Improving Virtual Keyboards When All Finger Positions Are Known

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ABSTRACT
Current virtual keyboards are known to be slower and less convenient than physical QWERTY keyboards because they simply imitate the traditional QWERTY keyboards on touchscreens. In order to improve virtual keyboards, we consider two reasonable assumptions based on the observation of skilled typists. First, the keys are already assigned to each finger for typing. Based on this assumption, we suggest restricting each finger to entering pre-allocated keys only. Second, non-touching fingers move in correlation with the touching finger because of the intrinsic structure of human hands. To verify our assumptions, we conducted two experiments with skilled typists. In the first experiment, we statistically verified the second assumption. We then suggest a novel virtual keyboard using our observations. In the second experiment, we show that our suggested keyboard outperforms existing virtual keyboards.

Author Keywords
Virtual keyboard; multi-touch input; touch-typing; touchscreen

ACM Classification Keywords
H.5.2. [Information interfaces and presentation]: User interfaces – input devices and strategies.

INTRODUCTION
Recently, virtual keyboards have been adopted in many touchscreen devices. Because they are primarily based on software technology, virtual keyboards can be flexibly applied to touchscreen devices of any size and are open to potential improvements by state-of-the-art technologies, e.g., computer vision technologies. Despite these advantages, most virtual keyboards simply imitate physical QWERTY keyboards. This approach only emphasizes their intrinsic restrictions, e.g., no tactile feedback in contrast to the physical keyboards, which decreases typing speed and efficiency [13].

Findlater et al. [7] observed the natural typing patterns of skilled typists with virtual keyboards on an interactive tabletop. They reported that typing on two-handed virtual keyboards can be as quick as typing on physical keyboards if they can be typed as the users wish. However, typing errors always occur for many reasons. One major reason that current virtual keyboards are slower to use is that users occasionally unintentionally enter adjacent keys in the same row or column [9]. For example, the most frequent errors were B-V, U-I, U-J, J-K, and I-K. In order to reduce the row or column typing errors in virtual keyboards, we propose two ideas.

To reduce horizontal typing errors, which are caused by unintentionally hitting adjacent keys in the same row, we focus on the typing habits of skilled typists. Fundamentally, several online typing tutorial sites [14] unanimously use the physical keyboard finger positions shown in Figure 1. Based on these tutorials, we assume that skilled typists already know all the key locations and which finger to use to enter a given letter. Therefore, we propose that each key column is allocated to the corresponding finger, as in Figure 1. In other words, each finger is permitted to enter its pre-allocated keys only. For example, the Q, A, Z, and P keys must be entered with the little fingers, and the W, S, X, O, and L keys must be entered with the ring fingers.
Specifically, although the left ring finger might touch the Q, A, and Z key locations, the W, S, and X keys are entered because of our pre-allocations. Therefore, we can prevent most horizontal typing errors by not allowing the fingers that are accidentally touching the horizontally adjacent letters to enter them.

Second, to better determine the typist’s intended keys, we consider the correlations between all fingers, including the touching and non-touching fingers. To check whether these correlations exist, we observed whether non-touching fingers move in correlation with the touching finger when a finger touches a key on virtual keyboards during typing. If these correlations exist, we can use not only the touch point but also the movements of the other correlated fingers to determine which key is actually targeted. Furthermore, these correlations may help mitigate vertical typing errors, which occur when adjacent keys in the same column are unintentionally hit. For example, the O and L keys, which are commonly typed using the right ring finger, are located in the same column. Even when a typist intends to type the O key but accidentally touches the location of the L key, the O key could be entered instead by considering the positions of the non-touching fingers with respect to the ring finger.

In this paper, we design a novel virtual keyboard based on these two assumptions. In the first set of two experiments, our results statistically verify that there are correlations between most fingers when typing. In the second experiment, we show that our new virtual keyboard outperforms existing virtual keyboards. We also discuss how these correlations can be utilized for further improvement.

RELATED WORK
Common typing errors include substitution, intrusion, omission, and transposition [9, 25, 26]. One of the most frequent errors is the substitution error, where one character is substituted for another. These substitutions occur frequently between adjacent keys in the same row or column. Horizontal typing errors, which occur in the same row, comprise 43% of the substitution errors, and vertical typing errors, which occur in the same column, account for another 15% [9]. Moreover, each finger is known to have different error frequencies [27].

