layout, from the perspective of eye and finger movement control.

The theoretical framework we used to understand the changes that are associated with the transition from novice to skilled typists is that of adaptation to available resources (Howes et al., 2009). We assume that as users become familiar with a UI, they develop certain resources and skills, such as robust memory of the layout and ways to access key functionalities. At the same time, their behavior adapts to account for these internal changes. For instance, in touchscreen typing, a novice begins without knowing the location of the keys, resulting in long intervals between typed keys due to time spent visually searching the keyboard (Jokinen et al., 2017, 2020). Our results emphasize that typing – and learning to type – should be understood as a complex adaptive process, where both the personal resources available within the individual user (e.g., motor movement, vision, memory) and the general strategy for how these resources are applied adapt to each typing environment.

Previous studies regarding typing have mainly focused on motor performance, that is, the movement of the fingers over the keyboard. However, as demonstrated in our results, familiarity with a layout impacts not only pointing movements but also other essential components of typing, such as proofreading and error correction. Novices have to spend time visually searching between keypresses, resulting in an emphasis on accuracy over speed. As they grow confident in accuracy, fewer gaze shifts between the keyboard (searching for the target key) and the text entry area (checking the typed text for errors) are needed. Becoming more familiar and confident with the keyboard layout by typing on it results in tolerating more errors due to the lower relative cost of having to find and retype characters. This also results in more gaze shifts for proofreading. Finally, as users become increasingly familiar with the keyboard layout, they type progressively faster, resulting in the introduction of more typing errors. However, these behaviors at a higher level of skill are not detrimental to performance, as they permit faster movement and minimize time spent between keystrokes. The making of errors has become an acceptable strategic tradeoff, allowing faster typing, because the cost of errors is not as large as when the layout is not known. Furthermore, as the eyes are not constantly needed to guide the movement of the fingers, a larger fraction of the total typing time can be spent on monitoring the typed text.

The contribution of our work is to present and explain the learning process in the early stages of the development of typing skills with new keyboard layouts. Based on the tracking and analysis of eye and finger movements, we describe a detailed dataset that sheds light on the small but impactful changes in visuomotor control strategies that are associated with learning. We explain how users adapt their strategy of speed-accuracy trade-off and proofreading behavior based on the development of their skills such as key-searching and finger movement. These findings provide a reference for designers aiming to improve UIs with layout reform considering different levels of typing skill, as well as for researchers developing mental models for behavioral strategy predictions. We hereby release all data from the experiments reported herein making them freely available for further research.

2. Related work

Typing on touchscreens has been studied for decades from the perspective of performance outcomes, such as speed and error rate. Although such metrics can provide quick and easy-to-understand results for purposes like technique validation, comparison, and evaluation, they are silent on more detailed yet essential typing-related behaviors, such as finger movement and shifts in visual attention. Recently, researchers have started to analyze and even model these more detailed behaviors, such as touchpoints (Azenkot & Zhai, 2012, pp. 251–260; Bi et al., 2013), eye movement (Jokinen, 2017; Jokinen et al., 2017; Sarcar et al., 2018), and finger movement (Feit et al., 2016; Jiang et al., 2020). Here we introduce the related work on understanding typing-related behaviors on mobile touchscreen devices.

2.1. *Typing performance on mobile devices*

Although it has been 30 years since the first smartphone was invented (Lewis, 1996), typing speed on mobile touchscreen devices is generally slower than on a physical keyboard [35, 23 39]. While the average expert typing speed on a physical keyboard can reach 81 words per minute (WPM) (Varcholik et al., 2012), typing speed on the smartphone is still below 50 WPM (Azenkot & Zhai, 2012, pp. 251–260). Studies have explored the factors which influence typing speed, including the number of fingers used (one finger or two fingers) (Azenkot & Zhai, 2012, pp. 251–260; Buschek et al., 2018; Jiang et al., 2020; Nicolau & Jorge, 2012), the size of the device (Yi et al., 2017) and the virtual keys (Kim et al., 2013), and the conditions of typing tasks (copy typing or memorized typing) (Varcholik et al., 2012). Several conditions that are related to higher typing speed were found, including two-finger typing (Azenkot & Zhai, 2012, pp. 251–260; Buschek et al., 2018; Jiang et al., 2020; Nicolau & Jorge, 2012), moderate key size (Kim et al., 2013), and memorized typing (Varcholik et al., 2012). Even though limitations and challenges exist for typing on touchscreen mobile devices, some fast typists can still reach speeds of over 80 WPM (Palin et al., 2019). This finding raises the question: could there be a learning regime – perhaps using intelligent tutoring – that could improve most users' typing performance considerably? In order to answer this question, it is important to improve our understanding of how learning occurs with touchscreen keyboards.

Errors happen more frequently during typing on touchscreen devices (between 7% and 10.8% (Azenkot & Zhai, 2012, pp. 251–260)) compared with typing on a physical keyboard (between 0.47% and 0.76% (Feit et al., 2016)). It is hard for users to ensure correct keystrokes without tactile feedback on the flat featureless screen. For a more detailed analysis of error correction, two situations were taken into account as metrics: 1) immediate error correction, meaning that users correct errors soon after they occur, with only one backspace and a correct keystroke; and 2) delayed error correction, indicating that the user realizes and corrects the error some moments after it happened. In the latter case, users have to press the backspace key multiple times and then input the correct letters. Typing on a mobile device with two thumbs results in more delayed error correction in typing each sentence (0.93) than with one index finger (0.41) (Jiang et al., 2020). One direct reason for errors in typing is the failure of the finger to land inside the bounding box of the keys.

Studies found that the touchpoints for keys are generally distributed below the center of the keys (Azenkot & Zhai, 2012, pp. 251–260; Henze et al., 2012), indicating that users prefer less occlusion of the buttons during key-pressing. In order to help users confirm the touchpoint locations, measures like showing the touchpoint with dots were designed and proved to be effective in reducing the error rate (Henze et al., 2012). However, showing touchpoints slowed the typing speed by up to 5.2% (Henze et al., 2012), due to more attention being paid to the dots instead of to the typing task itself.

2.2. Learning in typing

The position of Qwerty as the standard layout has been debated for decades, from the application of typewriters to the use of keyboards in a variety of scenarios such as mobile devices and virtual reality. Researchers have proposed new keyboard layouts with different key arrangements (Bi & Zhai, 2016; Dunlop & Levine, 2012; Jokinen et al., 2017), key shapes (Gunawardana et al., 2010; Hunter et al., 2000), and letter grouping (Dunlop et al., 2012; Sarcar et al., 2018). These designs (sometimes via optimization) have brought new possibilities for improving usability and user experience of typing, but one of the main problems for their more widespread adaptation is the time it takes to learn new layouts. For instance, a study using a stylus to type made the user a "novice" by randomizing the soft keyboard after each tap on the key; the typing speed on the randomized keyboard (around 5 WPM) was significantly slower than on a Qwerty keyboard (around 20 WPM) (MacKenzie & Zhang, 2001).

