Exploring Smartphone Keyboard Interactions for Experience Sampling Method driven Probe Generation

Surjya Ghosh
Centrum Wiskunde & Informatica
Amsterdam, The Netherlands
surjya.ghosh@cwi.nl

Salma Mandi
Indian Institute of Technology Kharagpur
Kharagpur, India
salmamandi@kgpian.iitkgp.ac.in

Bivas Mitra
Indian Institute of Technology Kharagpur
Kharagpur, India
bivas@cse.iitkgp.ac.in

Pradipta De
Microsoft Corporation
Atlanta, USA
prade@microsoft.com

ABSTRACT

Keyboard interaction patterns on a smartphone is the input for many intelligent emotion-aware applications, such as adaptive interface, optimized keyboard layout, automatic emoji recommendation in IM applications. The simplest approach, called the Experience Sampling Method (ESM), is to systematically gather self-reported emotion labels from users, which act as the ground truth labels, and build a supervised prediction model for emotion inference. However, as manual self-reporting is fatigue-inducing and attention-demanding, the self-report requests are to be scheduled at favorable moments to ensure high fidelity response. We, in this paper, perform fine-grain keyboard interaction analysis to determine suitable probing moments. Keyboard interaction patterns, both cadence, and latency between strokes, nicely translate to frequency and time domain analysis of the patterns. In this paper, we perform a 3-week in-the-wild study (N = 22) to log keyboard interaction patterns and self-report details indicating (in)opportune probing moments. Analysis of the dataset reveals that time-domain features (e.g., session length, session duration) and frequency-domain features (e.g., number of peak amplitudes, value of peak amplitude) vary significantly between opportune and inopportune probing moments. Driven by these analyses, we develop a generalized (all-user) Random Forest based model, which can identify the opportune probing moments with an average F-score of 93%. We also carry out the explainability analysis of the model using SHAP (SHapley Additive exPlanations), which reveals that the session length and peak amplitude have strongest influence to determine the probing moments.

CCS CONCEPTS

• **Human-centered computing** → **Keyboards**; **Smartphones**; *Human computer interaction (HCI)*; User interface design.

KEYWORDS

Smartphone, Keyboard interaction, Typing, Experience Sampling Method, ESM, Opportune moment, Notification

ACM Reference Format:
Surjya Ghosh, Salma Mandi, Bivas Mitra, and Pradipta De. 2021. Exploring Smartphone Keyboard Interactions for Experience Sampling Method driven Probe Generation. In *26th International Conference on Intelligent User Interfaces (IUI '21), April 14–17, 2021, College Station, TX, USA.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3397481.3450669

1 INTRODUCTION

Keyboard interaction on smartphone, one of the widely used input modalities, has been leveraged to develop many emotion-aware services such as adaptive interface design [2, 22], optimized auto-suggestion usage [12], guided response generation [15], mental state tracking [3, 9, 13, 29, 32]. The backbone of such applications is a supervised machine learning model, which correlates typing characteristics with self-reported emotion labels to infer emotion [3, 10, 27, 32]. Often, the emotion self-reports are collected from a long-term Experience Sampling Method (ESM) study, which requires users to repetitively respond to survey probes; thus demands user attention and often results into survey fatigue, participation burden [1, 21, 23]. Hence, suitable self-report probing strategies based on user attention are essential.

In the existing literature, several approaches exist to deliver smartphone notifications at opportune moments [19, 20, 24, 31]. For example, Ghosh et al. developed a 2-phase model driven ESM schedule to optimize the probing rate and self-report timeliness [11]. Fischer et al. showed that participants react faster to probes when they are delivered immediately after completing a task on mobile (e.g., reading a text message) [7]. Ho et al. demonstrated that placing the probe between two physical activities (like sitting and walking) may attract user attention quickly [14]. In [25], authors demonstrated that last survey response, phone's ringer mode can be leveraged to identify suitable probing moments. However, to the best of our knowledge, most of the prior work overlooked the signatures exist in the smartphone typing activities to identify the opportune probing moments.

