Impact of Variable Positioning of Text Prediction in Gaze-based Text Entry

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ABSTRACT

Text predictions play an important role in improving the performance of gaze-based text entry systems. However, visual search, scanning, and selection of text predictions require a shift in the user's attention from the keyboard layout. Hence the spatial positioning of predictions becomes an imperative aspect of the end-user experience. In this work, we investigate the role of spatial positioning by comparing the performance of three different keyboards entailing variable positions for text predictions. The experiment result shows no significant differences in the text entry performance, i.e., displaying suggestions closer to visual fovea did not enhance the text entry rate of participants, however they used more keystrokes and backspace. This implies to the inessential usage of suggestions when it is in the constant visual attention of users, resulting in increased cost of correction. Furthermore, we argue that the fast saccadic eye movements undermines the spatial distance optimization in prediction positioning.

CCS CONCEPTS

• **Human-centered computing → Interaction techniques**;

KEYWORDS

text entry, gaze input, variable position, text prediction, interaction

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1 INTRODUCTION

Text entry is a complex process that involves the primary task of selecting desired keys to form words and sentences and then reading through the collected input with the eyes to check for correctness. This complex task becomes further challenging when a wrong entry is detected leading to greater effort in correcting it. In static dwell time activated gaze-based text entry, both the inspection of the virtual on-screen keyboard and the selection of the keys from the keyboard is done by gaze with the help of an eye tracker. The user fixates on the designated key that they would like to select and it gets selected based on the set *dwell time*. This task being cognitively demanding [Sengupta et al. 2017b] leads to slower gaze-based text entry speed, even for an advanced user. Another reason for the slow speed of eye typing is that eyes do not allow parallel processing like normal hand typing does with ten fingers [Räihä and Ovaska 2012].

Several novel approaches to improve gaze-based text entry exists [Morimoto and Amir 2010; Panwar et al. 2012; Pedrosa et al. 2015; Sarcar et al. 2013; Sengupta et al. 2017a]. Amongst them, one significant methodology is the exploitation of intelligent text prediction methods for more efficient text entry [MacKenzie and Zhang 2008]. Using the text prediction feature, one can reduce the number of keystrokes required to write the word, thus improving the speed and the efficiency. The role of the interface design and accessibility of text predictions also forms an important direction to improve gaze-based text entry experience.

Another concern for text entry on virtual on-screen keyboard (for both touch-based and gaze-based) is the time taken for visual search - the process of searching/scanning letters or correct predictions on the virtual keyboard. Visual search leads to a shift focus from the area of the keyboard layout. To overcome this challenge of visual search and scan time in touch-based virtual keyboards, variable positioning of text predictions have been analyzed [Griffin et al. 2015b; Morin et al. 2011]. In gaze-based text entry keyboard layouts, text predictions have been placed at different positions [Best and Duchowski 2016; Johansen et al. 2003]. It is, however, unclear if this variable positioning of text predictions reduces the visual search and scanning cost. Furthermore, research approaches in the eye tracking

[1]https://github.com/OptiKey/OptiKey/wiki

environment ascertain the null effect of variable positioning of objects since eye saccades and movements and are very fast [Sibert and Jacob 2000]. Hence, we attempt to comprehend the phenomena by studying if text prediction spatial positioning has any impact on the performance of gaze-based text entry.