From the perspective of skill acquisition, three main phases were proposed by (Fitts & Posner, 1967) to explain how task performance becomes automatic through practice (Keith & Ericsson, 2007). First, in the *initial cognitive phase*, individuals learn the underlying structure of the activity and develop strategies for the task. Then, in the *associative phase*, the elements that are necessary for successful task execution become integrated into sequences of actions. Finally, in the *autonomous phase*, task performance becomes more automatic, and at the same time, less attentional resources are required for doing the task.

In the case of typing, novice typists usually start with a "hunt-and-peck" typing style, while building the memory of the keyboard layout. With the development of memory, typists entered the second associative phase and type faster. As the experiences accumulate, movements become more automatic. Typists could finally master the keyboard with a "touch-typing" method.

Generally, it takes 90 hours for a user to transform from a novice typist to being a relatively skilled typist on the physical keyboard (typewriter) (Chapman, 1919). Apart from complete novices, users who are not familiar with the underlying structure of the particular activity or who lack fully developed strategies for the task can also learn (Fitts & Posner, 1967; Keith & Ericsson, 2007). As typing skill is largely affected by learning and practicing – especially deliberate practice (Keith & Ericsson, 2007) – understanding how users acquire and improve typing skills is vital to the development of typing techniques and interfaces. As typing skill has been mastered pervasively among touchscreen users, in order to capture the learning process we pushed the users back to a novice state by randomizing the keyboard layout. In this way, the existing embedded memory of the keyboard layout is no longer able to serve the user well. Other research methods with the same purpose include scrambling the order of letters in words (Crump & Logan, 2010b; Yamaguchi & Logan, 2016) and adding noise masks to the stimuli of the target materials (Yamaguchi & Logan, 2016).

2.3. Eye and finger behavior on touchscreens

Operations on touchscreens are largely guided by vision, as the flat screen is not capable of providing enough tactile feedback for touch operations without visual guidance. While typing on touchscreen devices, attention is allocated for purposes like key searching, finger guiding, and proofreading. Frequent attention shifts among screen areas posed a negative effect on the typing speed. In a typing study on a split keyboard on the tablet, subjects were asked to use peripheral vision to guide their finger movements instead of a direct eyes-on manner. They found that using peripheral vision reduced attention switch and led to a 28% faster typing speed (27 WPM) over the typical eyes-on typing mode (Lu et al., 2019). As for typing on a smartphone, the keys are normally smaller than the fingertips, due to the limitation of screen size. In such a condition, touch was guided by the eyes more than half of the time (60% for two-finger typing, 70% for one-finger typing) in order to operate accurately (Jiang et al., 2020). However, as proofreading was also needed during typing, users had to frequently shift their attention between the text input area and the keyboard. Such attention shifts led to breaks in the current task and switching to another task consumed cognitive resources and time. Two-thumb typing reduced the frequency of attention shift, compared with one-finger typing. However, the cost is that more errors (especially with delayed error correction) happened during typing. Such findings indicated the importance of understanding eye and finger movement in the discussion of the speed-accuracy trade-off during typing.

From the perspective of speed-accuracy strategies, previous studies also demonstrated that users respond to costly typing errors with risk aversion by reducing their typing speed to minimize typing errors (Banovic et al., 2017). In general, to understand typing behaviors, the effects of attention shift, speed, and accuracy should be thoroughly discussed. In this study, we explored such details in the learning process of a given keyboard layout and compared experienced with novice typing behaviors induced by keyboard randomization. Specifically, we seek to uncover the dynamic balance between attention shift, speed, and accuracy with detailed data for eye and finger movement. Findings will provide a reference not only for keyboard designers but also for users of soft keyboards on mobile devices.

3. Method

We aim to understand the typing strategies and their adaption during the learning process by collecting and analyzing typing data with Qwerty and randomized keyboards. In a previous study (Jiang et al., 2020), a Qwerty keyboard (without intelligent typing aids) was used to establish a dataset of one-finger and two-finger typing. In this study, we collected typing data by designing an experiment with transcription tasks on randomized keyboards under the same setup and with the same participants. We set up two task blocks under keyboard randomization and asked the participants to type with the index finger of their dominant hand (Fig. 1a), so the comparison with (Jiang et al., 2020) was mainly focused on one-finger typing. Our interest is in the eye and finger movements, especially how these movement strategies adapt after a new randomized keyboard layout is introduced, and how this compares with the same strategies on the standard Qwerty keyboard. In order to ensure that the participants focused on typing itself without other distractions, we excluded intelligent typing aids from the keyboard. The interface used in the experiment is shown in Fig. 1c. The green boxes visible therein were used for data collection purposes; we manually checked the gaze data collected after the experiment and confirmed that the boxes did not attract much attention during eye movements. We collected typing behavior by tracking eye movement, finger movement, alongside a log of keypress events on the touchscreen. All data were synchronized in time, and all positions were transformed into a unified coordinate system of the touchscreen device.

3.1. Participants

Of the 33 participants recruited, the data of three were excluded due to gaze-data loss (device error), resulting in a dataset with N = 30 (18 females; age range 18–45, $M = 25.5$, $SD = 5.9$). The sample size was decided following (Caine, 2016) and (Alroobaea & Mayhew, 2014, pp. 48–56). All of the 30 subjects were native Finnish speakers, having a normal or corrected-to-normal vision. Among them, three reported being left-handed. Out of the 30 subjects, 28 reported using touchscreen devices (mobile phones or tablets) several times a day. The average typing speed of the participants ranged from 19.1 to 33.3 WPM on a touchscreen Qwerty keyboard with one index finger. At the end of the experiment, each participant was compensated with two movie tickets (total worth about €20) for their time.

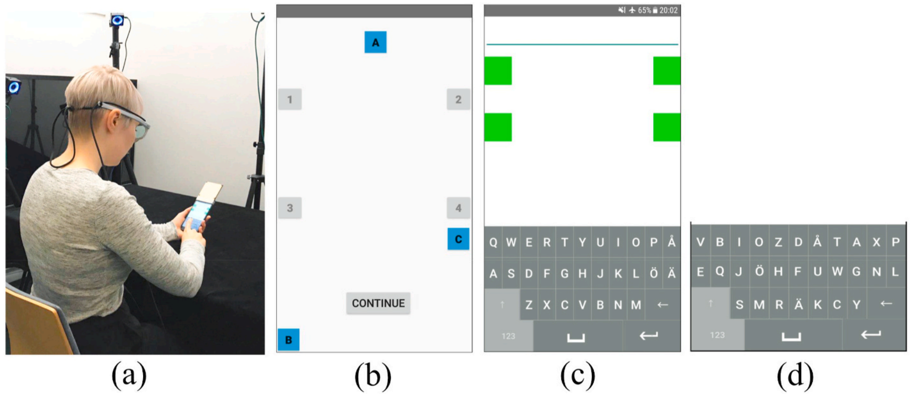

Fig. 1. The (a) experiment setup, (b) calibration screen, (c) typing interface, and (d) an example of a randomized keyboard. In the condition of a statically randomized (SR) keyboard, a keyboard like (d) with the randomization of all the letter keys was presented to the participant while typing the trial sentences; in the condition of the dynamically randomized (DR) keyboard, new randomization was formed after each keypress. Note: Adapted with permission from (Jiang et al., 2020) CC BY-NC.