Compared to physical keyboards, virtual keyboards suffer from degraded typing performance [1, 4, 7, 30, 35]. However, Findlater et al. [7] showed the possibility of improving typing performance on virtual keyboards to speeds as fast as those on physical keyboards. After investigating all the touch patterns of skilled typists, they suggested that personalization, such as key size and keyboard shape, should be considered to improve virtual keyboards.

Several researchers have studied the effect of key and touch screen sizes [4, 7, 17, 18, 31]. They determined that keys that occupy a smaller space generate higher error rates [31]. However, smaller keys do not cause any significant reduction in typing speed [4, 17]. They also determined that larger touch screen devices (e.g., tabletop PCs versus tablet PCs) achieve much lower performance [7, 18].

To improve virtual keyboards, some studies have proposed keyboard layout adaptation, which adjusts the shapes and positions of keys considering a typist’s hands or fingers [6, 8, 10, 13, 28]. Other approaches have considered different virtual keyboards using unique layouts and sizes [15, 18, 30]. Approaches providing users with tactile feedback were also suggested [19, 20, 24, 34]. Finally, improving text entry using the back of the device has also been studied [2, 29].

On the other hand, several virtual keyboards designed with computer vision technologies have been introduced [12, 33]. Although they showed potential advantages, e.g., their deployment is not limited by screen size, detailed performance assessments about typing speed and error rates have not yet been reported.

Recently, Choi et al. demonstrated the possibility that each touching finger could be correlated with its neighboring fingers when typing on virtual keyboards [5]. They also discussed how these correlations might help improve two-handed virtual keyboards. In this paper, we statistically confirm their simple findings with several experiments and then experimentally show that finger correlations affect typing performance on virtual keyboards.

EXPERIMENT 1
This experiment investigates the correlated movement of all fingers including touching and non-touching fingers when typing on virtual keyboards. We first built a touch surface capable of tracking all finger positions in real time. We then checked every combination of touching and non-touching fingers when entering each alphabetic key. The objective was to check whether correlations exist and could be utilized to infer a typist’s intention more accurately than existing virtual keyboards that only consider touch location.

Participants
Ten participants (4 females), ranging in age from 22 to 29 years (M = 25.3), who had regularly typed on physical keyboards were recruited. Before the main experiment, we ran a typing test with physical keyboards to determine their typing speeds. For the typing test, the Mackenzie phrases set [16] was used and the mean typing speed was found to be 72.4 words per minute (WPM) (SD = 17.7).

Experimental setup
Figure 2 shows our experiment setup under restricted light conditions. To establish a touch surface on top of the transparent box, we used the Laser Light Plane method with two infrared plane generators and an infrared camera [21]. All fingertips were then tracked by an RGB camera using several color markers in real time.
Figure 2. Experimental setup with an RGB camera, an infrared camera, two infrared plane generators, and a display.

Figure 3. Keyboard layout generated based on 10 finger touch points (green circles) on a display in the initialization phase.

Keyboard design
As shown in Figure 1, we designed a virtual keyboard prototype with pre-allocated keys based on our first assumption. Each finger was permitted to enter the pre-allocated keys only. This fundamentally prevented most horizontal typing errors from occurring.

We note that researchers have found that personalization is an important factor for improving virtual keyboards [7]. We thus asked participants to touch all their fingers when preparing to type, just as they do on physical keyboards, which we call the initialization phase. Based on the 10 finger touch points in the initialization phase, we generated a keyboard layout for each participant. It was usually arch-shaped, as shown in Figure 3. After these touch locations were stored and a participant removed their fingers from the touch surface, we asked the participants the start typing while keeping their wrists still.

If a character was entered with the correct finger, we then stored the two dimensional world coordinates of all fingers, i.e., the x- and y-coordinates of the touch surface. To alleviate the effect of the participants’ mistakes, we did not store finger locations when the wrong finger touched the location to enter a given character, e.g., when the left middle finger touched the location of the W key. When a mistake happened, a red rectangle briefly popped up on the display as a visual warning feedback.