We, in this paper, investigate the role of the smartphone keyboard interactions to identify the opportune probing moments for emotion self-report collection. The smartphone typing depict two

IUI '21, April 14–17, 2021, College Station, TX, USA

ACM ISBN 978-1-4503-8017-1/21/04…$15.00
https://doi.org/10.1145/3397481.3450669

key facets - *timing* and *rhythm*, based on a person's typing pattern [5, 16]; hence we perform both time-domain and frequency-domain analysis respectively on the keyboard interaction data (Section 3). Precisely, (a) we analyze the time-domain characteristics such as *typing speed, error rate, session length, session duration* of typing instances to discriminate between inopportune and opportune probing moments (Section 3.1). Side by side, (b) we transform the typing intervals to frequency-domain using Discrete Fourier Transform (DFT) [33, 34]. We detect peaks [6] from the real coefficients of the frequency-domain representation, and analyze the *number & value of peak amplitudes* to discriminate between inopportune and opportune moments (Section 3.2). Drawing on these, we develop an aggregate (all-user) machine learning model, leveraging on both time & frequency domain features, to predict the opportune probing moments for emotion self-report collection (Section 4).

For experimental evaluation of the proposed model, we conduct a 3-week in-the-wild study involving 22 participants. We develop & distribute an Android smartphone keyboard, which traces user's typing interactions (not the text content) and collects the emotion self-reports (*happy, sad, stressed, relaxed*), once the user completes typing in an application. Additionally, the self-report survey pop-up allows the user to indicate (via *No Response* label) whether the current probing moment is (in)opportune (Section 2). The analysis of the collected ≈3500 sessions reveals that time-domain features (session length, session duration) and frequency-domain features (number and value of peak amplitudes) exhibit the capacity to mark the probing moment as inopportune. Finally, the proposed model achieves an average F-score of 93% to correctly predict the opportune probing moments, while explainability analysis of the model reveals that session length and peak amplitude to have the strongest influence on the model accuracy (Section 4.2).

2 FIELD STUDY AND DATASET

2.1 Experiment Apparatus

We have designed the keyboard app (Fig. 1) based on Android Input Method Editor (IME) facility. It is same as QWERTY keyboard with additional capability of tracing user's typing interactions. We do not store any alphanumeric character because of privacy reason.

Tracing Keyboard Interactions: We define *session* as the time period spent by the user at-a-stretch on a single application. We record the timestamp of every touch event within a session and compute the interval between two consecutive touch events as *Inter-tap duration (ITD)*. For instance, we represent a session S of length $S_l(=n)$ as a sequence of timestamps $[t_1, t_2, t_3, ...t_n]$, depicting the respective touch events, with session duration $S_d = t_n - t_1$. We measure ITD as $v_i = t_{i+1} - t_i$, which reflects the typing speed of the user; higher value of ITD indicates lower typing speed. Hence, a session S may be further expressed as a sequence of ITDs, $S = [v_1, v_2, v_3, ..., v_n]$, where v_i indicates the i^{th} ITD. Additionally, we record the usage of the backspace or delete keys pressed in a session, which helps to identify the amount of typing mistakes made in a session.

Collecting Emotion Self-reports & Labelling Probing Moments: We also collect self-reported emotions from users. Once user completes typing in an application and switches from the current application, we probe her for the emotion self-report (*happy, sad, stressed, relaxed*) as shown in Fig. 2. We select these emotions based on the Circumplex model (Fig. 3) of emotion [26], as they represent largely represented emotion from separate quadrants, which makes self-reporting easier for the user. We keep the interface simple by explicitly recording emotion and do not consider the intensity of perceived emotion, which can make self-reporting difficult. We also keep the provision of *No Response*, so that user can skip self-reporting by selecting this option. Whenever the user reports *No Response*, the probing moment is considered inopportune, while any emotion (*happy, sad, stressed, relaxed*) response is considered opportune.

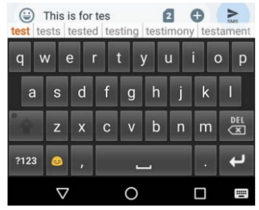


Figure 1: App keyboard

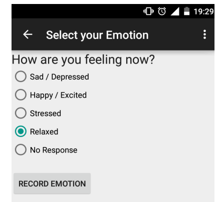


Figure 2: Self-reporting UI

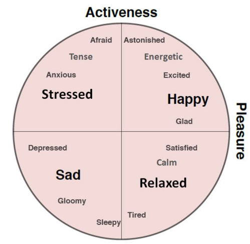


Figure 3: Circumplex model [26]