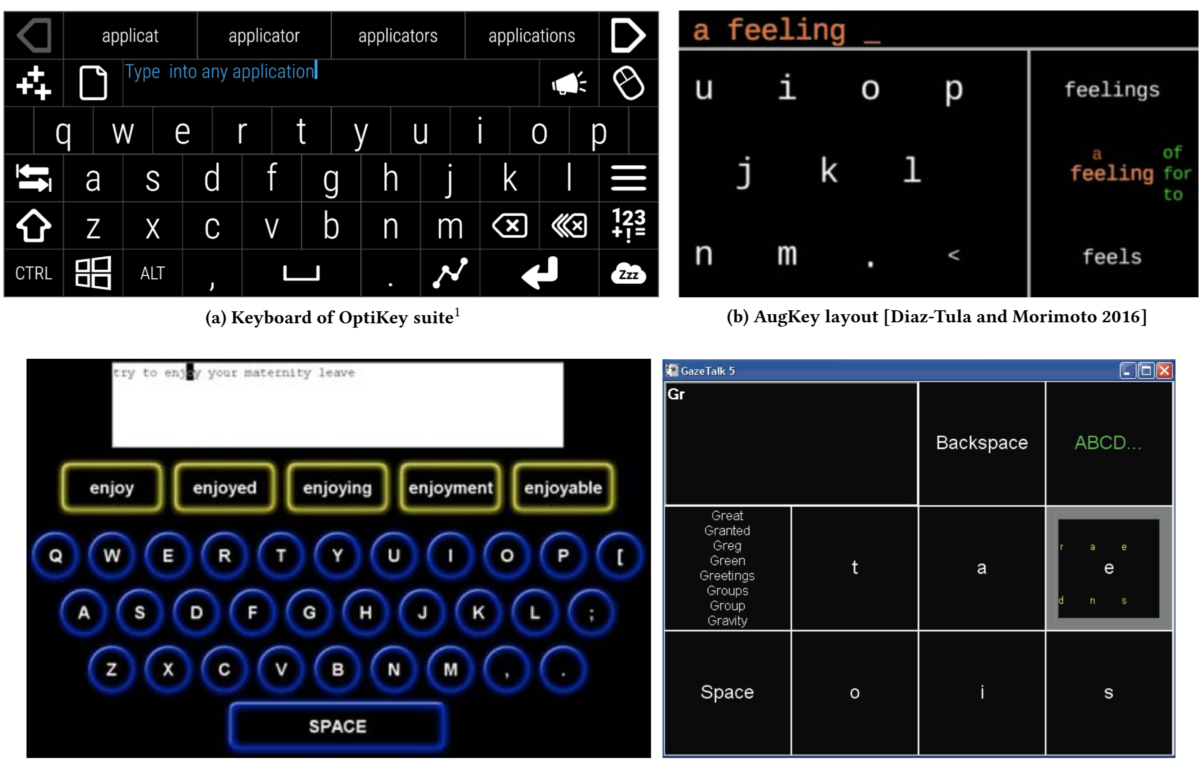
In this work, we performed a comparative analysis of three different designs of QWERTY keyboards layouts having dwell time activation of keys. We evaluated in this summative study, if the positioning of text predictions correlate with the performance for gaze-based text entry. We found that all the three designs performed almost the same when it came to text entry speeds. However, the cost of correction increased as the position of text predictions were brought closer into the area of visual focus. This implies that bringing text predictions closer to the visual focus for gaze-based text entry does not necessarily enhance the performance. It might actually influence users to be overly dependent on text predictions thereby hampering its usability.

2 TEXT PREDICTION AND THEIR POSITIONING IN VIRTUAL KEYBOARDS

Text predictions are generated from a language corpus or a dictionary containing the word frequency. Predictive algorithms help the user in suggesting words from the corpus that are most likely to occur after a particular sequence of user-selected characters. Research focused on letter predictive models like n-gram [Janpinijrut et al. 2011] and k-gram [Miró-Borrás and Bernabeu-Soler 2009], which suggest the following terms of a given sentence based on the previous terms. Reflective text entry [Sandnes 2015] improved the user experience of text entry as it considered abbreviated forms of words.

There have been several gaze-based text entry systems [Diaz-Tula and Morimoto 2016; Johansen et al. 2003; MacKenzie and Zhang 2008] that use text prediction as an essential feature in the virtual keyboard space. Prediction mechanisms are particularly valuable for text entry with virtual keyboards (for gaze-based as well as touch-based systems) [de Sousa Gomide et al. 2016; Sharma et al. 2010]. The success and usability of text predictions depend highly on the presentation and user interface parameters [Garay-Vitoria and Abascal 2006]. This includes (i) the number of suggestions to display (too few might miss relevant suggestions, and too many will add extra delay of scanning long list), (ii) layout of the presentation (horizontal, vertical, triangular etc.), and most importantly (iii) the positioning of suggestion in the screen space of keyboard. Positioning of text predictions is a crucial aspect since it deals with the visual attention of user while typing letters and relates to cognitive and perceptual influence.

Figure 1 showcases a few gaze-based text entry systems, signifying the variable positioning of predictions in different approaches. For most of the conventional designs, a predicted word list is placed on top of the keyboard layout near the text entry area. This can be



(a) Keyboard of OptiKey suite[1]

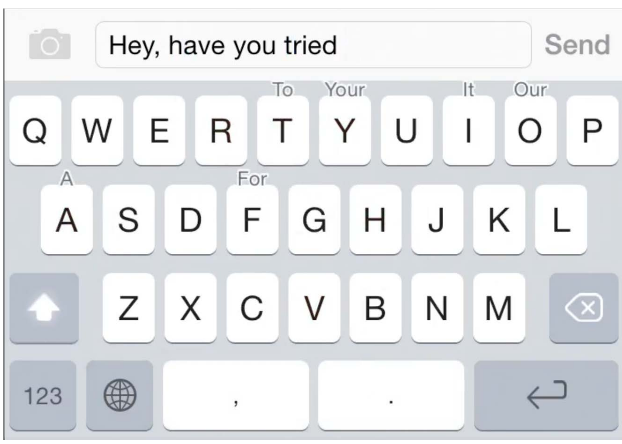
(b) AugKey layout [Diaz-Tula and Morimoto 2016]