Procedure
After the participants completed the physical keyboard typing test, they completed 20 practice phrases to become familiar with our keyboard design, followed by 80 test phrases over four sessions. To consider all letters in the alphabet, all test phrase sets consisted of English pangrams, which are incorporating all the letters of the alphabet, such as “the quick brown fox jumps over the lazy dog”. The number of characters in one pangram ranged from 31 to 73. We requested the participants to type comfortably and accurately, just as if on physical keyboards. Each participant spent almost 1.5 hours to perform all sessions.

Data collection and processing
As a result, we obtained 41,123 labeled locations of the touching finger and non-touching fingers. Because the two thumbs were used only for the space bar, we did not collect their locations.

Before the analysis, each finger location was transformed into a new coordinate system whose x- and y-axes locations were obtained to millimeter accuracy with respect to the average touch point of the corresponding home row key. The reason for this coordinate transformation is described in later discussion. For example, the left middle finger’s location data was transformed into new data based on the average touch point of the D key. On the other hand, the location data of the right little finger was transformed into values relative to the touch point of the semi-colon key, which was obtained from the average touch point of the P key. As the x- and y-axis values of a finger increase, the finger moves in the leftward and upward directions, respectively, in our experimental setup.

For reader convenience, we denote the location of each finger using the form “Axis indicator” + “Finger indicator.” For example, the x-axis value of the index finger is denoted by $X_{index}$, and its y-axis value is denoted by $Y_{index}$. We also denote the keys allocated to each finger using the form “K” + “Finger indicator.” For example, the keys allocated to the index finger are denoted by $K_{index}$. The distinction between right and left hands is made when clarification is needed.

Multinomial logistic regression model
We then analyzed the correlations between all finger locations with each targeted alphabetic key using multinomial logistic regression with a cutoff value of 0.5.

Logistic regression is used to analyze the relationship between a categorical dependent variable and several independent variables [3, 11]. In the case of our experiment analysis, the dependent variable was the keys allocated to
each finger, and several independent variables were the two-dimensional locations of all fingers. In other words, each model had one dependent variable (the keys allocated to each finger) and eight independent variables (the two-dimensional locations of all fingers).

The categorical dependent variable in logistic regression model for each finger should have a reference category and response categories. For easy comparison, the lowest pre-allocated key for each finger was defined as the reference category for each model. For example, the Z, X, C, V, M, K, L, and Enter keys were defined as the reference categories for each logistic regression model, and other keys were defined as the response categories.

Each independent variable for each key in logistic regression models is related to several parameter estimates, e.g., B coefficient and odds ratio $Exp(B)$. As the value of an independent variable with significant positive B coefficients (p < .05) increases, the inference probability of that response category with respect to the reference category also increases. Accordingly, the corresponding odds ratio, $Exp(B)$, which is the probability of belonging to the corresponding response category with respect to a reference category, has a value greater than 1.0. In contrast, as the value of an independent variable with significant negative B coefficients (p < .05) increases, the inference probability of that response category with respect to the reference category decreases. In that case, the corresponding odds ratio has a value less than 1.0. All B coefficients and $Exp(B)$ for a reference category are zero.

To infer the entered key when a finger touches the surface, the logistic regression equation $g$ was established by using the B coefficient of each independent variable for each key. The equation $g$ expressed as follows.

$$g = \text{Intercept} + A_1 * X_{\text{Index}} + A_2 * Y_{\text{Index}} + A_3 * X_{\text{Middle}} + A_4 * Y_{\text{Middle}} + A_5 * X_{\text{Ring}} + A_6 * Y_{\text{Ring}} + A_7 * X_{\text{Little}} + A_8 * Y_{\text{Little}}$$ (1)

The B coefficients for each independent variable are assigned from $A_1$ to $A_8$. When a finger touches the surface, the x- and y-locations of each finger are multiplied by the corresponding B coefficients and accumulated in all logistic regression equations. At that time, the key that has the highest $g$ value among all equations of the keys allocated to the touching finger is inferred as the target. Furthermore, logistic regression also presents the prediction accuracies of category classification of dependent variable with these equations. In the case of our model, our model could show the inference (prediction) accuracies of key classification.

As a result, we established eight logistic regression models for all fingers (excluding both thumbs) and acquired 27 logistic regression equations for all alphabetic keys and the Enter key. Using the logistic regression models, we checked whether using the two-dimensional locations of all fingers helps infer the typing target.

