Predicting Users' Attention Breakpoints During Mobile Text Entry: Revisiting Prior Work

Ioulia Simou
University of Patras
Rio, Greece
simo@ceid.upatras.gr

Andreas Komninos
University of Patras
Rio, Greece
akomninos@ceid.upatras.gr

Abstract

Mobile text entry often involves unnecessary gaze shifts from the keyboard to the text area to check for errors, which introduces additional cognitive overhead. This paper summarizes previously published work investigating the prediction of such attention breakpoints to enable better-timed error feedback. Using gaze and touch data from 30 participants under one-finger and two-thumb typing conditions, a lightweight model was developed to predict attention shifts. Results indicate that these breakpoints can be predicted with promising accuracy, particularly during two-thumb typing, supporting the design of more efficient text entry systems.

CCS Concepts

• **Human-centered computing → Text input**; **Touch screens**; **Smartphones**.

Keywords

Mobile text entry, eye-tracking, attention management

ACM Reference Format:
Ioulia Simou and Andreas Komninos. 2026. Predicting Users' Attention Breakpoints During Mobile Text Entry: Revisiting Prior Work. In . ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction and Motivation

Text entry is a complex process that can be viewed as consistent of two parallel, or interleaved sub-tasks: *determining and planning* the text to enter, and *executing* the appropriate motor functions to enter it [2]. There is, however, a third, less explicitly discussed sub-task in text entry, which is the need to check the text that has been entered for correctness. Mobile text entry requires users to frequently shift their attention between the screen keyboard and the text entry area to check for errors. While this behaviour supports accuracy, many of these checks are unnecessary, as users often verify input even when no errors have occurred. Prior research has shown that users frequently interrupt typing to verify correctness, even in the absence of errors [4, 5]. Gaze-tracking studies indicate that a substantial portion of user attention, up to 25%, is allocated to the text entry area during typing [7]. These frequent attention shifts and task switching between typing and checking introduce cognitive costs, including interruption overhead and increased mental load [3], potentially reducing typing efficiency.

While previous approaches have attempted to support error awareness through continuous feedback, such methods may be distracting [1, 6]. Delivering feedback at *opportune* moments is therefore a more promising approach. This paper summarizes previously published work presented at MobileHCI'23 [8], investigating whether it is possible to predict moments when users are likely to interrupt typing to check their input. It focuses on the effectiveness of lightweight models and their ability to generalize across typing conditions, highlighting the potential of simple gaze- and touch-based features for real-time deployment in mobile text entry systems.

2 Methodology

The study utilized an existing dataset [4] of gaze and touch data collected from 30 participants performing transcription tasks under two conditions: one-finger typing and two-thumb typing. The dataset contained thousands of gaze and touch events and was preprocessed to remove inconsistent data. Gaze data were divided into two regions: the keyboard area (lower part of the screen) and the text entry area (upper part of the screen). A clustering-based method was used to detect gaze shifts from the keyboard to the text entry area, as it more accurately reflected user behaviour compared to a threshold-based approach. To predict attention shifts, gaze and keystroke data were examined together, to extract features that might provide information about an imminent gaze shift. The selected features were: 1) the last typed character, 2) the number of characters typed since last *space* event, 3) the number of gaze events since the last check, 4) the time elapsed since the last gaze shift, 5) the number of characters typed since the last check. These features attempt to capture both the likelihood of errors and the cognitive effort since the previous error check. A Support Vector Machine (SVM) classifier was used to predict whether the next gaze event would represent a gaze shift away from the keyboard. SVM was selected due to its efficiency, suitability for binary classification, and feasibility for deployment on mobile devices. Two evaluation strategies were used, a 10-fold cross-validation and a Leave-One-Person-Out validation, to assess both general performance and generalization to unseen users.

This paper is based on work previously published in the Proceedings of the 25th International Conference on Mobile Human-Computer Interaction (MobileHCI '23 Companion), Athens, Greece, 2023.

Conference'17, Washington, DC, USA

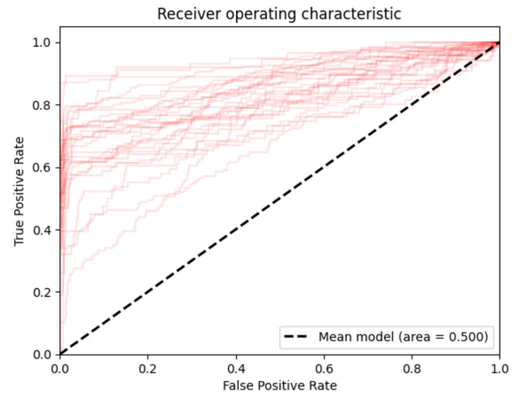
ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn

3 Results

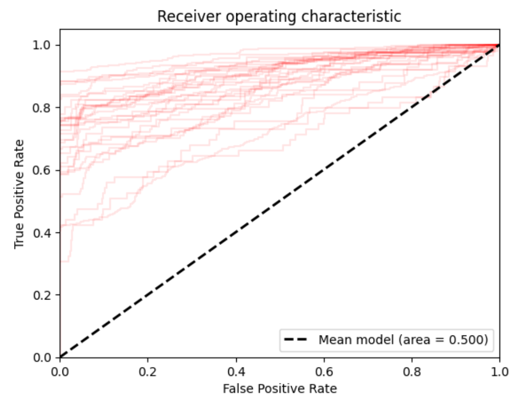
Using 10-fold cross-validation, the model achieved strong and consistent performance across both typing conditions. For one-finger typing, the macro F1-score reached a mean of $\approx 0.82, \sigma = 0.01$, while for two-thumb typing it improved to $\approx 0.89, \sigma = 0.01$. Accuracy was high in both cases ($\approx 0.97, \sigma = 0.001$ for one-finger and $\approx 0.96, \sigma = 0.002$ for two-thumb typing) and ROC-AUC scores ($\approx 0.83, \sigma = 0.07$ and $\approx 0.88, \sigma = 0.07$ respectively) indicate reliable discrimination between gaze classes. However, recall was lower in the one-finger condition ($\approx 0.75, \sigma = 0.01$) compared to two-thumb typing ($\approx 0.86, \sigma = 0.01$), suggesting that predicting upward gaze shifts (i.e. attention switches to the text area) is more challenging when users type with a single finger. Overall, performance was consistently better in the two-thumb condition, likely due to more stable and predictable typing behaviour.

