Intelligent LED Keyboard

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1 ABSTRACT

Nowadays mobile keyboards often present error corrections and word completions (suggestions) as candidates for anticipated user input. However with growing use of mobile devices for text input, in activities such as email, internet browsing, texting, and social media, users tend to rely more on such intelligent text entry methods. Although earlier studies explored the effect of these ITE methods on input performance in mobile devices (virtual keyboards), there is no information on the effectiveness of these methods when used with physical keyboards.

The main goal of this study was to examine to which extent led-based word suggestion effect text input performance on physical keyboards. One Keyboard with fully customizable per key colors was used to show suggested words. 20 Participants completed 3 copy typing tasks to experience led-based words suggestions conditions, each task contained 11 phrases. Typing performance (speed and accuracy), user demographics and test condition (word suggestion use) was collected for each of the tasks. Participants were divided into two groups based on median of typing speed reached in the test without use of word prediction feature of the physical keyboard. The data set enabled statistical analysis of the effect of the word prediction feature f the led keyboard among and between participants groups.

Results showed that led-based word prediction impaired the average typing speed of all participants groups. We fund no evidence of the effect of led-based word prediction on the error rates.

CCS Concepts: • **Human-centered computing → Keyboards**.

Additional Key Words and Phrases: Intelligent text entry methods, ITE

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2 INTRODUCTION

This paper contributes to understanding impact of intelligent text entry methods on typing performance. a large number of intelligent text entry techniques exist, the effectiveness of which is still a field of many future studies.

Various studies have been conducted to understand the effect these ITE-methods on typing performance on mobile devices and how they correlates with typing style and experience (See related works). These studies have consistently found that the use of ITE-methods influence the typing performance negatively. Despite this, the effectiveness of these intelligent text entry methods on physical keyboards have yet to be robustly researched. This paper sets out to address this research gap.

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We investigated the effect of words suggestion on the typing performance (speed and accuracy) on a physical keyboards. It was hypothesized that a led-word word suggestion could impact positively the text entry performance on computer keyboards, thus the use of ITE on physical keyboard yields lower error rates and higher text entry speeds.

3 RELATED WORKS

A large numbers of recent studies emerged seeking to better understand the factors affecting typing performance on mobile and desktop keyboards. In the following, we briefly review some of the main findings and results.

3.1 Intelligent text Entry Methods

A frequently employed technique to improve user performance is the observation and analysis of user's interactions to detect potential errors or predict the intended step. Many recent studies explored differences in performance with the use of ITE-methods on mobile devices [5] and on desktop keyboards [6].

Palin and Feit [5] found that participants using prediction only were the slowest, with 10 WPM less than those using auto-correction for example. Auto-correction has a moderate positive correlation with WPM ($r = 0.237$) while word prediction (suggestions) has a small negative correlation with performance ($r = 0.183$). Another finding is that without ITE the faster typists tend to generate less errors. These results were confirmed by a recent study [6] that showed decreased performance rates for heavy use of word prediction.

3.2 Impact of typing styles and experience on visual information's usage:

We could identify only two previous studies that investigated how different sources of information are used during typing on a computer keyboard.

Rieger and Bart [7] compared touch typists and non-touch typists and reported that typing task, typing proficiency, and typing style influence how attention is distributed during typing. They found that faster typists rely less on visual information about the typing process (e.g. location of fingers on keyboard) and in copy typing higher typing ability coincided with less attention to the keyboard. the findings were based on self-reporting by participants.

Feit and Weier [3] captured hand and finger movements for a sample of 36 users with a motion-capture system. They reported several differences in performance, gaze deployment and movement strategies. The analysis of eye gaze confirms the the findings of Rieger and Bart [7] that touch typists spent less time looking at the keyboard and required less gaze shift.

4 METHOD

A controlled experiment was designed with word prediction (within group) and typing experience (between group) as independent variables and text entry speed (WPM) and total error rate as dependent variables.

4.1 Participants

Table 1 summarize the demographic background of the 20 voluntary 15 male and 5 female participants. 15 participants self reported that they are not typist, one of them has visited a touch typing course, while 5 consider them self a typist, of these only 2 have done in the past touch typing course. 19 of them reported the use of both hands for typing (95%) and reported range of 4 to 10 used fingers ($M = 6.9$, $SD = 2.29$). On average Participants were 23.92 ($SD = 2.31$) years old , the majority of which were German native speaker and were relatively experienced in typing in English (2 always, 6 usually, 9 sometimes and 3 rarely).