3.2. Experiment design

The published study (Jiang et al., 2020) consisted of two conditions, namely: one-finger typing on a Qwerty keyboard and two-finger typing on a Qwerty keyboard. In our experiment, we asked the same participants to type with the index fingers of their dominant hand under two conditions, which are statically randomized (SR) keyboard and dynamically randomized (DR) keyboard. Here, the Qwerty keyboard refers to the Finnish Qwerty keyboard which contains all letter keys of the English Qwerty keyboard, with a few extra letters on the right side for Finnish language use. An SR keyboard was generated by shuffling all the letter keys of a Qwerty keyboard. The SR keyboard assigned to each participant was kept unchanged during typing (see Fig. 1c). Similar to SR, the DR keyboard re-shuffled itself after each touch of the keys during typing.

We planned to ask the participants to type 20 sentences under both SR and DR conditions, however, as typing on a dynamically randomized keyboard was time-consuming and tiring, we lightened the burden by reducing the number of sentences in the DR condition from 20 to 15. In general, each participant typed 75 sentences in random order. Specifically, they typed 20 sentences each with one and two fingers on the Qwerty keyboard in a counterbalanced order, then they typed 20 sentences on the SR keyboard, and 15 sentences on the DR keyboard. Our statistical methods for data analysis were not negatively impacted by this, as they do not assume equal group sizes.

The data of the one-finger and two-finger Qwerty keyboard was published in (Jiang et al., 2020). Here we analyze and discuss the results in the condition of one-finger typing on Qwerty, SR, and DR keyboards.

3.3. Material

A Samsung Galaxy S6 smartphone (1440 × 2560, 577 ppi) with a screen size of 5.1 inches was used for the typing task. To capture detailed touch behavior during typing and support the application of the randomized keyboard, a typing application on the smartphone was developed. The height of the keys was 10.06 mm. The sentences used were selected from the Enron Mobile Email Database (Vertanen & Kristensson, 2011) and then translated to Finnish by a native speaker. The average sentence length was 20 characters ($SD = 4$). All the sentences were relatively simple and easy to remember. No special characters, numbers, or punctuation were included in the sentences. All typing was done in lowercase.

3.4. Procedure

First, the purpose of the study was explained to the participants, namely to analyze the movement of the eyes and fingers during smartphone typing. They were then asked to sit in a chair at a height-adjustable table to fill in the background questionnaire. The smartphone used in the experiment was then given to the participant, who was asked to hold it in the non-dominant hand, resting elbows on the table. The table was adjusted to a comfortable height.

Before the experiment, participants spent 5 min practicing with the phone and its keyboard. They were then given the eye-tracking glasses and a marker for motion tracking was placed on the index fingernail of the dominant hand. After inputting the necessary information such as participant ID and keyboard layout, the interface for calibration and synchronization was shown to them (see Fig. 1b). Participants were asked to do a 3-point calibration for the eye-tracking glasses and to press four buttons marked with the numbers 1 to 4 in ascending order for synchronization purposes.

During the experiment, the participants transcribed sentences. Each sentence was referred to as one trial. At the start of each trial, a sentence was presented aurally using a speech synthesizer. The participants were told to always repeat the sentence aloud to confirm that it was heard correctly and to make it more memorable. This meant that the participants did not need to move their eyes to read the target sentence, and typing a message from working memory instead of copying it from some other source is more like real-life typing, where messages are composed internally during typing. Each participant held the smartphone in the non-dominant hand and typed the sentences with the index finger of their dominant hand. They were asked to strive for both speed and accuracy and to correct errors using the backspace key. No cursor movement or other typing aid was provided during the experiment. Three-minute rests were provided after each condition. Re-calibrations were done before each of the following conditions.

3.5. Apparatus and data processing

During the experiment, three types of data were collected: eye movement, finger motion, and key-pressing log. We used the SMI eye-tracking glasses (60 Hz at 30 FPS) to track eye movements. Two infrared cameras tracked eye movements and a forward field camera recorded the screen of the smartphone which was in their hands. Corrective lenses with a strength between −4 and +4 could be attached. In the three-point calibration, participants were asked to focus on the blue rectangles on a calibration screen (Fig. 1b), one at a time. During typing, green rectangles in the interface (Fig. 1c) were captured by the forward field camera on the eye tracker; the information was used in data processing to transform the eye-tracking coordinates into device screen coordinates.

For finger movement, we used an OptiTrack Prime 13 motion-capture system that provides 3D precision of up to 0.2 mm at close proximity. To track the relative locations between the finger and the smartphone screen, we not only attached a marker on the index finger used for typing, but we also attached four markers on the smartphone with a marker board (Fig. 1a). The motion tracking system was calibrated at the start of each condition. For the purpose of synchronization, we asked each participant to click on the four numbered buttons in ascending order. We captured the clicking behavior in the motion tracking system, the touch event on the smartphone, and the pre-defined flash at the moment of clicking on the smartphone screen with the eye-tracking glasses.

Following previous work, trials with an uncorrected (typing) error rate higher than 25% were removed regardless of the condition (Banovic et al., 2017; Dhakal et al., 2018; Palin et al., 2019). Some gaze and finger data were lost due to occlusion or other technical problems. For analysis, we filtered the data on the eyes, finger, or the interaction between the eyes and finger, based on the following rule: if the corresponding data were captured for less than 90% of the keystrokes of a trial, the data of that trial were dropped. The loss due to this rule was not correlated with sentence length (Table 1).

We then converted the coordinates from the raw data of eye and finger movements into the common coordinate system on the smartphone screen: the upper-left corner of the screen is the origin (0,0,0), with x-axis values increasing ward the right of the device and y values from top to bottom. The distance from the screen facing upward is the positive z value. The unit in the data refers to one pixel of the smartphone screen. For the presentation of the results, we transformed the unit of length into centimeters.

4. Results

To better understand the learning process of typing, we compared the typing behavior by analyzing the data under different levels of typing skills. Behavior under the Qwerty condition indicates an expert typing state as the users reported that they were familiar with typing on the Qwerty keyboard. The novice typing behavior was captured using a dynamically randomized (DR) keyboard, as the users can never learn by remembering the keyboard layout. The learning process was captured by using a statically randomized (SR) keyboard. Although users were unfamiliar with the layout of an SR keyboard, they can gradually accumulate experience and learn to type with it during the experiment. Here we first report the observed behaviors from the perspective of typing, eye movement, finger movement, and the interaction between eyes and finger. We summarize the difference between novice and skilled typing behavior, together with the behavioral adaptation and the learning process of typing. We present metrics for evaluating typing performance in Table 2. To test the effect of learning throughout the trials (Fig. 2), we ran a linear mixed model analysis in R (version 3.5.3) using the lme4 package (Bates et al., 2015). Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies

Table 1
Details of data filtering and the effect on sentence length for the analysis of gaze, finger, and the combination of gaze and finger. Numbers in parentheses refer to the standard deviations.

