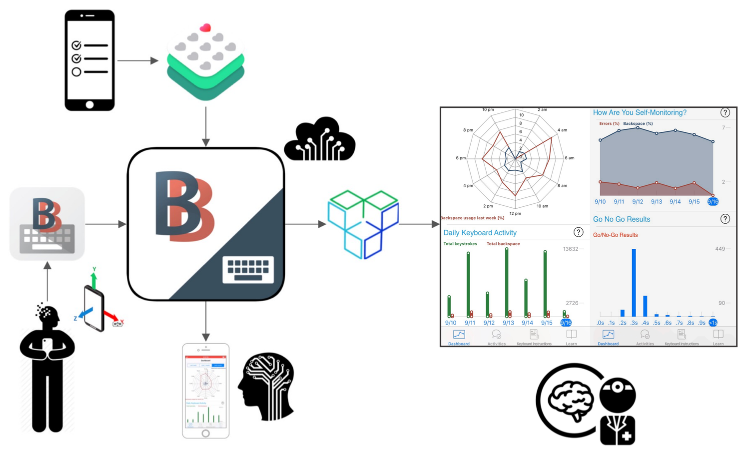
Characterizing Passively Collected Real-world Keyboard Dynamics in Mood Disorders as a Function of Age and Time-of-day

Homa Rashidisabet[1], Claudia Vesel[1], Alexander Demos[1], John Zulueta[1], Casey Bennett[2], Jonathan Stange[1], Jennifer Duffecy[1], Faraz Hussain[1], Andrea Piscitello[1], John Bark[1], Scott Langenecker[3], Shannon Young[4], Erin Mounts[4], Larsson Omberg[4]. Peter Nelson[1], Raeanne Moore[5], Olusola Ajilore[1], Alex Leow[1]

Background

Current advances in mobile health technologies and wearable devices can be leveraged for long-term, continuous and unobtrusive data collection that can reconcile shortcomings in current neuropsychological assessment of mood symptomatology and cognitive performance, by providing ecological validity and high temporal richness of measurements to address intra-individual variations. To this end, we present the largest to date naturalistic crowd-sourced study on typing kinematics from a demographically diverse sample, enriched for mood disorders.



Objectives

Our research is focused on BiAffect, a mobile health application leveraging Apple's ResearchKit, that collects typing kinematics metadata (i.e., number of characters, autocorrect, backspaces, typing speed), while preserving content anonymity. Our aim was to:

1. Assess how circadian rhythms and age affect cognition and mood as measured by passively collected typing metrics
2. Assess how depression alters speed-accuracy relationship while controlling for demographics and typing mode (one vs two handed typing).