(c) Eye Typing by MacKenzie & Zhang [MacKenzie and Zhang 2008]

(d) GazeTalk Keyboard [Johansen et al. 2003]

Figure 1: Gaze-based text entry keyboards with text predictions at different places

(a) Blackberry Keyboard



(b) Octopus Keyboard

Figure 2: Virtual mobile keyboards that bring text prediction close to the keys

seen in the interface (Figure 1a) of a popular open-sourced gaze-based interaction tool *OptiKey*. Figure 1c shows the eye typing approach with word and letter predictions by McKenzie and Zhang [MacKenzie and Zhang 2008]. Their design, however, places text predictions below the text area. Figure 1b shows the *AugKey* approach [Diaz-Tula and Morimoto 2016] where word suggestions are framed at the right side of the keyboard and also include prefixes around the key to exploiting the foveal region of visual perception. The *GazeTalk* system [Johansen et al. 2003] provides both word and letter prediction features (Figure 1d), where the list of predicted words are on the left side of the key layout, and the preview of the next character layout is available within the cell that is currently being selected.

In the field of touch-based text entry on virtual keyboards (e.g., text entry on mobile displays), the representation and positioning of text predictions have received significant consideration. Some modern virtual keyboard layouts in touch-based text entry domain present the predictions closer to the attention of the user by embedding them in the keypad as inter-spaced and in-letter dynamic predictions [Griffin et al. 2015a,b]. Figure 2 shows these popular designs on Blackberry (Figure 2a[2]) and iOS keyboards (Figure 2b[3]). Cuaresma *et al.* [Cuaresma and MacKenzie 2013] showed that, bringing predictions closer to user's attention by in-letter suggestions in mobile phone keyboards, enhances their ability to interact with predictions and significantly improves the typing speed by touch interaction.

These approaches emphasize the role of word prediction in gaze-based text entry. However, it is unclear if the variable positioning of these predictions has any impact on the performance by reducing eye movements, visual search or scanning time. Majranta *et al.* [Majaranta 2009] argued that an increase in perceptual and cognitive load occurs due to the shift of focus from the keyboard to text prediction list and also while scanning it. However, there have been no concrete studies to investigate if the variable positioning of text predictions have a correlation with visual attention and could enhance the user experience while typing. Thus, in this work, we decided to investigate whether the representation and positioning of text predictions correlate with the performance for gaze-based text entry.

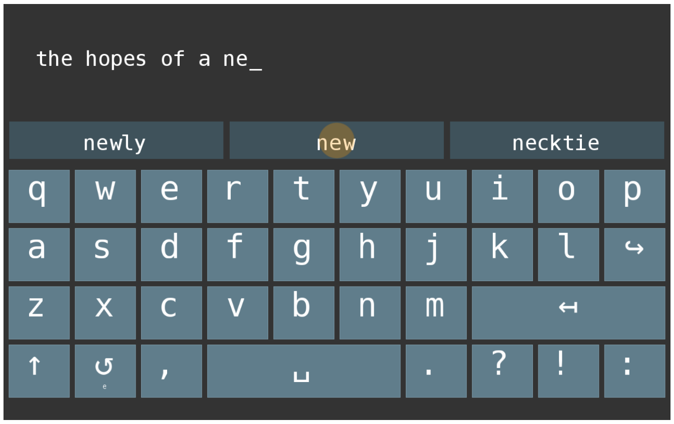
3 DESIGN

Design of virtual keyboards (for both touch and gaze-based text entry systems) involve not only the design and layout of the keys of the keyboard, but also the position of text predictions. For our investigation that involved variable positioning of text predictions to understand its impact of gaze-based text entry, we designed three different keyboards *A*, *B* and *C*.

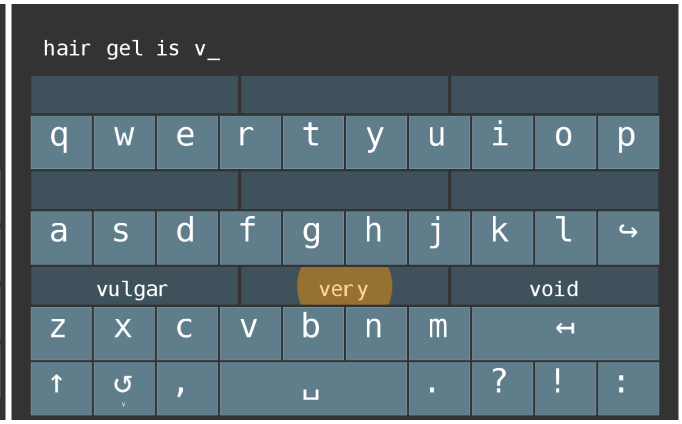
Keyboard A (Figure 3a) has a single line of text predictions on top of the key area. This design has been adapted from the most conventional design of touch-based text entry keyboards. This also represents the most prevalent design for gaze-based text entry keyboards. *Keyboard B* (Figure 3b), is an inter-spaced keyboard that has been designed to bring the text predictions inside the keyboard layout. The predictions are displayed as inter-spaced in the line over the last triggered letter to reduce the visual distance to the last area of fixation. The inter-spacing was inspired from keyboards as shown in Figure 2. This design was also made to investigate if the findings by Cuaresma *et al.* [Cuaresma and MacKenzie 2013] for mobile phone keyboards also hold for gaze-based text entry systems. *Keyboard C* (Figure 3c), embeds the prediction related to the letter on the representative key. This was done to bring the visual focus on the keys. It also has the single line of text prediction on the top of the keyboard area to ensure accessibility to increased number of text predictions. In all the keyboards, the most relevant text prediction was placed in the *middle* followed by *left* and *right* for all the text prediction positions across the three keyboards.