A total of 17 reported the use of the QWERTZ keyboard layout, which is the same layout used in the experiment, while only 3 reported having a QWERTY keyboard. 15 Participants self reported that they are used to a low profile keyboard. Their self-reported average daily typing with their computer/physical keyboard varied between 1 and 10 hours (M = 3.30, SD = 2.52).

The participants were assigned to two groups depending on their typing speed in the test without any intelligent text entry method: Experienced(WPM over the Median) and Inexperienced (WPM below the Median).

Table 1. Participants demographics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Age	20	23.600	2.257	21	21.8	25	28
Average Daily Typing	20	3.300	2.515	1	1.8	5	10
Finger Usage	20	6.900	2.292	4	4.8	8.5	10

4.2 Apparatus

The experiment was conducted with one Logitech G815 mechanical keyboard with GL-Switches keys and Lightsync RGB with a color spectrum of 16.8 million colors. The keyboard had a height of 22 mm, 1.5 mm actuation distance and 45 g actuation force. The keyboards had the QWERTZ layout.

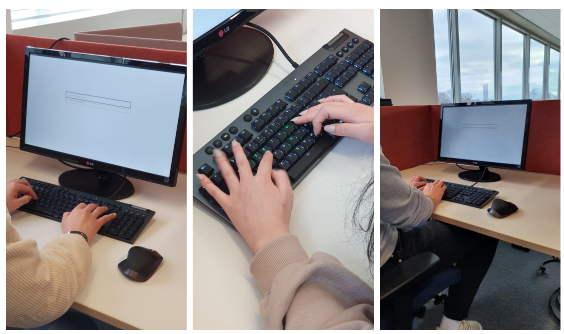

Fig. 1. Experimental setup

4.3 Implementation

For the purpose of the study we developed a desktop application 1 that controls the led keyboard to show the predicted set of characters. The app was implemented using javascript (electronJS), html and css (bootstrap). For data storage we integrated a NoSQL database (Mongodb) to store participants data and tests settings. The Application was used to collect participant data, predict next possible characters based on a prefix and control the led back-light of the keyboard to show the predicted set of characters. To record text entry metrics we integrated a web application named webTEM. Please refer to section 4.6. [1]

4.4 Experiment design

A repeated-measures design was used to determine how word prediction usage effect user typing performance. The independent variable experience had only 2 levels while word prediction had three levels, namely off, normal and enhanced. Off is the condition where the keyboard doesn't offer any visual help while normal is where the

[1]https://github.com/AmineAmzil/led-based-word-prediction

keyboard suggests words with led backlighting. The last condition, enhanced, the keyboard always suggest only the next letter that should be copy typed.

4.5 Procedure

Before performing the typing tasks participants were asked to fill in a questionnaire. In addition to the questions related to demographics and typing experience asked by Dhakal et al. [2] we also asked for keyboard layout they are used to and whether they consider them self typist or not. After submitting the questionnaire participants had to complete 3 tasks, one after the other, before each task they were told to chose one specific settings for word prediction (off, normal or enhanced). Participants were asked to transcribe 11 short English phrases from the MacKenzie and Soukoreff [4] set with with each of the settings. The application displayed all phrases in lowercase and in random order. Participants were asked to enter the phrases as fast and accurately as possible. Error correction was encouraged but not forced. There was neither a auditory feedback nor a practice block, but the keyboard was demonstrated before the tests.

4.6 Measures

A web application named webTEM [1] developed by Sabbir Arif and Mazalek to record text entry metrics was used internally in the experiment software to record text entry metrics. After the completion of each task the webTEM app sends an email with metrics file attached.

5 RESULTS

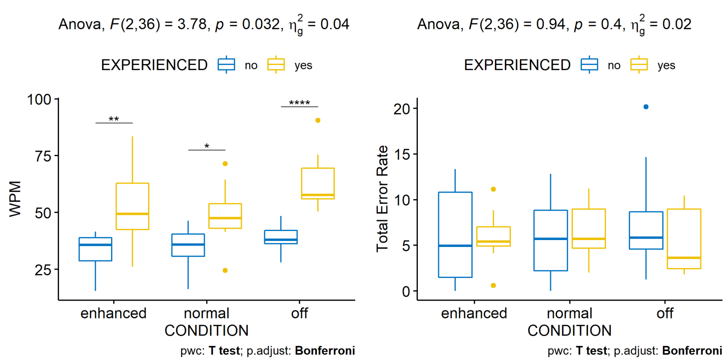

Fig. 2. Box plot for effect of experience and condition on WPM and total ER

5.1 Performance Measures

An overview of the participants performance measures is given in Table 2.