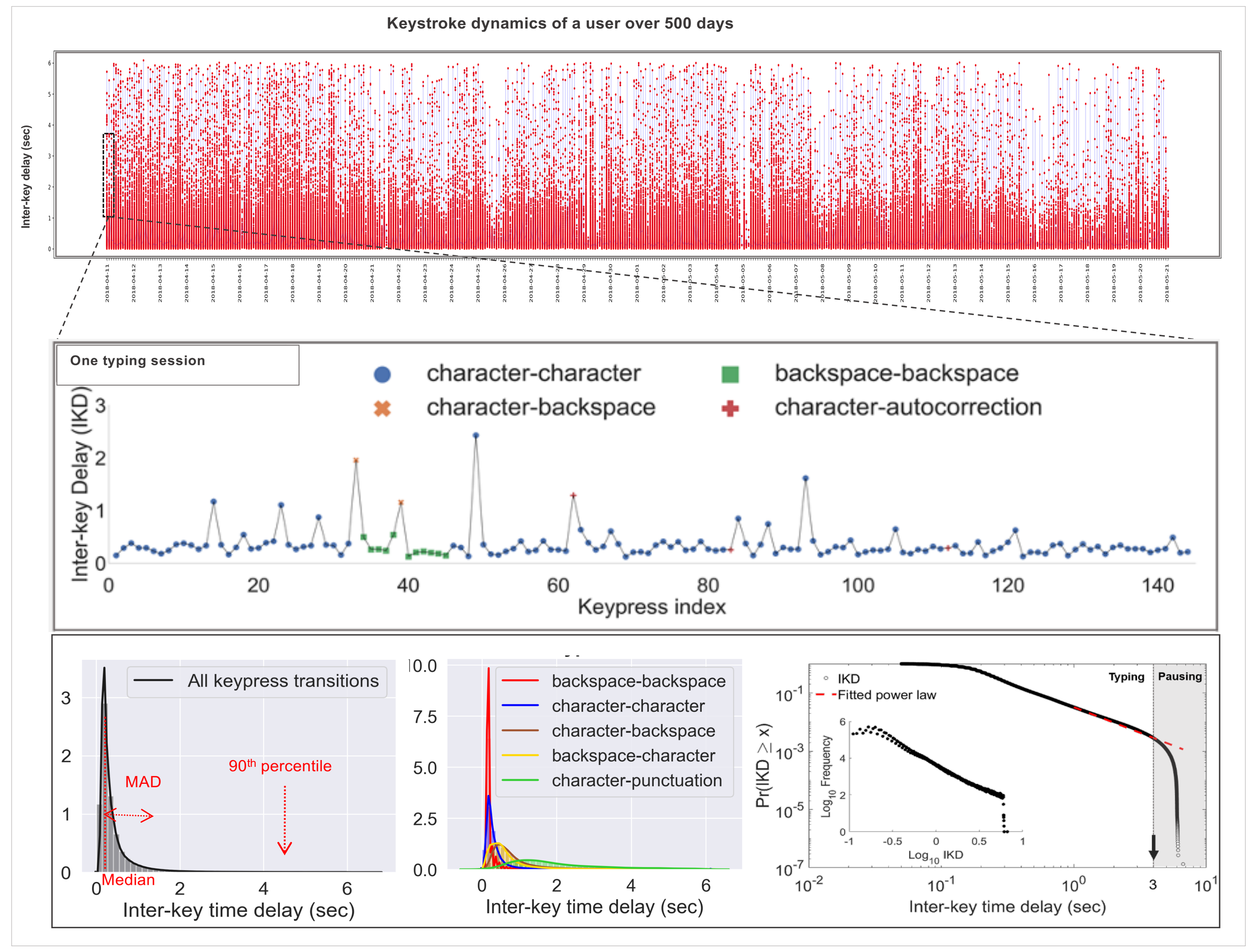
Key findings

1. Established the utility of collecting keyboard dynamics in the wild to examine the association between typing performance and aging in the context of diurnal patterns
2. Demonstrated the sensitivity of our keyboard-derived metric to changes in severity of depressive symptoms
3. Support the feasibility of BiAffect in successfully recruiting participants using a crowd-sourced open-science research paradigm.

Our ultimate goal is to provide real-time feedback on tying performance, that can be used by participants to gain insight into their neuropsychological state.

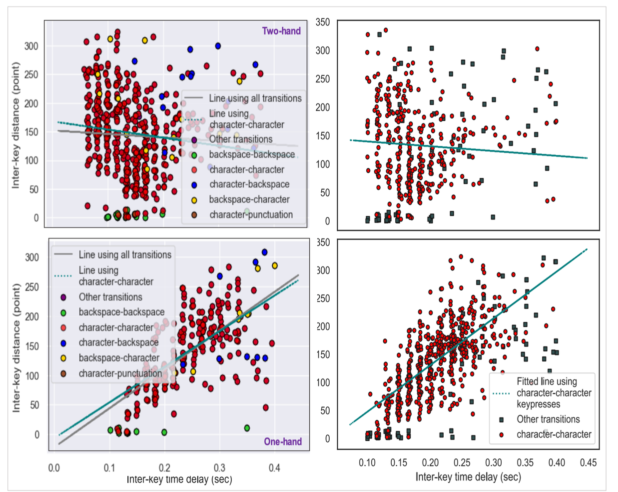
Methods

Data collection and demographics: Since March 2018 we collected >40 million keypresses from 998 users. After performing data quality control, cleaning and all preprocessing steps, we isolated a dataset comprising of 248 most active participants who reported their age (range: 18-82, mean = 37.7, SD = ± 11) and gender (71% females 27% males and 2% non-binary). To investigate effects of depressive symptoms on typing performance, a secondary analysis was conducted on 146 users who completed the Patient Health Questionnaires 8 (PHQ, omitting suicidality question).



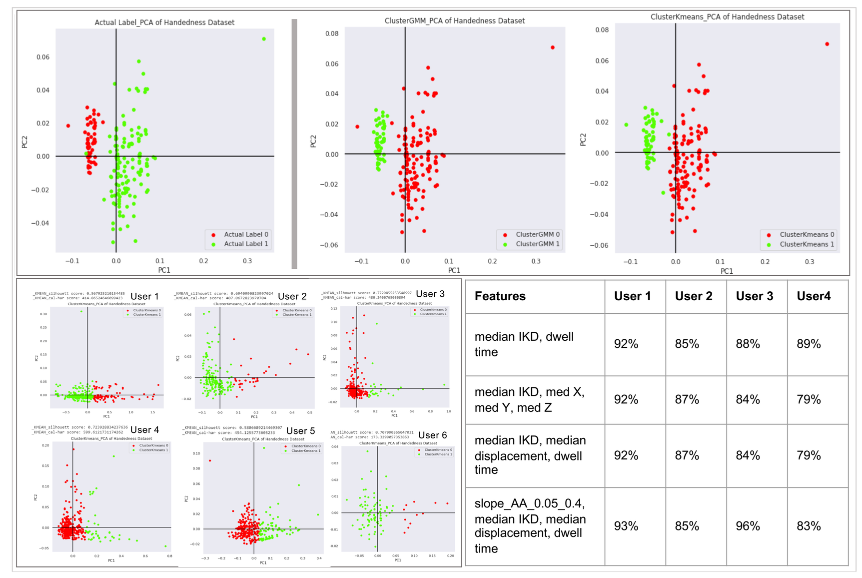
Prediction of typing mode (deterministic model)

To distinguish between one- vs. two-handed typing, the inter-key delay (IKD) and inter-key distance of keypress-transition-of-interest were linearly regressed in each typing session. Typing sessions with positive and significant regression slope were labeled as one-handed typing, otherwise they were labeled as two-handed Typing. The accuracy of this model validated on over 500 sessions from 6 different users is 96%-99%.