For Keyboard A and Keyboard C, the complete keyboard layout along with the text prediction area took approximately 65% of the screen space. For Keyboard B, it was 77% of the screen space. The on-key suggestions for Keyboard C occupied approximately 30% of the space of the key on which it was initially displayed.

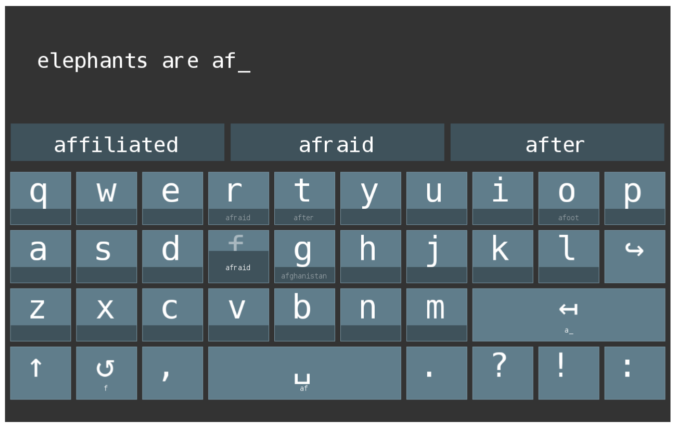
[2] https://www.donmckenzie.ca/portfolio/bb-virtual-keyboard/
[3] http://ok.k3a.me



(a) Keyboard A: Conventional Keyboard



(b) Keyboard B: Bringing text prediction inside Keyboard



(c) Keyboard C: Bringing text prediction inside keys

Figure 3: Keyboard A, B and C designed to evaluate impact of variable text prediction position

For the virtual keyboard interface, both the keys and the word predictions are main responsive elements, arranged in QWERTY order. The QWERTY layout was modified to include the most used punctuation [Cook 2014] for quicker access. The change in layout with the above mentioned dimension percentages was done to utilize the limited space and eye tracker's accuracy. The font on these elements is rendered in white while the fore- and background is kept in shades of dark and unsaturated green to provide a clean and non-distracted experience.

Interaction is implemented via dwell time of 1.0 seconds for key activation. The status of dwelling is queried to the user with a transparent orange circle centered in the middle of the element and growing at fixation until filling the complete element. When the complete element is filled, the key or prediction is activated and the content added to the collected input.

Keys in *Keyboard C* feature a two-step dwell time approach. It requires a second dwell time for activation of the offered text predictions. Once the letter is selected by the first step of dwelling, the key switches to selection of the prediction on it during the second step of dwelling. Same duration of fixation dwell time is necessary to trigger the input of the displayed text prediction. The *space* and the *backspace* key in *Keyboard C* include a preview of the currently edited word after activation of these keys. This integrates into the concept of locating the visual focus on the keys. All the keyboards include a special key in the lower left part to repeat the last letter for double-lettered words. This was necessary only for *Keyboard C* as it does not allow for repetitive key activation. The offered suggestion gets activated during a second dwell time phase instead of the selected letter again.

The experimental keyboards are implemented in C++ and utilizes OpenGL API for rendering. Font rasterization is being done by FreeType2[4] library which renders font letters onto bitmaps. DejaVU-Sans Mono[5] has been chosen as the font for both text and letters on the keys. The generated letter bitmaps are collected on a texture atlas in an OpenGL texture object. This provides a completely customized visual representation and interaction. It enabled us to create the three different keyboard layouts with similar designed elements while only differing the text prediction positioning.