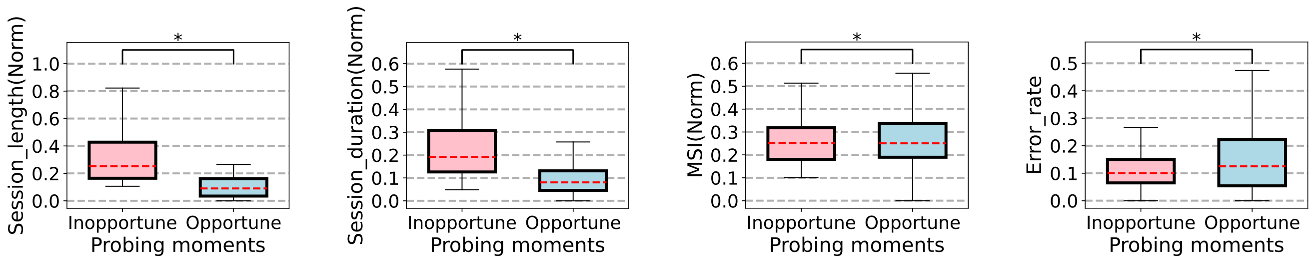
2.2 Study Procedure & Dataset

We recruited 22 university students (18 M, 4 F) aged between 20 to 35 years. We installed the application on their smartphones and asked them to use it for 3 weeks for regular typing activities and emotion self-reporting. We also informed that once they complete typing in an application and change it, they may receive a self-report pop-up, where they have to record their perceived emotion. They were further instructed that if the probe appears at an inopportune moment and they want to skip responding, they should select the *No Response* button instead of dismissing the pop-up.

We have collected a total of 3463 sessions, out of which 2883 (83.3%) sessions are opportune and 580 (16.7%) sessions are inopportune. The average number of sessions per user is 157.4 (std. dev 93.8). We observe that for 6 users (3, 9, 16, 17, 20, 21), all the sessions are opportune; for 16 out of 22 participants at least 95% sessions are opportune.

3 DATA ANALYSIS

In this section, we analyze the smartphone typing behavior and demonstrate the role of time-domain and frequency-domain features to discriminate the opportune and inopportune probing moments.



(a) Session length (b) Session duration (c) Session speed (d) Error rate

Figure 4: Comparison of different time-domain characteristics between inopportune and opportune probing moments - (a) session length (b) session duration (c) session speed and (d) error rate. This comparison reveals all these parameters vary significantly (for session speed, $p < 0.05$; for others, $p < 0.001$) between these two probing moments.

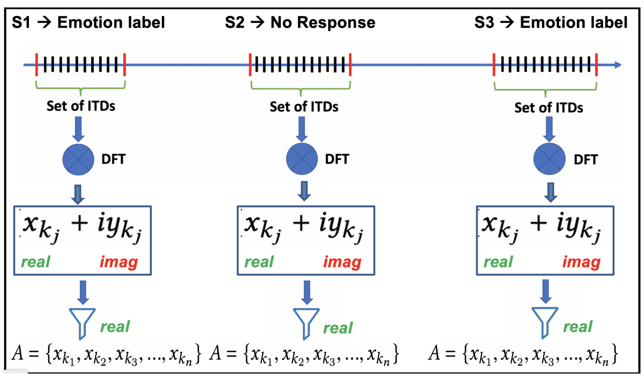


Figure 5: Schematic diagram of transforming set of ITD(s) to frequency domain. The set of ITD(s) obtained from different sessions (e.g. S1, S2, S3) are transformed using Discrete Fourier Transform (DFT) to obtain the frequency domain representation. From this set of coefficient-pairs, we filter out the imaginary ones and consider only the real ones for future processing.

3.1 Time-domain Typing Features

We propose the time domain features of a session S as (a) typing speed (S_{MSI}), (b) error rate (S_{Er}), (c) session length (S_l), (d) session duration (S_d) to characterize the inopportune moments. We represent the typing speed in a session S as Mean Session ITD (MSI), where we compute the mean of all ITDs present in session S as $S_{MSI} = \frac{\sum_{i=1}^{n-1} v_i}{n-1}$. We also compute the typing mistakes performed in a session by counting the total number of backspace (or delete) key pressed in a session (say, c), and compute as $S_{Er} = \frac{c}{n}$. To handle the inter-subject variability [4, 30], we normalize each time-domain feature as $x' = \frac{x - min(X)}{max(X) - min(X)}$, where $X \in \{S_{MSI}, S_{Er}, S_l, S_d\}$ is the set of values recorded for a feature across all individuals, x is one instance of the set X, $min(X)$, $max(X)$ indicate minimum and maximum of the set X.