	Before filtering		After filtering		Percentage of dropped
	Num. of trials	Sentence Length	Num. of Dropped trials	Sentence Length	
Gaze data	1648	20.39 (2.18)	364	20.46 (2.16)	22.09%
Finger data			16	20.42 (2.17)	0.97%
Gaze & finger data			373	20.43 (2.17)	22.63%

Table 2
Overview of the results for the Qwerty, statically randomized (SR), and dynamically randomized keyboard (DR) conditions. Numbers in parentheses refer to the standard deviations.

	Qwerty	SR	DR
IKI (s)	0.38 (0.07)	0.92 (0.28)	1.79 (0.42)
WPM	28.59 (7.67)	13.55 (4.31)	6.99 (1.52)
KSPC	1.26 (0.37)	1.13 (0.30)	1.07 (0.15)
Corrected error rate (%)	9.44 (11.63)	4.63 (9.31)	2.77 (5.82)
Uncorrected error rate (%)	0.49 (1.65)	0.55 (1.97)	0.45 (1.57)
Immediate error correction	0.57 (0.50)	0.32 (0.47)	0.29 (0.46)
Delayed error correction	0.47 (0.96)	0.15 (0.53)	0.11 (0.41)
Gaze shift	3.91 (1.48)	2.56 (1.33)	4.53 (1.33)
Gaze keyboard ratio	0.70 (0.14)	0.86 (0.11)	0.85 (0.10)
Proofreading time (s)	0.45 (0.14)	0.38 (0.09)	0.38 (0.11)
Gaze path per character (cm)	4.58 (1.33)	8.06 (2.94)	14.50 (4.67)
Keys before proofreading	5.97 (3.06)	7.22 (4.07)	4.93 (3.63)
Finger speed (cm/s)	10.44 (1.57)	8.22 (1.50)	6.77 (1.25)
Finger efficiency	0.44 (0.07)	0.28 (0.07)	0.20 (0.04)
Eye-hand distance (cm)	3.33 (1.22)	2.53 (0.89)	2.99 (0.89)

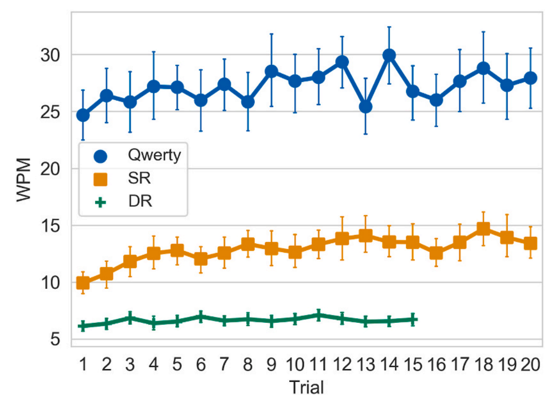

Fig. 2. Changes in average typing speed through trials under the conditions of Qwerty, Statically Randomized (SR), and Dynamically Randomized (DR) keyboards.

Satterthwaite's method to estimate the degree of freedom and generate p-values for mixed models. Post-hoc comparisons were done with lsmeans using Tukey correction. Based on the statistical analysis above, we summarized the change of the behaviors under each of the conditions through time. Results provide a reference for further explanation on the learning and development of skills in typing.

4.1. Typing performance

We first report on the distribution of typing speed measured in words per minute (WPM), which was calculated as the number of standard words (every five characters in the final input text) divided by the time spent on typing. average, typing on the Qwerty keyboard (28.59 WPM) was faster than on the randomized keyboards (Table 2). This effect of layout on WPM is statistically significant, $F(2, 58) = 740.4$, $p < .001$, with the participant as a random intercept and data being aggregated within the participant by the condition. Typing speed on a Qwerty keyboard was three times faster than on a dynamically randomized (DR) keyboard (6.99 WPM), $t(58) = 37.5$, $p < 001$, $d = 2.3$. Other pairwise comparisons were also statistically significant: Qwerty and statically randomized (SR) $t(58) = 26.2$, $p < .001$, $d = 1.6$; and SR and DR, $t(58) = 11.4$, $p < .001$, $d = 0.7$.

We then investigated how learning within a condition impacts WPM. We first scaled trials within conditions due to the DR condition having fewer trials, and without aggregating (in order to retain trial-by-trial information) predicted WPM by condition, trial, and their interaction effect, as well as using the participant as a random intercept. The impact of the trial on WPM was statistically significant, $F(1, 1603) = 20.8$, $p < .001$, and the interaction effect between trial and condition was significant as well, $F(2, 1603) = 3.6$, $p = .03$. Firstly, this means that within a condition, the participants got faster at typing as they progressed under that condition. Secondly, there are differences between conditions in how large an impact a trial has on WPM. In a post-hoc inspection of this effect, we found significant effects of the trial on WPM for Qwerty ($\beta = 0.11$, $t(564) = 2.37$, $p < .05$) and SR ($\beta = 0.15$, $t(565) = 6.95$, $p < .001$), but not for DR. This means that learning as visible in faster WPM happened on the keyboards with fixed layouts, compared with the layout that was dynamically changing during typing (Fig. 2).

As for error correction behavior, we adopted three measurements from (Soukoreff & MacKenzie, 2003): keystroke per character (KSPC, calculated as the length of input stream divided by the length of the transcribed text), corrected error rate, and uncorrected error rate. To calculate the error rate, four types of keystrokes were defined:

- Incorrect Not Fixed (INF): The minimum string distance (MSD) between the target sentence and the transcribed text. Specifically, it refers to the minimum number of primitives (insertions, deletions, or substitutions) to transform one string into the other.
- Correct (C): The correct characters in the transcribed text.
- Fixes (F): The editing functions, in this case, refers to backspace pressings.
- Incorrect Fixed (IF): Keystrokes in the input stream, but not in the transcribed text, that are not editing keys. Based on the definitions, corrected error rate and uncorrected error rate were calculated as follows:

$$\textit{Corrected error rate} = \frac{IF}{C + INF + IF} \times 100\% \tag{1}$$

$$\textit{Uncorrected error rate} = \frac{INF}{C + INF + IF} \times 100\% \tag{2}$$

The total error rate, calculated as the sum of the corrected and uncorrected error rates, was the highest on the Qwerty keyboard (9.93%), and the lowest on the DR keyboard (3.22%). The effect of the condition was statistically significant, $F(2, 58) = 47.5$, $p < .001$, with all pairwise post-hoc comparisons significant as well. The same trend was also found in the corrected error rate, but the uncorrected error rate showed the highest value on the SR keyboard (Table 2), and here the effect of the condition was not statistically significant.