[4]http://www.freetype.org
[5]https://dejavu-fonts.github.io

Presage[6] library was employed for word predictions. It is able to predict the completion of the currently typed word or the upcoming one while delivering multiple results with a different probability. All advanced features were deactivated to avoid bias in the experiment. An n-gram corpus of 50 thousand random English sentences from Tatoeba[7] was initialized. In addition, the words contained in the experimental data set were also added to the prediction machine's dictionary in random order. This ensured existence of all required words but does not lead to a perfect suggestion system where the next word is predicted after a few typed letters.

4 METHODOLOGY

The study involved five consecutive eye typing sessions on different days. The participants were asked to perform the experiment on the keyboard layout that was allotted to them as per the Latin Square ordering. This was done to nullify the effect of bias. The experiment was conducted in a controlled lab environment with artificial illumination. (See Figure 4 for the experimental setup). The

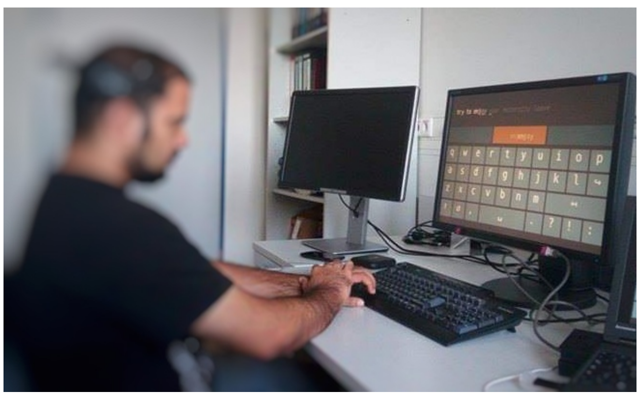


Figure 4: Experimental Setup: A participant (for privacy issues, the face is blurred) performing the experiment for Keyboard A evaluation on a monitor equipped with an eye tracker.

dependent (measured metrics: wpm, backspace usage, error rate, keystroke saved), *independent* (test conditions: keyboard layouts, suggestion positioning, visual feedback) and *controlled* variables (ambient lighting, font size, font colour, key size, key colour, suggestion size, visual feedback colour etc.) were clearly noted for proper execution of the experimental process. Before the actual experimental study, a pilot test was conducted with four participants to validate the experimental procedure. The participants were asked to enter each time a single sentence which is presented in the text area in the upper region of the keyboard interface. At first keystroke, the sentence disappeared and the participant had to recall the sentence in order to continue. This procedure simulates free writing and prohibits the participants from comparing the collected input with the desired result, which would influence the gaze data strongly [Kurauchi et al. 2016].

[6]http://presage.sourceforge.net
[7]https://tatoeba.org/eng

4.1 Participants

The main experimental session consisted of 10 participants (5 Male and 5 Female). The participants' age ranged between 21 to 30 years (mean = 24.8, SD = 2.348). Due to technical challenges, we considered 9 participants as the data recorded for 1 of the participants got corrupt and could not be recovered. 70% of the participants wore spectacles and none of them had prior experience with eye tracking/typing environment. However, all of them have adequate experience with computer usage and all of them were familiar with the QWERTY layout of a keyboard. All the chosen participants were well versed in English, although none of them were native English speakers.

4.2 Apparatus

An SMI REDn eye tracker running at 60Hz was attached to a 24-inch monitor that displayed 1280 x 800 pixels. The participants were asked to sit on a height adjustable chair that was adjusted prior to the calibration process to center the eyes in a distance about 70 cm from the screen. Calibration of the SMI eye tracker was done by SMI calibration tool. However, when participants reported about too much drift, re-calibration was done.

4.3 Procedure

The experiment consisted of five sessions for each keyboard and each session had five sentences. The sentences were given from a phrase set by Mackenzie and Soukoreff [MacKenzie and Soukoreff 2003]. The area of the collected text can be seen in Figure 3a, 3b and 3c. Each participant was introduced to a *training phase* which consisted of two sessions of 5 sentence each for the participants to get familiarized to the environment. The system was reset for every session so that predictive engine would not lead to any bias for text prediction. Participants were instructed to use the physical space bar on the physical keyboard in front of them to access the next sentence in the experiment. In summary, the design was:

9 participants ×
3 keyboard designs ×
5 sessions ×
5 sentences in each session (excluding practice phrases)
= 675 submissions in total.

5 RESULTS

Standard metrics for text entry evaluation include [MacKenzie and Tanaka-Ishii 2007a; MacKenzie and Zhang 1999]: (i) Words Per Minute, (ii) Error, (iii) Keystrokes Saved. We have evaluated two other parameters to understand the usage of text prediction in a gaze typing scenario (iv) Backspace Key usage and (v) Text Prediction usage. The metrics below give a detailed direction to the findings. While performance from typing speed does indicate non-significant change, there is, however, a high usage of suggestions and backspace keys.