The model maintained good performance in the second approach. The macro F1-score was $\approx 0.80, \sigma = 0.08$ for one-finger typing and $\approx 0.88, \sigma = 0.06$ for two thumb-typing, with accuracy remaining high ($\approx 0.97, \sigma = 0.014$ and $\approx 0.96, \sigma = 0.019$ respectively). ROC curve analysis (Fig. 1) shows that performance is consistently better than random across all users, although variability is observed, particularly in the one-finger condition.

Across both evaluation approaches, the model demonstrated robust performance, with consistently better results in two-thumb typing. The findings suggest that attention breakpoints during mobile text entry can be predicted with good accuracy, even in scenarios where no prior data from a specific user is available.



(a) One-finger typing



(b) Two-thumbs typing

Figure 1: ROC curves for all participants using Leave-One-Person-Out validation.

4 Conclusion

This paper presented a summary of previously published work on predicting users' attention breakpoints during mobile text entry. The findings demonstrate that it is feasible to predict moments when users are likely to shift their attention away from the keyboard using lightweight machine learning models based on gaze and touch data. The reported results show that such predictions can be achieved with good accuracy and can generalize reasonably well across users, highlighting the potential for practical deployment in mobile text entry systems. By identifying opportune moments for delivering feedback, these approaches may help reduce unnecessary interruptions and improve typing efficiency.

However, several limitations exist. The approach relied on gaze tracking, which may not be widely available in everyday mobile devices. Moreover, the dataset was relatively small and collected in controlled laboratory settings. In real-world scenarios, attention shifts may also be driven by external factors such as environmental distractions, movement, or multitasking, which are not captured in the dataset. As a result, the reported performance may not reflect "in-the-wild" conditions. Future work should therefore investigate the robustness of such models in ecologically valid settings.

A further practical consideration concerns the computational cost of real-time feature extraction and inference. While the use of a lightweight SVM classifier and simple feature set suggests that inference can be performed efficiently on mobile devices, continuous monitoring of gaze data may significantly increase battery consumption. Future work should evaluate energy consumption in real-world deployments and explore models that rely solely on features derived from users' typing behaviour.

Overall, this work illustrates how modeling user attention during text entry can inform the design of more adaptive and supportive interaction techniques. Reconsidering these findings in new contexts may further contribute to the development of more efficient and inclusive mobile interaction experiences.

References

[1] Ohoud Alharbi, Ahmed Sabbir Arif, Wolfgang Stuerzlinger, Mark D. Dunlop, and Andreas Komninos. 2019. WiseType: A Tablet Keyboard with Color-Coded Visualization and Various Editing Options for Error Correction. In *Proceedings of Graphics Interface 2019 (GI 2019)*. Canadian Information Processing Society, Kingston, Ontario. doi:10.20380/GI2019.04

[2] Yuichi Higashiyama, Katsuhiko Takeda, Yoshiaki Someya, Yoshiyuki Kuroiwa, and Fumiaki Tanaka. 2015. The Neural Basis of Typewriting: A Functional MRI Study. *PLoS ONE* 10, 7 (July 2015), e0134131. doi:10.1371/journal.pone.0134131

[3] Shamsi T Iqbal and Eric Horvitz. 2007. Disruption and Recovery of Computing Tasks: Field Study, Analysis, and Directions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 677–686.

[4] Xinhui Jiang, Yang Li, Jussi P.P. Jokinen, Viet Ba Hirvola, Antti Oulasvirta, and Xiangshi Ren. 2020. How We Type: Eye and Finger Movement Strategies in Mobile Typing. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. doi:10.1145/3313831.3376711

[5] Andreas Komninos. 2022. The Value of Open Data in HCI: A Case Report from Mobile Text Entry Research. *Multimodal Technologies and Interaction* 6, 9 (Sept. 2022), 71. doi:10.3390/mti6090071

[6] Andreas Komninos, Emma Nicol, and Mark D. Dunlop. 2015. Designed with Older Adults to SupportBetter Error Correction in SmartPhone Text Entry: The MaxieKeyboard. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 797–802. doi:10.1145/2786567.2793703

[7] Andreas Komninos, Angeliki Tsiouma, Georgia Gogoulou, and John Garofalakis. 2022. Don't Look up: The Cost of Attention to Stimulus Phrases in Mobile Text Entry Evaluations. In *26th Pan-Hellenic Conference on Informatics with International Participation*. ACM, ACM, Athens, Greece. doi:10.1145/3575879.3576015

[8] Ioulia Simou and Andreas Komninos. 2023. Predicting Users' Attention Breakpoints During Mobile Text Entry. In *Proceedings of the 25th International Conference on Mobile Human-Computer Interaction* (New York, NY, USA, 2023-06-26) *(MobileHCI '23 Companion)*. Association for Computing Machinery, 1–7. doi:10.1145/3565066.3608747