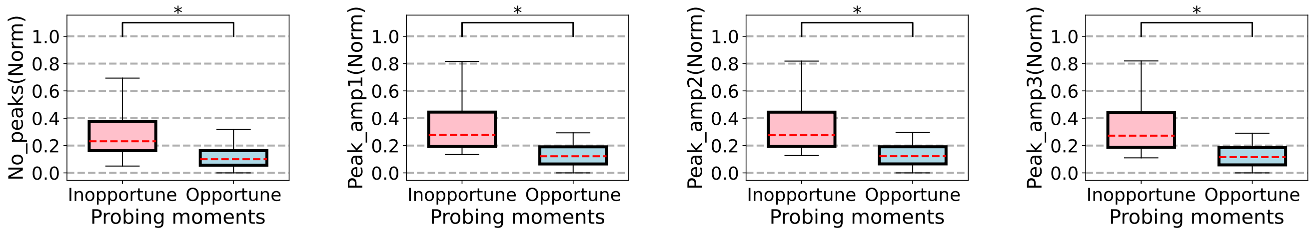
Role of features at inopportune moments: In Fig. 4a, we observe that the session length (S_l) of the sessions labelled as inopportune moments are comparatively high. Precisely, the median session length (normalized) for inopportune and opportune moment sessions are 0.250 and 0.090, respectively. Since session lengths are not normally distributed ($p < 0.05$ with Shapiro-Wilk test)[1], we perform the unpaired Mann-Whitney U test and observe a significant effect of probing moment on the session length (U = 1467164, Z = 28.727, p < 0.001, r = 0.488). Similarly, in Fig. 4b, we report the significant effect of probing moment on session duration (S_d) (U = 1404436, Z = 25.870, p < 0.001, r = 0.439). This points to the fact that users prefer to skip ESM probes while engaged in lengthy and longer typing sessions. In Fig. 4c, 4d, we observe that typing speed (S_{MSI}) and typing mistakes (S_{Er}) vary significantly between two types of probing moments (S_{MSI}: {U = 787688, Z = -2.202, p < 0.05, r = 0.037}, S_{Er}: {U = 738410, Z = -4.446, p < 0.001, r = 0.076}). In case of the inopportune moments' sessions, the typing speed is comparatively high (low MSI) and the typing mistakes are comparatively low. These suggest that (a) when users are typing fast in a session or (b) when users are more attentive while typing (making few mistakes), they prefer to skip ESM probes in those moments.

3.2 Frequency-domain Typing Features

We apply Discrete Fourier Transform (DFT) on the ITDs present in a session S to obtain the equivalent frequency-domain representation. Here the session S of dimension n is represented as the a combination of n periodic signals $\{x_{k_j} + iy_{k_j}, \forall j \in \{1, \ldots, n\}\}$, where each real component x_{k_j} represents the amplitude of the respective signal with frequency k_j [28]. Since we focus on the amplitude only, we discard the imaginary part and deal with only the real part of the coefficients [8]. We compute the resultant amplitude x_k of the session S for the signal with frequency k Hz as $x_k = \sum_{j=0}^{n-1} v_j \times cos(2\pi k * j/n)$. For a session S of dimension n, we repeat this procedure for all the n signals to generate the amplitude vector $A = \{x_{k_j}, \forall j \in \{1, \ldots, n\}\}$ as the frequency-domain representation of S (see Fig. 5). Note that depending on the session dimension, the cardinality of the amplitude vector may vary across various sessions. Next, we apply the peak detection algorithm [6] on this amplitude vector A and select the top-3 amplitudes[2] of every session S to use them as frequency-domain features. Like Section 3.1, we normalize each of these features using min-max scaling.