5.1 Words per Minute (WPM)

Words or Characters per minute forms one of the most basic metric for evaluating text entry. For this analysis, *WPM* was calculated as: $((|T| - 1) * 60) \div (5 * s)$ where $|T|$ is the length of the transcribed string and "s" is the time taken to transcribe the text in seconds, including backspaces and 5 represents the average characters in a word [MacKenzie and Tanaka-Ishii 2007b]. For each sentence and each session, the words per minute have been calculated.

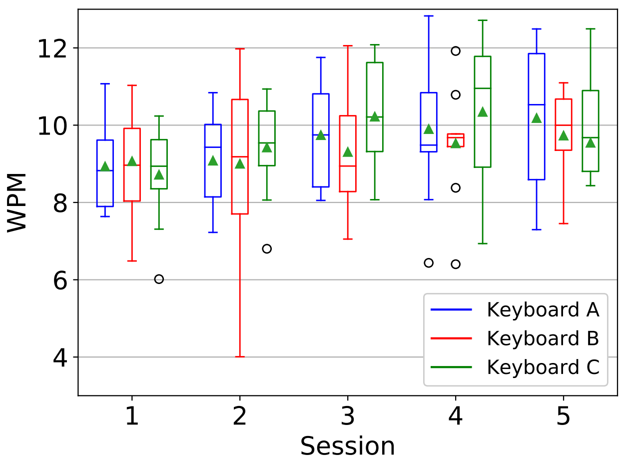


Figure 5: Words per Minute performance across different sessions for Keyboard A, B and C

WPM of 9 participants across 5 sessions for three different keyboards designs can be seen in Figure 5. ANOVA on *WPM* across different sessions for the three different keyboards reveal a non-significant effect, $F_{2,12} = 0.420, p = 0.67(ns)$, with the grand mean of each of the keyboards being very close to one another: *9.57*, *9.36* and *9.65* wpm for *Keyboard A, B and C* respectively. The values lie well within the range of 7-25 words per minute range reported in other setups [Majaranta et al. 2006; Ward and MacKay 2002], indicating reasonable eye typing speed. More specifically, for a dwell-based keyboard with no extensive training, the noted text entry rate lies on the upper range. For example, gaze-based text entry speeds using dwelling is about 10 wpm after about 10 training sessions [Majaranta and Räihä 2002].

No significant learning effect was observed across the performance of the three keyboards.

5.2 Error

Uncorrected errors are characters that are missed or wrongly entered in comparison to the original sentence and not corrected. *Levenshtein Distance* is one measure of calculating the edit distance that measures the deviation of the input sentence with respect to the original sentence. The grand mean of the uncorrected error for the three keyboards across different sessions are *0.56*, *1.36* and *0.88*. Figure 6 shows the errors left uncorrected by the participants across 5 sessions.

Shapiro Wilk Test revealed the data to be not normally distributed. Hence we used a Friedman test, which gave a significant result with $p = 0.02$. Keyboard A had the least number of errors followed by Keyboard C and B.

No learning effect for uncorrected error is observed across the performance on the three keyboards.

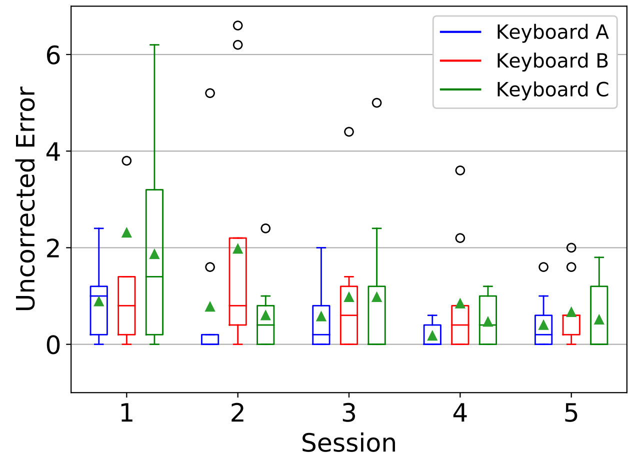


Figure 6: Uncorrected Error across different sessions for Keyboard A, B and C

5.3 Keystrokes Saved

Measurement of keystrokes is another important measure of performance in text entry system. Use of text prediction reduces keystrokes thus leading to faster text entry speed. In this experimental study, every keystroke was calculated and compared against the original count of letters for the sentence they were provided with. The percentage of keystrokes saved across different sessions for the three keyboards designs is shown in Figure 7. Grand mean of *35.48%*, *34.54%* and *28.16%* of saved keystrokes were recorded for the three keyboards across five sessions.

ANOVA shows significant result with $F_{2,12} = 9.56; p = 0.003$ indicating the use of significantly fewer keystrokes to achieve complete sentences in *Keyboard A* than in *B* and *C*.