**Result**

**Goodness of fit**

We first needed to determine if our logistic regression models for all fingers correctly approximate reality. In the case of our models, we used the pseudo R-square measure because all independent variables were continuous covariates, e.g., the x- and y-axis values of the index finger [3]. As shown in Table 1, the results of our logistic regression equations using the McFadden R-square measure were quite high (M = 81.05, SD = 5.23). Furthermore, the standard errors of all independent variables included in these equations had a small value (under 2.0). The high goodness-of-fit results above conclusively indicate that our logistic regression models were well designed.

**Finger correlation**

We then found that each finger has correlations with most of the other fingers in both hands (p < .05). For example, both index fingers and the left little finger correlated with the other fingers in the same hand (p < .01). However, the right ring finger does not correlate with the keys allocated to the right middle finger (horizontal: p = .135, vertical: p = .659). In contrast, the right middle finger correlates with the keys allocated to the right ring finger (p < .01). In other words, the two-dimensional locations of the right ring finger does not help infer which key among the ones

### Table 1. McFadden R-square results for eight logistic regression equations (M = 81.05, SD = 5.23).

<table>
<thead>
<tr>
<th></th>
<th>$K_{\text{Index}}$</th>
<th>$K_{\text{Middle}}$</th>
<th>$K_{\text{Ring}}$</th>
<th>$K_{\text{Little}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LEFT HAND</strong></td>
<td>81.2</td>
<td>84.9</td>
<td>82.5</td>
<td>74.8</td>
</tr>
<tr>
<td><strong>RIGHT HAND</strong></td>
<td>74.3</td>
<td>87.3</td>
<td>86.7</td>
<td>76.7</td>
</tr>
</tbody>
</table>

### Table 2. Likelihood ratio tests for the left hand where non-significant contributors are highlighted in red (p > .05).

<table>
<thead>
<tr>
<th></th>
<th>$K_{\text{Index}}$</th>
<th>$K_{\text{Middle}}$</th>
<th>$K_{\text{Ring}}$</th>
<th>$K_{\text{Little}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$X_{\text{Index}}$</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>$X_{\text{Middle}}$</td>
<td>.037</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>.0768</td>
</tr>
<tr>
<td>$X_{\text{Ring}}$</td>
<td>&lt;.01</td>
<td>.729</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>$X_{\text{Little}}$</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
</tr>
</tbody>
</table>

### Table 3. Likelihood ratio tests for the right hand where non-significant contributors are highlighted in red (p > .05).

<table>
<thead>
<tr>
<th></th>
<th>$K_{\text{Index}}$</th>
<th>$K_{\text{Middle}}$</th>
<th>$K_{\text{Ring}}$</th>
<th>$K_{\text{Little}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$X_{\text{Index}}$</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>$X_{\text{Middle}}$</td>
<td>.905</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>.135</td>
</tr>
<tr>
<td>$X_{\text{Ring}}$</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
<td>.0128</td>
</tr>
<tr>
<td>$X_{\text{Little}}$</td>
<td>&lt;.01</td>
<td>0.046</td>
<td>&lt;.01</td>
<td>&lt;.01</td>
</tr>
</tbody>
</table>
To better describe our models, several examples are presented here. Table 4 shows an example for the left middle finger. Because the C key was defined as the reference category for the left middle finger, the parameter estimates for two response categories, the E and D keys, are shown in Table 4. Note that all parameter estimates of the C key were zero. Note that $X_{\text{Index}}$ refers to the $x$-axis value of the left little finger with respect to the average touch location of the A key. According to the upper part of Table 4, the B coefficient for $X_{\text{Index}}$ is 0.081 ($p < .05$). This implies that as the left little finger moves left, there is a higher chance of entering the E key than the C key. On the other hand, $X_{\text{Index}}$ also had a positive B coefficient (B = 0.079). However, it turns out that $X_{\text{Index}}$ did not help much to distinguish between the E and C keys ($p = .070$). Similarly, because the B coefficient for $Y_{\text{Little}}$ is $-0.170$ and its odds ratio was 0.844 in the upper part of the table, there was a higher chance of entering the E key than the C key when the left little finger moved down ($p < .05$). According to the upper part of Table 2, $X_{\text{Ring}}$ did not help infer the target key from those keys allocated to the left middle finger ($p = .768$). Table 4 also shows that $X_{\text{Ring}}$ did not help much to distinguish between the E and C keys ($p = .468$) nor between the D and C keys ($p = .597$). Because it is difficult to show all parameter estimates for all logistic regression equations, Table 5 only shows the B coefficients for all those equations.