Words per minute. On average, participants typed at 45.096 WPM (SD = 14.153) with 75% of participants having a performance below 49.517 WPM. The fastest typists reached over 81.870 WPM where the slowest reached 22.622 WPM.

Error rate. On average, participants left 1.215% (SD=0.803) of errors uncorrected. 75% of participants left less than 1.777% of errors uncorrected.

Corrected error rate. On average, participants corrected 5.167% (SD=2.901) of errors. 75% of participants corrected less than 6.764% of errors.

Total error rate. On average, participants made 6.282% (SD=3.194) of errors. 75% of participants made less than 8.708% of errors.

5.2 Impact of Intelligent Keyboard and Experience

Table 2. Participants average overall performance

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Error Rate	20	1.215	0.803	0.181	0.567	1.777	2.889
Corrected Error Rate	20	5.167	2.901	0.484	3.124	6.764	12.163
Total Error Rate	20	6.282	3.194	1.171	4.264	8.708	14.110
Words Per Minute	20	45.096	14.153	22.622	36.600	49.517	81.870

5.2.1 ***Words per minute.*** Comparison of WPM between experience levels and keyboard conditions during copy typing can be seen in Figure 2. A two-way ANOVA was performed to analyze the effect of typing experience and intelligent keyboard on WPM. The results of statistical tests can found in the tables file 2. The two-way ANOVA revealed that there was a statistically significant interaction between the effects of typing experience and intelligent keyboard on WPM (F(2n, 36) = 3.781, p = 0.032). Simple main effects analysis showed that typing experience did have a statistically significant effect on WPM (p = 6.65e-04). Simple main effects analysis showed that intelligent keyboard did have a statistically significant effect on WPM (p = 4.79e-05).

Considering the Bonferroni adjusted p-value, Post-hoc comparisons showed that experienced participants were significantly faster than the inexperienced in all 3 intelligent keyboard settings: off ($p < 0.05$), normal ($p < 0.05$) and enhanced ($p < 0.05$). Surprisingly the use of word prediction had a relatively negative impact on the WPM as the figure 2 shows. A one-way ANOVA test revealed that these differences in WPM were only statistically significant by the experienced group ($p < 0.05$). Pairwise comparisons showed that the mean WPM score was only significantly different by the experienced group between enhanced and off word prediction setting ($p = 0.05$).

5.2.2 ***Error rate.*** To analyze the effect of typing experience and word prediction on total error rate, we performed a two-way mixed ANOVA, results of which can found in the tables file 2. The two-way ANOVA revealed that there was not a statistically significant interaction between the effects of typing experience and word prediction setting. Simple main effects analysis showed that that neither experience nor led-based word prediction had a statistically significant effect on total error rate. Comparison of total error rate between experience levels and keyboard conditions during copy typing can be seen in Figure 2.
[2]

6 DISCUSSION

In this work, we collected typing data from 20 volunteers using a software based transcription test. Participants were divided into two groups based on their WPM. The results indicate that experience had positive impact on WPM while the use of led-based word prediction impaired the text entry rates, especially by the more experienced participants. Statistical tests revealed that these differences were indeed significant. We observed also that the error rate is neither effected by the experience nor by the use of word prediction. These results are in line with prior studies on mobile typing [3, 5–7] confirming that the use of word prediction is not cognitive-free.

[2] Results of statistical tests

Generalizability of the sample is an issue: our participants were from a single computer science bachelor program. Many participants were young males from Germany good at typing. This is not representative of the general population and might bias the data towards representing a western, young, more technology-affine group of people.

Note that our analysis was limited to recording the text entry metrics. We were unable to log participants participants eye gaze movements. An eye tracker such the one used by Feit and Weir [3] could be used. This can be a subject of future works.

7 CONCLUSION

In this paper, we have reported observations from a transcription task with 20 volunteers. The participants were grouped into two groups based on their average WPM while word prediction was off. This allowed us to explore the effects of the led-based word prediction and typing experience on typing speed and total error rate.

Among other findings, experienced participants tend to be faster than inexperienced participants regardless of the use of word prediction. The use of led-based word prediction impaired the the typing speed by both experienced and inexperienced participants, in contrast neither typing experience nor use of word prediction had a statistically significant effect on the error rate.

The collected data set is very rich that it allows further more in depth analyses of the effect of the led-based word prediction on other metrics such as input time and visual scanning time. The presented analysis confirms prior findings on smaller other studies. However, more research is needed to disentangle confounds, and to investigate other factors and their interactions.

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