Apart from the perspective of corrected and uncorrected errors, we also measured the number of immediate and delayed error corrections (Jiang et al., 2020) for each trial, i.e., for each sentence typed. Immediate error correction refers to the errors immediately corrected with one backspace-pressing, when it appears in the text input area. Delayed error correction refers to the situation in which the subject realizes the error a few keystrokes after it happens. Normally, delayed error correction involves the deletion of multiple letters and the input of the correct ones. Immediate error correction reflected that the subjects tend to be sensitive about the content of the input. The average number of immediate and delayed error corrections could be seen in Table 2. However, this metric is sensitive to the number of errors actually made, so we controlled for the total error rate. After this correction, we found that the SR keyboard clearly had a smaller immediate error correction than the other conditions, with the effect of the condition being statistically significant, $F(2, 69) = 9.7$, $p < .001$. In the post-hoc pairwise comparisons, differences between SR and DR $d = 0.45$, $t\,(67) = 3.5$, $p < .001$ and between SR and Qwerty $d = 0.42$, $t\,(67) = 3.7$, $p < .001$ were found to be significant. The difference between DR and Qwerty was not statistically significant. This reflected that, while typing on a dynamically changing keyboard, the subjects were more sensitive to the contents they were typing, causing them to correct errors in a timely manner. To spot an error in the typed text, subjects could either recall the key they clicked and compare it with the target sentence or conduct brief proofreading. Next, we looked at gaze behaviors to find out which approach was preferred.

4.2. Eye movement

We measured gaze shift as the number of eye movements from the keyboard to the text input area during each trial of sentence typing (see Table 2 and Fig. 3, Gaze Shift). We found that gaze shift was most frequent on the dynamically randomized (DR) keyboard, followed by Qwerty and statically randomized (SR) keyboards. The effect of the condition on gaze shift was significant, $F(2, 57) = 8.6$, $p < .001$. In post-hoc comparisons, the differences between DR and SR $d = 0.9$, $t(57) = 4.1$, $p < .001$, and between Qwerty and SR $d = 0.6$, $t(57) = 2.6$, $p = .03$ were significant; the difference between Qwerty and DR was not significant. As error correction requires both proofreading and finger guiding, more error correction would increase the possibility of more gaze shifts. Controlling for the error rate, we found (F(2, 68) = 15.6, $p < .001$) that subjects performed the most gaze shifts with the DR keyboard, compared with the SR keyboard (d = 1.1, $t(60) = 5.4$, $p < .001$) and the Qwerty keyboard (d = 0.9, $t(80) = 3.8$, $p < .001$). The difference between SR and Qwerty was not statistically significant. To emphasize this finding, we repeat that, while looking at grand means, Qwerty and DR had similar amounts of gaze shifting, but when controlling for the actual number of errors made, the DR condition very clearly had the largest amount of gaze shifting.

In order to quantify the attention focused on the keyboard for key-searching and finger guiding, we measured the ratio of time that gaze stays on the keyboard area during typing (see Table 2 and Fig. 3, Gaze Keyboard Ratio). We found that the gaze ratio on the keyboard was the highest for typing on the statically randomized (SR) keyboard, followed by dynamically randomized (DR) and Qwerty keyboards, $F(2, 57) = 35.6$, $p < .001$. In post-hoc comparisons, the difference between Qwerty and SR was $d = 1.1$, $t(57) = 7.3$, $p < .001$, and between Qwerty and DR it was similarly significant $d = 1.1$, $t(56) = 7.3$, $p < .001$. The difference between SR and DR was not statistically significant. Typing on an unfamiliar keyboard (i.e., statically randomized (SR) and dynamically randomized (DR) keyboards) increased attention on the keyboard area compared to the familiar Qwerty keyboard.

Nevertheless, typing on a dynamically randomized keyboard without a fixed layout made subjects uncertain about their typed texts and they performed more proofreading. Proofreading time, measured in seconds, was the duration in which the gaze stayed in the text input area for each proofreading event (see Table 2 and Fig. 3, Proofreading Time). Generally, subjects spent more time for each proofreading while typing on the Qwerty keyboard, followed by similar duration between the SR and DR keyboards, $F(2, 56) = 7.7$, $p < .001$ (post hoc comparison between Qwerty and SR: $d = 0.7$, $t(57) = 3.5$, $p = .003$, and Qwerty and DR: $d = 0.6$, $t(56) = 3.3$, $p = .006$; comparison between SR and DR was not significant).

4.3. Finger movement

Detailed finger movement data were collected during the experiment, which enabled us to measure the difference in finger behavior across conditions, together with the adaptations over time. We measured average finger movement speed (centimeters per second) for each trial (see Table 2 and Fig. 3, Finger Speed), and found that in accordance with the typing speed, the finger moved fastest on the Qwerty keyboard, followed by the statically randomized (SR) and dynamically randomized (DR) keyboards. The effect was statistically significant, $F(2, 58) = 223.9$, $p < .001$, with all pairwise comparisons significant as well: Qwerty vs SR $d = 1.1$, $t(58) = 12.6$, $p < .001$, Qwerty vs DR $d = 1.9$, $t(58) = 21.0$, $p < .001$, and SR vs DR $d = 0.7$, $t(58) = 8.4$, $p < .001$.

As moving the finger across a distance takes time, the ideal strategy

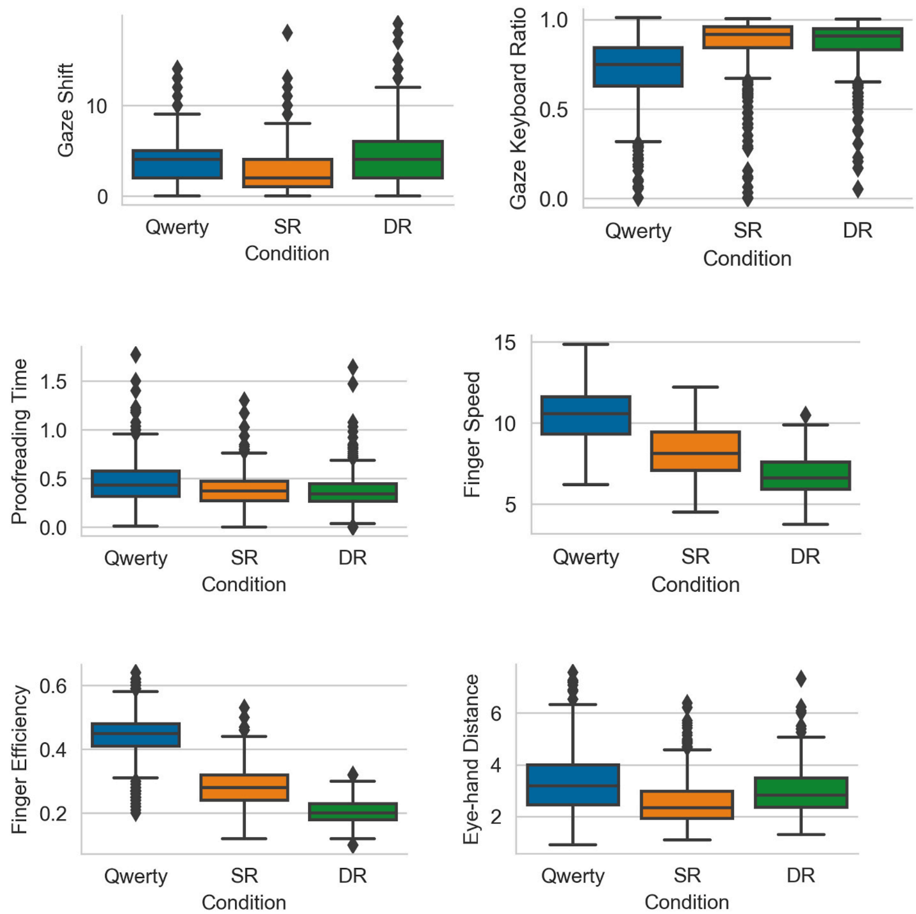

Fig. 3. Box plots for metrics on eye and finger behavior under the conditions of Qwerty, Statically Randomized (SR) and Dynamically Randomized (DR) keyboards.