### Table 4. Parameter estimates for the left middle finger. The reference category is the C key. Non-significant independent variables are highlighted in red ($p > .05$).

<table>
<thead>
<tr>
<th>Character Variable</th>
<th>B</th>
<th>Standard Error</th>
<th>P-value</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.518</td>
<td>.224</td>
<td>.000</td>
<td>-</td>
</tr>
<tr>
<td>$X_{\text{Index}}$</td>
<td>.090</td>
<td>.036</td>
<td>.011</td>
<td>1.094</td>
</tr>
<tr>
<td>$Y_{\text{Index}}$</td>
<td>.011</td>
<td>.028</td>
<td>.690</td>
<td>1.011</td>
</tr>
<tr>
<td>$X_{\text{Little}}$</td>
<td>-.153</td>
<td>.049</td>
<td>.002</td>
<td>.858</td>
</tr>
<tr>
<td>$Y_{\text{Little}}$</td>
<td>.591</td>
<td>.032</td>
<td>.000</td>
<td>1.805</td>
</tr>
<tr>
<td>$X_{\text{Ring}}$</td>
<td>-.023</td>
<td>.043</td>
<td>.597</td>
<td>.978</td>
</tr>
<tr>
<td>$Y_{\text{Ring}}$</td>
<td>.071</td>
<td>.027</td>
<td>.008</td>
<td>1.074</td>
</tr>
<tr>
<td>$X_{\text{Index}}$</td>
<td>.061</td>
<td>.020</td>
<td>.003</td>
<td>1.053</td>
</tr>
<tr>
<td>$Y_{\text{Index}}$</td>
<td>-.074</td>
<td>.026</td>
<td>.004</td>
<td>.929</td>
</tr>
</tbody>
</table>

To represent all correlations, Tables 2 and 3 show the $p$-values of the likelihood ratio test for all combinations of fingers in both hands. If the $p$-value is higher than 0.05, it implies that the finger location value does not help infer the target key of the corresponding touching finger from among those pre-allocated to it. For example, as shown in Table 2, the $x$-axis location of the left ring finger does not help infer the target of the left middle finger from among the E, D, and C keys ($p = .768$). Similarly, the $y$-axis value of the left index finger does not help infer the target of the left ring finger ($p = .729$). The values circled in red indicate that the corresponding independent variable (finger location) was not a significant contributor in inferring the corresponding dependent variable (target key out of those allocated to the given finger) ($p > .05$).

For inference accuracy of key classification

As evidence that supports our second assumption, Figure 4 compares two different key classification methods in terms of inference accuracy, which is called prediction accuracy in a statistical context [11]. Figure 4(a) presents key classification accuracy using logistic regression with only the location of the touching finger, while Figure 4(b) shows the values for logistic regression using the location of all fingers including the touching and non-touching fingers. Clearly, the logistic regression model using all finger positions has higher inference accuracies than the one using the touching finger position only.

Summary

A previous study showed that all fingers are correlated with adjacent fingers when the relative locations of all fingertips are tracked with respect to the wrist location [5]. However, the study did not show any performance evaluation of the design. In this paper, we track each finger position with respect to the average touch points of the corresponding home row key, which does not require any knowledge of wrist position. We also showed the degree to which all fingers are correlated when typing and how the correlation can be utilized to raise typing accuracy. Moreover, several interesting results are presented. For example, some non-touching fingers and the touching finger do not always move in the same direction when the target key is located in the lower or upper rows, such as the left little finger when the left middle finger types the E key (B: $-0.170$, $p < .05$).
PROPOSED VIRTUAL KEYBOARD PROTOTYPE

As shown in Table 5, we established the logistic regression equations (1) for each key. For example, in the equation for the E key, Intercept, $A_1$, $A_2$, $A_3$, etc., were set to .400, .079, −.115, −.153, etc., respectively. We then could infer the target key by considering which has the highest $g$ value among equations of the E, D, and C keys when the left middle finger touches. In the case of the left index finger, it allows us to choose the target key among equations of the T, R, G, F, B, and V keys.