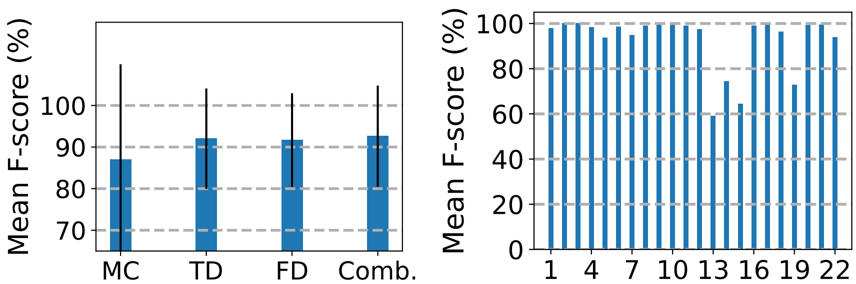
Role of features at inopportune moments: In Fig. 6a, we observe that the total number of peak amplitudes present in a session are comparatively high in case of sessions tagged as inopportune

[1] We have the same finding for session duration, MSI and error rates.
[2] Increasing the number of peak amplitudes beyond 3 does not influence the opportune moment identification performance significantly.



(a) Total no. of peaks **(b) First peak amp** **(c) Second peak amp** **(d) Third peak amp**

Figure 6: Comparison of different frequency-domain characteristics between inopportune and opportune probing moments - (a) total number of peaks (b) first peak amplitude (c) second peak amplitude and (d) third peak amplitude. This comparison reveals all these parameters vary significantly ($p < 0.001$) between these two probing moments.



(a) Model-wise F-score **(b) User-wise F-score**

Figure 7: Model performance - (a) model-wise F-score. Error bar indicates std. dev. (b) user-wise F-score

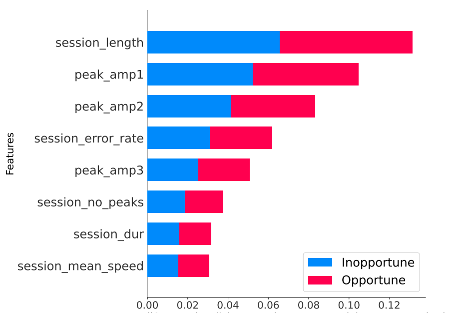


Figure 8: Model explainability using SHAP reveals that session length (time-domain), and peak amp1 (frequency-domain) have strongest influence in deciding in(opportune) moment.

moments (with U = 1447084, Z = 27.821, p < 0.001, r = 0.473 for Mann-Whitney's U test). Next, from the list of all peaks in a session, we select top-3 amplitudes and compare those values for opportune and inopportune probing moments. In Fig. 6b, 6c, 6d, we observe that the peak values of the top-3 amplitudes significantly vary between sessions labelled with two kinds of probing moments (with U = 1467354, Z = 28.735, p < 0.001, r = 0.488 for peak amplitude; U = 1466826, Z = 28.711, p < 0.001, r = 0.488 for second peak; U = 1466200, Z = 28.682, p < 0.001, r = 0.487 for third peak, respectively). These highlight that simple frequency-domain analysis of ITD values can find the difference between different types of probing moments.

4 OPPORTUNE PROBING MOMENT PREDICTION

Finally, we leverage on the aforementioned time-domain and frequency-domain features to develop an all-user model (**Comb**) to predict the opportune probing moments for self-report collection. We implement Random Forest to train the model by using 100 decision trees with setting maximum depth of the tree as unlimited, both of these (large number of trees, maximum depth) help to counter overfitting. Since there is data imbalance, we compare the performance of the proposed model with a personalized baseline model (**MC**), which always predicts the majority class for a user. Additionally, we implement two variants of our proposed model namely **TD** and **FD**, leveraging only on the time-domain and frequency domain features, respectively.

4.1 Model Performance

In Fig. 7a, we evaluate the proposed model (**Comb**) using leave-one-subject-out-cross-validation and obtain an average F-score of 93% (std. dev 12.2%), which comfortably outperforms the baseline model **MC** (F-score 87% with a high std. dev. of 23%). Interestingly, the **Comb** model does not exhibit significant performance benefit compared to both the model variants **TD** and **FD** (average F-score 91%), as the most discriminating **TD** model feature (session length, see Fig. 8) is highly correlated with all the **FD** model features (with avg. Pearson correlation coefficient 0.98). In Fig. 7b, we demonstrate the user-wise high prediction accuracy of the proposed **Comb** model; few users exhibit exceptional F-score which mostly stems from the presence of very few (e.g. 2) or no presence (e.g. 3, 9, 16, 17, 20, 21) of any inopportune label in their data.