was to go through direct movement paths between keys while typing. In order to see how efficiently the finger moved between keys, we looked at finger movement efficiency calculated as the inter-key distance divided by the finger movement path in the 3D space (see Table 2 and Fig. 3, Finger Efficiency). On average, subjects moved their fingers more efficiently while using a keyboard with a Qwerty layout, followed by statically randomized (SR) and Qwerty keyboards. The effect was statistically significant, $F(2, 58) = 488.2$, $p < .001$, with all pairwise comparisons significant as well: Qwerty vs SR $d = 1.5$, $t(58) = 20.5$, $p < .001$, Qwerty vs DR $d = 2.2$, $t(58) = 30.7$, $p < .001$, and SR vs DR $d = 0.7$, $t(58) = 10.2$, $p < .001$.

4.4. Eye-hand distance

Visual guidance for finger movements requires a relatively closer physical distance between the finger and the gaze point. To see the relationship between the finger and eye, we measured in centimeters the average distance between the gaze point and the projected finger coordinate on the touchscreen throughout the typing process of each trial (see Table 2 and Fig. 3, Eye-hand Distance). The longest distance was found with the Qwerty keyboard, followed by dynamically randomized (DR) and statically randomized (SR) keyboards. This effect was statistically significant, $F(2, 57) = 14.4$, $p < .001$ (post hoc comparison between Qwerty and SR: $d = 1.0$, $t(57) = 5.4$, $p < .001$, Qwerty and DR: $d = 0.5$, $t(56) = 3.3$, $p = .03$; and DR and SR $d = 0.5$, $t(57) = 2.8$, $p < .02$). Note that the eye-hand distance is also closely related to the proofreading behavior and the ratio of gaze on the keyboard, we looked at the average eye-hand distance controlling the gaze keyboard ratio. We found that, while considering the ratio of gaze on the keyboard, the average eye-hand distance is still the highest on the Qwerty keyboard (4.89 cm), compared with on SR (2.98 cm) and DR keyboards (3.54 cm). This means that, as the subjects became more familiar with the layout of the keyboard, the visual guidance of finger movements was less needed, or that it could be monitored from a longer distance during typing.

4.5. Behavior adaptation under keyboard randomization

Here we explain the process of typing behavior adaptation and learning throughout trials during the experiment. We grouped the data into five sentences per trial block and explained the learning process by looking at the metrics of inter-key interval (IKI), gaze keyboard ratio, finger efficiency, immediate error correction, gaze shift, gaze path per character, number of keys before proofreading, and total error rate (Fig. 4). The metrics were first Z-score standardized within conditions to facilitate comparisons regarding how they change between the trial blocks: in the charts, 0 refers to the average within-condition value, and one unit in the y axis is 1 *SD* of change.

We explain behavioral differences by selectively interpreting the metrics in Fig. 4. First, looking at IKI, learning across all three conditions was visible with lower relative intervals, by trial. However, as expected, this effect was clearly largest for the condition of the statically randomized (SR) keyboard and smallest for the dynamically randomized (DR) keyboard. We can assume that even with participants who were familiar with the Qwerty layout, there existed some learning of the unfamiliar device used in the experiment. With the SR keyboard, in addition to learning of the device, the learning of the layout itself is apparently noticeable. For the Qwerty keyboard, the overall improvement in IKI was a bit more than 0.2 *SD*, while for the SR keyboard, it was more than 0.6 *SD*.