With these logistic regression equations, we implemented the proposed virtual keyboard prototype which includes our two assumptions. It allocates each column key to the corresponding finger and considers a touch point as well as the correlations between all fingers in order to decide the entered key. We called this prototype as the Pre-allocation and Correlation-aware keyboard or PC-keyboard for short. This keyboard was expected to reduce horizontal typing errors as well as vertical typing errors.

We then planned the second experiment to investigate how effectively our prototype works. For performance comparison, we also implemented two additional keyboards using the same experimental setup.

The first keyboard, called the Normal keyboard, was a virtual keyboard without key pre-allocation and the logistic regression models. Therefore, more horizontal and vertical typing errors were expected to occur than when the other two keyboards were used. Each key size was determined to be equal to that of an 18 × 18 mm key physical QWERTY keyboard. When a touch event occurred, the nearest character to the touched location was entered.

The second keyboard, called the Pre-allocation keyboard or P-keyboard for short, was a virtual keyboard with key pre-allocation but no logistic regression models. Note that this keyboard has been used in experiment 1. Thanks to the pre-allocations, this keyboard should reduce horizontal typing errors caused by most fingers except the index fingers.

EXPERIMENT 2

The objective of the second experiment is to show the effectiveness of our novel keyboard design (PC-keyboard) based on our observations. To do this, we compared the Normal, P-, and PC-keyboards in terms of typing speed and three types of error rates proposed by Soukoreff and MacKenzie [32].

Participants

The nine participants who participated in experiment 1 were recruited again. Participants were compensated with $40.

Procedure

In this experiment, participants used an initialization phase to rest all fingers on the surface and rearrange the home row key positions before typing in each phrase. Because supporting the Backspace key might cause the posture of the right hand to be lost [7], we replaced the Backspace key with a right-to-left swipe gesture with all fingers touching except the thumb of the right hand.

The participants were asked to perform typing tasks with the Normal, P-, and PC-keyboards. All test phrase sets were randomly selected from the Mackenzie phrases set [16]. An experiment for each keyboard consisted of five sessions where each session included 20 phrases. The participants conducted one session for training per keyboard before they...
started the main sessions. They then performed five consecutive sessions per keyboard, which gave a total of 15 sessions per participant. The order in which the keyboards were used was counterbalanced. The 15 sessions were spread over three consecutive days.

Results

We analyzed the results using the two-way repeated measures ANOVA, followed by Tukey post-hoc analysis. Keyboard and Session are the within-subject factors. We reported significant findings at p < .05.

Figure 5 shows the results. To measure the typing speed, the WPM metric was used. To measure the typing error, three different metrics were used [32]. The Corrected Error Rate (CER) is the ratio of errors that are subsequently fixed by users during text entry. The Not Corrected Error Rate (NCER) is the ratio of errors that are left in the transcribed text at the end of each trial. Finally, the Total Error Rate (TER) is the sum of the CER and NCER.

For more detailed information, Table 6 lists the two-way repeated measures ANOVA results for the typing speed and three error metrics. Conclusively, Keyboard and Session had a significant main effect excluding NCER (p < .05). The interactions between the two factors do not have a significant effect for all metrics. To check the main effect of Keyboard in detail, we conducted a post-hoc analysis using Tukey HSD. The Normal keyboard (M = 23.26) was slower than both the P-keyboard (M = 28.897, p < .05) and PC-keyboard (M = 31.618, p < .05).

The Normal keyboard (M = 10.242) also had greater error rates than both the P-keyboard (M = 8.812) and PC-keyboard (M = 7.594). However, there were no significant difference between the P- and PC-keyboards (p = .334) by Tukey post-hoc analysis. By simply counting errors, we compared the three different keyboards with respect to vertical and horizontal typing errors. As a result, the horizontal typing errors of the PC-keyboard were almost 54.07% lower than the Normal keyboard, but there was no difference between the P- and PC-keyboards. In case of vertical typing errors, the Normal and P-keyboards were approximately 7.33% and 2.01% higher than the PC-keyboard, respectively.