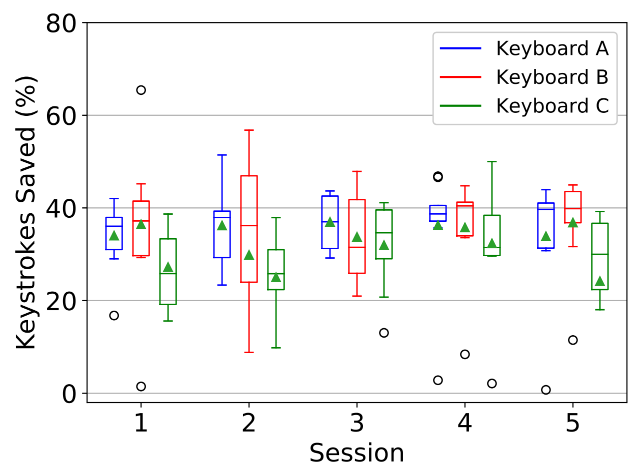


Figure 7: Percentage of Keystrokes saved across different sessions

No learning effect was observed for keystroke savings across the three keyboards.

5.4 Backspace

Backspace usage indicates the number of corrections performed before confirming a sentence. It is also an indication of the corrections the participants needed to make when they accidentally selected a wrong letter or a wrong word prediction from the list. Grand mean of *0.72*, *1.17* and *1.44* backspace hits for the three keyboards were recorded across five sessions. Figure 8 indicates the efforts required to formulate a sentence was much higher for Keyboard C and B by means of deleting the characters. Further investigation of the backspace usage revealed the high amount of backspaces were used for correcting/editing the picked suggestions.

ANOVA shows a non-significant result with $F_{2,12} = 3.25; p = 0.07(ns)$.

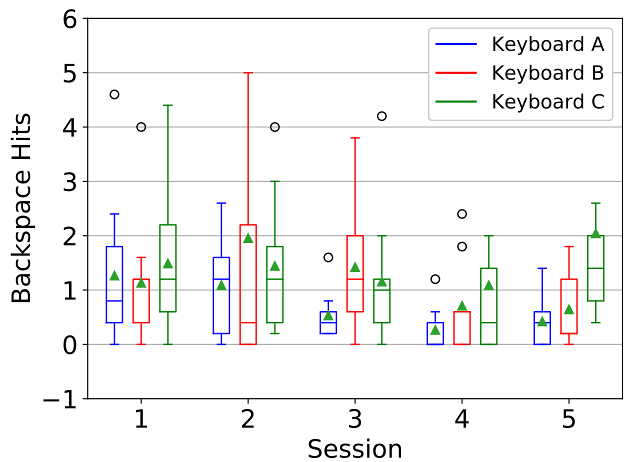


Figure 8: Backspace Key Usage across different sessions for Keyboard A, B and C

5.5 Text Prediction Usage

This metric measures the usage of suggestions while formulating the sentence. It gives us an indication of how effective were the predictions and how easy was it to access them.

For the Keyboard A with only one suggestion line at the top, the suggestion usage was 90.12%, over 91.11% for the inter-spaced Keyboard B, and 93.21% in the Keyboard C with suggestions on the keys itself. ANOVA gave a non-significant result $F_{2,12} = 0.08; p = 0.92(ns)$. Figure 9 shows us the session based performance across the three keyboards.

Further analysis show, suggestions within the layout were well accepted by the participants. For the inter-spaced layout B, 46.61% of the used suggestions are chosen from the top, 33.88% from the center and 19.51% from the bottom positioned line. In the design C with suggestion enhanced keys 54.37% of utilized suggestions are taken from the keys instead of the single suggestion line on top.

In spite of high text-prediction usage, there is no significant learning effect for any of the keyboards.

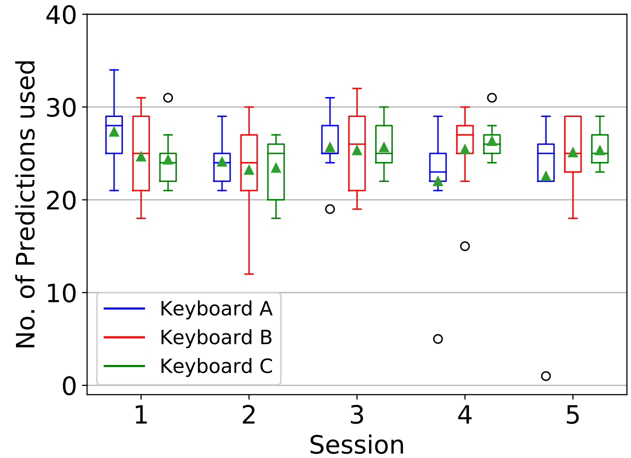


Figure 9: Usage of Text Predictions across different sessions for Keyboard A, B and C

6 DISCUSSION

The experimental evaluation indicates that bringing the suggestions closer to the visual attention of user does not have a significant impact on text entry performance. Several implications of gaze-based interactions could arguably be the reason behind these findings.