Gaze shift was not largely affected by practicing with the Qwerty and

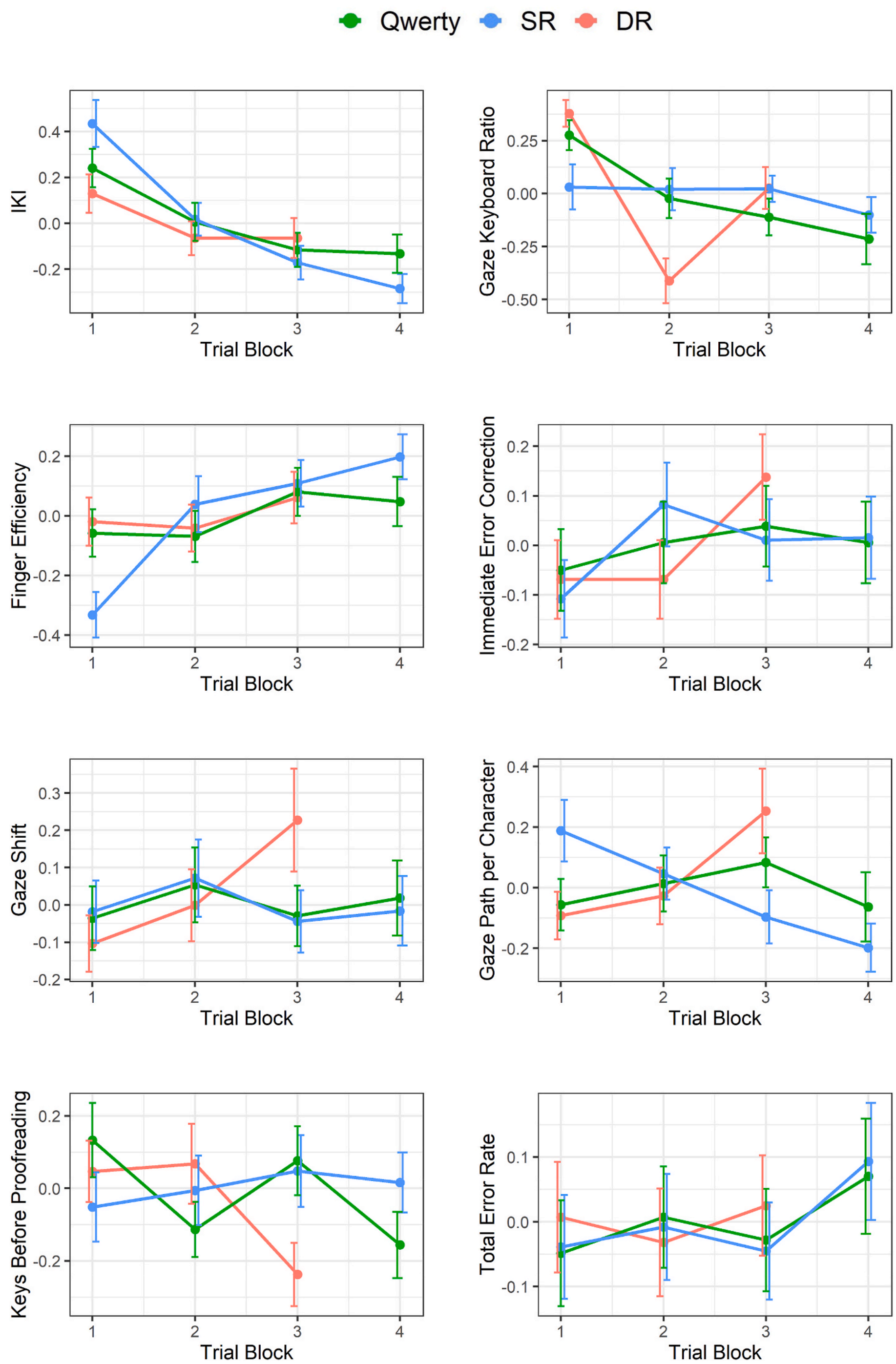

Fig. 4. Changes in typing metrics through time under the conditions of Qwerty, Statically Randomized (SR), and Dynamically Randomized (DR) keyboards. Error bar indicates the standare error of each trial block.

SR keyboards (variation around 0.1 *SD*), while the number of gaze shifts per sentence visibly increased throughout the typing trials (0.3 *SD*). We assume that the reason for the trend was fatigue caused by constant key-searching while typing on a dynamically randomized (DR) keyboard. Subjects gradually lost the confidence that they could type correctly and, as a consequence, they conducted more gaze shifts to the text input area for proofreading. More efficient key searching could be seen in the decrease of the gaze path per character in the SR keyboard condition (around 0.4 *SD*), compared with an increase in the DR keyboard condition.

As for finger movement, a clear increase in finger efficiency on the SR keyboard could be observed throughout the trials (more than 0.5 *SD*), compared with a variation around 0.2 *SD* for both the Qwerty and the DR keyboards. As the subjects gradually built their memory of the keyboard layout, their fingers moved more efficiently with better guidance. Next, we describe in chronological order how individuals adapted their behaviors throughout the development of their typing skills.

4.6. Development of typing skills

When given a new keyboard layout in the statically randomized (SR) keyboard condition, subjects could be regarded as novices as there was no memory of the keyboard layout to guide their typing operations.

They had to visually search for keys before clicking, leading to relatively long inter-key intervals (Fig. 4, IKI - SR - Trial Block 1) and longer gaze path travel before each keystroke (Fig. 4, Gaze Path per Character - SR - Trial Block 1). Under such constraints, the cost of each keystroke was the highest in this condition. To minimize the time cost of error correction, subjects tended to be cautious while trying to make as few errors as possible. This resulted in a relatively low total error rate (Fig. 4, Total Error Rate - SR - Trial Block 1). Thus, they tended to be more confident about the text they typed and conducted fewer gaze shifts for proofreading (Fig. 4, Gaze Shift - SR - Trial Block 1), which led to fewer immediate error corrections (Fig. 4, Immediate Error Correction - SR - Trial Block 1).

As the subjects gradually became familiar with the new layout, they developed the memory of the key locations and used it for more efficient key-searching (Fig. 4, Gaze Path per Character - SR - Trial Block 2 and 3, decreasing gaze path per character) and more direct finger movements to the keys (Fig. 4, Finger Efficiency - SR - Trial Block 2 and 3, increased finger movement efficiency between keys). As a result, typing speed increased (Fig. 4, IKI - SR - Trial Block 2 and 3, decreasing IKI reflects higher typing speed). Here we observed the speed-accuracy trade-off in typing: error rate increased as a result of higher typing speeds (Fig. 4, Total Error Rate - SR - Trial Block 2). To keep the typed text correct, subjects proofread more frequently (Fig. 4, Gaze Shift - SR - Trial Block 2), leading to more immediate error correction (Fig. 4, Immediate Error Correction - SR - Trial Block 2).

Although there is no suggestion that the subjects were able to reach the expert level in just 20 trials of sentence typing, we could nevertheless see a clear difference in their strategies as the subjects gained experience. In the final phase, subjects reached the highest level of typing speed during the experiment (Fig. 4, IKI - SR - Trial Block 4, the lowest IKI reflects the highest typing speed). Typing error increased dramatically in this phase with the highest total error rate (Fig. 4, Total Error Rate - SR - Trial Block 4). However, the benefit of fast typing speed not only compensated but also outweighed the costs of more errors and error corrections, leading to a generally faster overall typing speed with WPM (Fig. 2).

5. Discussion

To understand how skills were developed for typing on a touchscreen mobile keyboard, we pushed individuals back to a novice state of typing by randomizing the letter keys of a Qwerty keyboard. We captured the eye and finger movements of each of the participants and analyzed how their patterns covaried with experience with the layout. Here we discuss the findings from the perspective of learning, and the strategies for proofreading and key-searching that relates with the phenomenon of the speed-accuracy tradeoff. Finally, we provide implications for text input application design.

5.1. Learning and behavior adaptation

We found that even though participants were only assigned 20 sentences for typing on the Qwerty and statically randomized (SR) keyboards, they still showed significantly improved typing speed. With the Qwerty layout – with which everyone should be familiar – this improvement is probably due to the learning experience in the use of the specific device, or by adjusting to the experimental setup generally. Our results provide a new perspective for understanding behavioral adaptation due to learning experience, especially during the early stages of learning. This is in comparison with traditional theories of skill acquisition (Fitts & Posner, 1967), which divide skill acquisition into three steps: an initial cognitive phase, an associative phase, and an autonomous phase.

As novice users in the first step, individuals learn the underlying structure of the activity and develop strategies for the task. The method we applied here for pushing users back to the novice stage via keyboard randomization is in accordance with the first step, by replacing the underlying structure of the activity (i.e., the keyboard layout) with a new one. Then, as a general observation, the more experience people had typed on the keyboard with a fixed new layout, the faster they typed. This observation is consistent with previously published studies on keyboard learning (MacKenzie & Zhang, 1999) and (Keith & Ericsson, 2007).

We expected a marginal learning effect on the dynamically randomized (DR) keyboard as there is no fixed layout for participants to learn, the result confirmed this. Subjects had to search for the keys on each of the new layouts, with no guidance from their memories and this slowed their typing speed. This indicated that keyboard input optimization methods should avoid constant changing of the layout, so that users can learn and improve their performance via familiarization through practice and consistent usage. Apart from randomizing the keyboard layout, study on the learning of typing also tried randomizing the text for input (i.e., comparing meaningful vs. nonsense materials); researchers found that even though interpreting the nonsense material took time, it was still possible to improve typing skills through practice (Keith & Ericsson, 2007).