Figure 6 shows two touch-offset clouds of the left middle finger when typing on the (a) Normal and (b) PC-keyboards. The standard deviations of two dimensional variables of the left middle finger of the PC-keyboard were larger than them of the Normal keyboard.
In the first experiment, we obtained logistic regression equations considering all participants. However, the private logistic regression equations for an individual gave higher inference accuracies than the ones considering all participants. In particular, the keys allocated to the index fingers could be classified as accurately as the other keys with private logistic regression equations. This may imply that the equations considering all participants do not show individual characteristics precisely and leads to open questions about individualization for improvement. All participants were asked to respond to a questionnaire after the final experiment was complete. All questions were answered using a five-point scale. The questions about each keyboard were given as follows.

1. Was the keyboard comfortable for your hands during the experiment?
2. Were the distances between keys adequate?
3. How many times did you look at the keyboard layout on the display during experiments?
4. How often did the keyboard incur unintended typing errors?

We used two-way ANOVA to analyze the answers. The factors were Keyboard condition (Normal, P-keyboard, and PC-keyboard) and Gender (male and female). Each subfigure in Figure 8 shows the results for each question. In summary, the main effect of Gender was significant only for the distances between all keys, as shown in Figure 8(b) ($F(1, 8) = 19.505, p < .05$). The females felt as if the keys were further apart than the males for each Keyboard condition (female: $M = 2.75$, $SD = 1.165$; male: $M = 3.87$, $SD = 0.64$; $p < .05$). Most female participants (participants 2, 5, and 8) preferred typing on the PC-keyboard to the other keyboards but they said that the keys allocated to the

![Figure 7](image)

**Figure 7.** Examples showing how to correct vertical typing errors on the PC-keyboard. Even when the left index finger touches the same location in both figures, somewhere between the F and R keys, either F or R is correctly selected for typing based on the postures of the other correlated fingers ($p < .05$).

<table>
<thead>
<tr>
<th></th>
<th>LEFTHAND</th>
<th>RIGHTHAND</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$X$ (AVG/STD)</td>
<td>$Y$ (AVG/STD)</td>
</tr>
<tr>
<td>INDEX</td>
<td>-0.3/7.142</td>
<td>0.3/6.996</td>
</tr>
<tr>
<td>RING</td>
<td>-1.3/9.388</td>
<td>-3.2/7.686</td>
</tr>
<tr>
<td>LITTLE</td>
<td>-2.8/10.594</td>
<td>2.4/7.148</td>
</tr>
</tbody>
</table>

Table 7. Average variations and standard deviations of the distances between two values, where one is the average home row key touch points and the other is the initialization touch points for each finger.
index fingers, such as the T, Y, and B keys, were further away than they expected to reach with their fingers. Generally speaking, we concluded that this result was caused by the hand size difference between the two genders.

**Limitations**

Despite the several interesting findings above, our work has some limitations.

First, our experimental setup was sensitive to light. In particular, the several markers and infrared lasers were not usable without restricting the level of light. Putting several markers on all fingertips of a user whenever he/she uses our keyboards definitely caused inconvenience. Therefore, our design is not practically feasible until an elaborate finger tracking algorithm that does not require any markers is proposed. At this point in time, capacitive displays capable of detecting hovering gestures may be a realistic alternative [22].

Second, we only considered the alphabetic and Enter keys for basic text editing tasks. The frequently used auxiliary keys, e.g., Shift, Period, and comma, were not considered. However, these keys can be assigned to some empty locations in our keyboard layout. For example, the Shift key can be assigned to an empty location on the left side of the Z key. The comma key can be assigned as the lowest row key of the right middle finger.

Finally, we asked users to fix their wrists after the initialization phase to prevent unintended hand drift over the sessions. However, although the users fixed their wrists, we observed that this did not completely prevent unintended hand drift. Thus, we asked users to repeat the initialization phase to rearrange home row key positions before they started each phrase. In future work, it would be desirable not to require users to fix their wrists for their convenience by relying on other reference points of the user or by acquiring highly accurate regression equations.

**CONCLUSION**

Traditional virtual keyboards suffer from frequent horizontal and vertical typing errors. To reduce these errors, we propose novel concepts for keyboard design. First, pre-allocating a set of keys to each finger fundamentally prevents most horizontal typing errors. Second, utilizing correlated finger locations when a touch occurs helps reduce vertical typing errors. Our experimental investigation confirms that there are finger correlations. We experimentally showed that our novel virtual keyboard that uses pre-allocated keys and finger correlations outperforms existing virtual keyboards with respect to typing speed and error rates.

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