4.2 Model Explainability

We perform explainability analysis of our proposed model using SHAP (SHapley Additive exPlanations) [18], where Shapley index of a model feature exhibits its contribution to determine the predicted class for an instance [17]. In Fig. 8, we compute the shapley index for each of the features on the test set and show the mean absolute SHAP values for each feature. This analysis reveals that the session length (time-domain feature) has the strongest influence, followed by peak amplitude and second peak amplitude (frequency-domain feature). Among time-domain features, error rate exhibits moderate effect, followed by session duration and typing speed, while among frequency-domain features, third peak amplitude and number of peaks are found to have a moderate impact on the model.

5 DISCUSSION AND CONCLUSION

Keyboard interaction patterns hide signatures in both frequency and time domain. Leveraging such patterns, one can identify periods of inactivity but engaged state of the user suitable for probing the user for any information. Experience Sampling Method (ESM), which relies on probing users with a questionnaire, and eliciting a response, can benefit significantly in increasing the response rate. The major implication of this work is the ability to develop smart ESM strategies based on keyboard interaction. In this paper, we perform an in-the-wild study to log the keyboard interaction details on smartphone to determine suitable probing moments to deliver ESM probes. We analyse the collected typing interaction data both in time-domain and frequency-domain to find that interaction characteristics such as text length, typing duration, typing speed (in time-domain), and number and value of peak amplitudes (in frequency-domain) significantly vary between the opportune and inopportune probing moments. Leveraging these, we develop a machine learning model, which can identify the probing moments with an average F-score of 93%, thus underscoring the importance of keyboard interactions while developing smartphone-based intelligent ESM schedules.

REFERENCES

[1] Niels Van Berkel, Denzil Ferreira, and Vassilis Kostakos. 2017. The Experience Sampling Method on Mobile Devices. *ACM Computing Surveys (CSUR)* 50, 6 (2017), 93.

[2] Nabil Bin Hannan, Khalid Tearo, Joseph Malloch, and Derek Reilly. 2017. Once More, With Feeling: Expressing Emotional Intensity in Touchscreen Gestures. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces.* 427–437.

[3] Matteo Ciman and Katarzyna Wac. 2016. Individuals' stress assessment using human-smartphone interaction analysis. *IEEE Transactions on Affective Computing* 9, 1 (2016), 51–65.

[4] Michael E Dawson, Anne M Schell, and Diane L Filion. 2017. The electrodermal system. (2017).

[5] Clayton Epp, Michael Lippold, and Regan L Mandryk. 2011. Identifying emotional states using keystroke dynamics. In *Proceedings of ACM SIGCHI.*

[6] Attila Felinger. 1998. *Data analysis and signal processing in chromatography.* Elsevier.

[7] Joel E Fischer, Chris Greenhalgh, and Steve Benford. 2011. Investigating episodes of mobile phone activity as indicators of opportune moments to deliver notifications. In *Proceedings of ACM MobileHCI.* 181–190.

[8] M. Garrido, K. K. Parhi, and J. Grajal. 2009. A Pipelined FFT Architecture for Real-Valued Signals. *IEEE Transactions on Circuits and Systems I: Regular Papers* 56, 12 (2009), 2634–2643.

[9] Surjya Ghosh, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2017. Evaluating effectiveness of smartphone typing as an indicator of user emotion. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII).* IEEE, 146–151.

[10] Surjya Ghosh, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2017. Tapsense: Combining self-report patterns and typing characteristics for smartphone based emotion detection. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services.* 1–12.

[11] Surjya Ghosh, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2019. Designing an experience sampling method for smartphone based emotion detection. *IEEE Transactions on Affective Computing* (2019).

[12] Surjya Ghosh, Kaustubh Hiware, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2019. Does emotion influence the use of auto-suggest during smartphone typing?. In *Proceedings of the 24th International Conference on Intelligent User Interfaces.* 144–149.

[13] Surjya Ghosh, Sumit Sahu, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2019. EmoKey: An emotion-aware smartphone keyboard for mental health monitoring. In *2019 11th International Conference on Communication Systems & Networks (COMSNETS).* IEEE, 496–499.

[14] Joyce Ho and Stephen S Intille. 2005. Using context-aware computing to reduce the perceived burden of interruptions from mobile devices. In *Proceedings of ACM SIGCHI.* 909–918.