5.2. The balance between key searching and proofreading

A study of performance improvement over a longer time scale showed that, apart from effort and practice, typing performance is also substantially affected by factors like strategies and subjective expectations: attending typing classes and setting up the subjective goal in everyday typing contributed to the prediction of typing speed (Keith & Ericsson, 2007). As there are no conventional rules or instructions like touch-typing methods for typing on a mobile touchscreen keyboard, users develop their own strategies in daily practice. Such development involves a dynamic balance between eye-finger movement patterns and the speed-accuracy tradeoff.

Although subjects were forced to return to a novice state in both conditions of statically randomized (SR) and dynamically randomized (DR) keyboards, their behaviors in those two conditions were different. Here we mainly focus on the discussion of the proofreading strategies. While typing on the SR keyboard, subjects were presented with a new keyboard layout that remained unchanged (static) throughout the sentence typing trials. They were able to gradually learn the key locations during use. As the subjects build a memory of the keyboard layout, the average gaze path traveled before each keypress decreased with a correspondingly decreased length in the intervals between individual keypresses (Fig. 4, Gaze Path per Character, and IKI).

To achieve a higher level of typing speed with a Qwerty keyboard, users usually conduct operations in an overlapping manner, i.e., they start searching for the next key even before the finger reaches the current target key (Jiang et al., 2020). However, on a dynamically randomized (DR) keyboard, all letter keys were randomized after each keystroke. This means that searching for the next key before the current keystroke was useless as all keys would be repositioned. In such a situation, users could either wait for the keystroke to be finished and then search for the next key, or they could utilize this moment of time to quickly proofread. Our observations showed that users were more likely to shift their attention to the text input area for proofreading during this brief time interval, which further increased the possibility of finding an error immediately after it occurs. This explained why the immediate error correction (controlling the total error rate) was the highest under the dynamically randomized (DR) keyboard condition.

A study of expert mobile text entry showed that, the aversion to costly typing errors leads to intentional speed control (Banovic et al., 2017). The study demonstrated that users respond to costly typing errors by reducing their typing speed to minimize typing errors. The conventional understanding of a costly error is that a typing error requires a user to correct it, which takes time. In the case of the dynamically randomized (DR) keyboard, the cost was amplified as the difficulty and time used for typing were much greater and longer while the layout was constantly changing. Thus, to minimize the potential cost, subjects conducted proofreading more frequently, which was evident in the increased number of gaze shifts (Fig. 4, Gaze Shift). When frequent proofreading demand came with key-searching moves for each keypress, the competition for attentional resources became much stiffer.

5.3. Implications for design

This study provided new and more detailed findings regarding the details of eye and finger movement in the process of learning to type. Although studies on the learning of new keyboard layouts have demonstrated changes in typing performance such as speed and error rate (Anderson et al., 2007, pp. 874–878; Keith & Ericsson, 2007; MacKenzie & Zhang, 1999), it was still not clear how attention and motor control play a role in this process. The implications of the findings of this study can be summarized in the following guidelines for text input user interface design:

- Firstly, typing on a dynamically changing keyboard increases both the cognitive load and the competition of attentional resources, and hinders the learning and improvement of typing performance. We suggest that keyboard optimization should limit changes of layout during use.
- Secondly, proofreading during typing is related to the typist's confidence in the correctness of their typed text. For typists who lack confidence, proofreading tends to be more frequent. The eye movements required for proofreading interrupt key searching and finger guidance and create a cycle of performance deterioration. We suggest that the typed text (i.e., proofreading area) be set close to the keyboard, to reduce the travel distance for the eyes.
- Thirdly, searching for the next key takes most of the time and energy of typists who are unfamiliar with the keyboard layout. We, therefore, suggest lowering the effort required for key-searching behaviors at the beginning of use by, for example, highlighting the predictions of keys that are to be typed.

5.4. Limitations and future work

The critical manipulation of our study was done by shuffling the letters of the Finnish alphabet on a Qwerty keyboard. In order to generalize our results, future studies should look into different languages as well as keyboard designs, such as the split keyboards of tablets and the T9 keyboard for Chinese input. As the underlying logic for typing differs dramatically among those keyboards, there might be substantial differences in performance and strategies. Future work could cover the learning of those keyboards, and confirm if the same strategies are shared among different languages and scenarios. Furthermore, our participants were young adults with a lot of smartphone experience, meaning that their learning focused on the layout rather than, for instance, on how touchscreens in general work. Future studies could have more representative demographics, including older adults, people with accessibility requirements, and those who are not generally familiar with touchscreen devices.

6. Conclusion

Users of today's technologies are constantly exposed to new or changed user interfaces (UIs). To facilitate ease of adoption and fluent adjustment to changes, it is important to understand how users obtain skills and change their behaviors during interaction with technologies. In this study, we manipulated the typists' abilities between novice and skilled, observing the learning process as visible changes of eye and finger movements. Insights into adaption are at the core of our analysis of skill and skill development. We explain different levels of skill – or experience with touchscreen typing – in terms of how users adapt their mental resources, especially the memory of the UI. Via practice, this memory is updated and developed, permitting more efficient performance via behavioral adaptation in order to better exploit the evolving resources.

In some highlights of our results, increases in finger movement efficiency and decreases in the length of the path traveled by eye gaze are indicative of the aforementioned adaptation and an attempt to maximize gain. Designers can utilize this information to aid in an attempt to gauge their users' skill levels, as well as optimize interactions for these levels. For instance, knowing that a user has spent some time with a UI leads to expecting improved finger movement efficiency, which can be accounted for in a more targeted design. Based on our description of changes in typing behavior due to the gathering of experience, a question arises: What makes really fast typing possible? Studies have shown that WPM values as high as 80 can be reached while typing on touchscreens (Palin et al., 2019). The changes in visuomotor patterns described herein may shed light on what makes these really fast typists perform so well. Hypothetically extrapolating from our results, the development of peak performance is a combination of strict motor control and visual guidance that adapts to it. As finger movements become more precise, less visual guidance is required for fast but relatively error-free pointing. This frees the vision for continuous checking of the typed message, permitting the immediate correction of errors – unlike with those who type fast on physical keyboards (Feit et al., 2016). Our results hint towards this explanation by showing that, improved finger efficiency and speed, as well as increased proofreading time and less time spent with the gaze on the keyboard, exist in skilled typing. This finding can be used to design a training regime for achieving faster typing, as we pinpoint that some of the fastest and most impactful ways to train are related to finger efficiency and gaze deployment.

The detailed analysis of the learning process reported here provides a basis of reference for HCI researchers and designers on how touch screen typists adapt their behavior and strategies, balancing between the need for efficient typing and correctness of the final input, according to the development of skills through experience. This work encourages the consideration of the user's typing skill and experience during UI design and provides detailed information that can contribute to the development of better models of UI adaptation and skill.

Credit author statement

Xinhui Jiang: Conceptualization, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Data Curation, Visualization, Jussi P.P. Jokinen: Conceptualization, Methodology, Visualization, Investigation, Writing - Original Draft, Antti Oulasvirta: Conceptualization, Supervision, Resources, Xiangshi Ren: Conceptualization, Supervision, Resources.

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Ethics

All study procedures were in accordance with the ethical standards of the responsible committee on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Declarations of competing interest

None.

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