One major observation is the inessential usage of suggestions by participants. Text predictions offer users the possibility to reduce effort by auto-completing the words. However inter-spaced and in-letter predictions bring the suggestions in the constant visual attention of users, which might lead them to be overly reliant on predictions (as we can see with the increment of suggestion usage for Keyboard B and C). We observed that the participants even picked partially relevant suggestions with additional suffixes, e.g., a participant selected the predicted word *organization* after typing *or*, and then edited the terms to write the desired word *organize*. Such instances require additional usage of backspace keys and it makes the actual benefit of predictions much smaller than anticipated, i.e., picking a suggestion does not necessarily correlate with less keystrokes to complete the desired word since it involves the editing task of the picked suggestion which is a non-trivial task in eye typing

The results in Section 5.4 (Backspace) confirm this assumption, as the usage of backspace, is much higher for Keyboard C and B compared to A. To further investigate this phenomenon, we calculated the number of backspace hits after selection of a suggestion, since the use of backspace on selected suggestions exhibit the user behavior on picking partially relevant suggestions. Grand mean of 9 participants across 5 sessions was recorded as *2.56*, *3.67*, *5.56* for the three keyboard designs. This indicates that for Keyboard B and Keyboard C participants tend to use partially correct suggestions and hence applied more backspaces to correct the suggestions. This eventually aligns with the result on Keyboard B and C needing significantly more keystrokes compared to A (see Section 5.3), despite of having similar text entry rate.

Dwelling on individual keys to compose a text is demanding and tedious task, hence user is keen on any additional help by the system to ease the task. Text prediction helps user in this aspect, however like any other recommendation engine, predictions may not always be absolutely relevant and helpful for user. We can contemplate that bringing predicted words closer to user attention has the affect on user cognition, as they become more keen on picking the suggested options. However this does not translate to the improved text entry performance.

Another reflection on performance is the rapid eye movements invalidating the effect of positioning benefit. The major variation in the design of Keyboard B and C was to bring the predictions closer to visual focus while selecting letters, so that the user does not need additional time to switch attention to the external text prediction list. However, for gaze-based interaction the fast eye movements might nullify this effect. It has been noted that eye movements are so fast that it provides an interaction medium potentially faster than the conventional mouse [Sibert and Jacob 2000]. More specifically, eye saccades (movement between two consecutive fixations) are extremely fast movements that commonly takes 30 to 120 ms having an amplitude range between 1° and 40° (average 15° to 20°) [Duchowski 2007]. The inspection and selection of prediction can be done quicker since it requires only one saccade or more saccades in the same direction. More specifically for the individual keyboard designs, users retain the position information of word list and hence can predetermine path to reach the list. The user can *mark ahead* path [Kurtenbach and Buxton 1993] and hence the time can be significantly minimized. Furthermore, the variant position does not correlate with the scanning cost of text predictions since the user still has to scan for relevant words to be picked from presented suggestions irrespective of the positions, i.e., for both Keyboard A and B user has to look at all three predicted words to find out if the relevant suggestions are present in the list, for Keyboard A user has to look at a distant top layout, however, the additional time required is not very significant due to fast eye movements.

In comparison to touch-based text entry virtual keyboards, eyes always start moving toward the target before the hand and as eye movements are quite rapid, the eyes usually arrive at the target before the hand starts to move [Abrams et al. 1990]. For touch-based input it's the combination of hand movement with eye movements since users need to first look and scan if the suggested word is relevant and then perform the selection by hand. Therefore, touch-based selections of text predictions require additional physical movement, which is not correlated with eye movements [Bekkering et al. 1994], i.e., hand movements need substantial time for interaction distinguished from eye movements. Hence the keyboard designs to bring the predictions closer for touch-based inputs [Griffin et al. 2015b] invariably helps in reducing the effort of selecting predictions, and respectively improve the user experience and performance.

7 CONCLUSION

Text prediction is a valuable feature to enhance typing experience. For text entry with virtual keyboards, representation of relevant text prediction to end-users become significantly important. In this paper, we assess the visual representation of text predictions by evaluating three similar designs of dwell-time based keyboards with the variable spatial positioning of text predictions. The evaluation indicates that for gaze-based text entry, the methodology of predictions near the visual fovea makes users heavily dependent on the given suggestions. While this can be beneficial if the predictions are useful, it does lead to extensive usage of suggestions that could inherently hamper the usability.

The variant position does not correlate with the scanning cost of word predictions since user still has to scan for relevant words to be picked from presented suggestions. An interesting future direction would be to investigate this phenomena in large scale studies and understand understand how the scan time affects typing process and how it can be minimized to improve the performance.

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