[15] Chieh-Yang Huang, Tristan Labetoulle, Ting-Hao Kenneth Huang, Yi-Pei Chen, Hung-Chen Chen, Vallari Srivastava, and Lun-Wei Ku. 2017. Moodswipe: A soft keyboard that suggests messages based on user-specified emotions. *arXiv preprint arXiv:1707.07191* (2017).

[16] Keystroke Dynamics 2020. https://searchsecurity.techtarget.com/definition/keystroke-dynamics.

[17] Scott M. Lundberg, Gabriel Erion, Hugh Chen, Alex DeGrave, Jordan M. Prutkin, Bala Nair, Ronit Katz, Jonathan Himmelfarb, Nisha Bansal, and Su-In Lee. 2020. From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence* 2, 1 (2020), 2522–5839.

[18] Scott M Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In *Advances in Neural Information Processing Systems 30*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.). 4765–4774.

[19] Abhinav Mehrotra, Mirco Musolesi, Robert Hendley, and Veljko Pejovic. 2015. Designing content-driven intelligent notification mechanisms for mobile applications. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing.* 813–824.

[20] Abhinav Mehrotra, Veljko Pejovic, Jo Vermeulen, Robert Hendley, and Mirco Musolesi. 2016. My phone and me: understanding people's receptivity to mobile notifications. In *Proceedings of the 2016 CHI conference on human factors in computing systems.* 1021–1032.

[21] Abhinav Mehrotra, Jo Vermeulen, Veljko Pejovic, and Mirco Musolesi. 2015. Ask, but don't interrupt: the case for interruptibility-aware mobile experience sampling. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers.* ACM, 723–732.

[22] Fariba Noori and Mohammad Kazemifard. 2016. AUBUE: An Adaptive User-Interface Based on Users' Emotions. *Journal of Computing and Security* 3, 2 (2016), 127–145.

[23] Veljko Pejovic and Mirco Musolesi. 2014. InterruptMe: designing intelligent prompting mechanisms for pervasive applications. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing.* ACM, 897–908.

[24] Martin Pielot, Bruno Cardoso, Kleomenis Katevas, Joan Serrà, Aleksandar Matic, and Nuria Oliver. 2017. Beyond interruptibility: Predicting opportune moments to engage mobile phone users. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–25.

[25] Martin Pielot, Rodrigo de Oliveira, Haewoon Kwak, and Nuria Oliver. 2014. Didn't you see my message?: predicting attentiveness to mobile instant messages. In *Proceedings of the ACM SIGCHI.* 3319–3328.

[26] James A Russell. 1980. A circumplex model of affect. *Journal of Personality and Social Psychology* 39, 6 (1980), 1161–1178.

[27] Ensar Arif Sağbaş, Serdar Korukoglu, and Serkan Balli. 2020. Stress detection via keyboard typing behaviors by using smartphone sensors and machine learning techniques. *Journal of Medical Systems* 44, 4 (2020), 1–12.

[28] Stephen So and Kuldip K Paliwal. 2018. Reconstruction of a signal from the real part of its discrete Fourier transform [tips & tricks]. *IEEE Signal Processing Magazine* 35, 2 (2018), 162–174.

[29] Yoshihiko Suhara, Yinzhan Xu, and Alex'Sandy' Pentland. 2017. Deepmood: Forecasting depressed mood based on self-reported histories via recurrent neural networks. In *Proceedings of the 26th International Conference on World Wide Web*. 715–724.

[30] Ronnie Taib, Jeremy Tederry, and Benjamin Itzstein. 2014. Quantifying driver frustration to improve road safety. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems*. 1777–1782.

[31] Aku Visuri, Niels van Berkel, Tadashi Okoshi, Jorge Goncalves, and Vassilis Kostakos. 2019. Understanding smartphone notifications' user interactions and content importance. *International Journal of Human-Computer Studies* 128 (2019), 72–85.

[32] Rafael Wampfler, Severin Klingler, Barbara Solenthaler, Victor R Schinazi, and Markus Gross. 2020. Affective State Prediction Based on Semi-Supervised Learning from Smartphone Touch Data. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.

[33] S Weinstein and Paul Ebert. 1971. Data transmission by frequency-division multiplexing using the discrete Fourier transform. *IEEE transactions on Communication Technology* 19, 5 (1971), 628–634.

[34] Shmuel Winograd. 1976. On computing the discrete Fourier transform. *Proceedings of the National Academy of Sciences* 73, 4 (1976), 1005–1006.