Prediction of typing mode (Unsupervised learning)

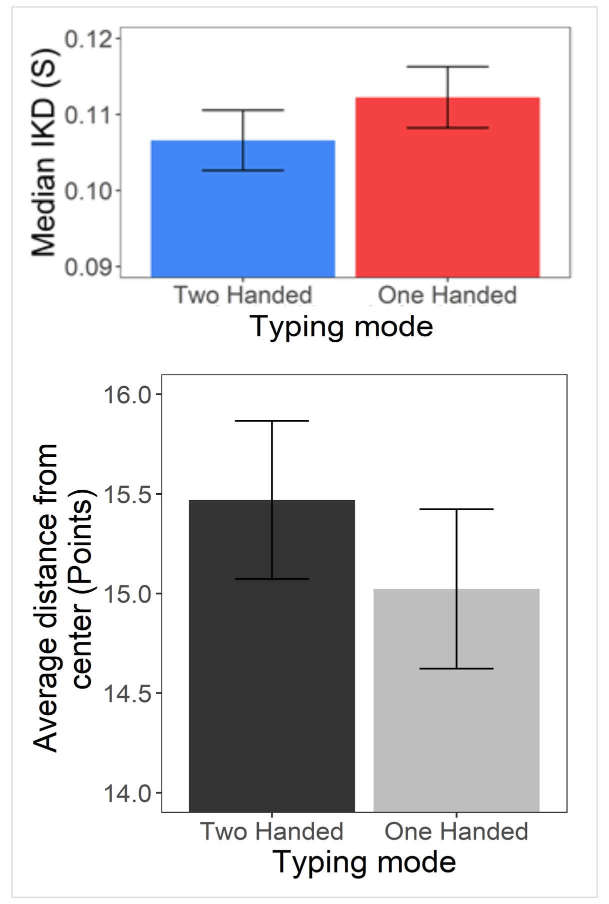
We predicted typing mode via K-means and GMM clustering with total accuracy of 90%-93%. This method was validated via independent test data for over 500 sessions collected on internal testing phones for 6 different users yielding 85%-96% accuracy per user using different keystroke dynamics features.



Results

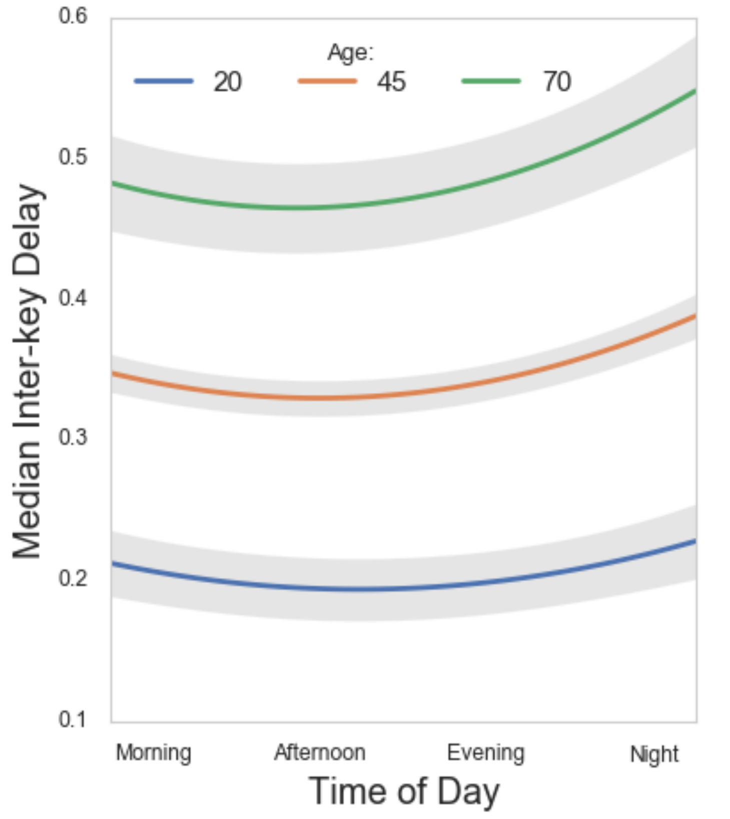
Effects of typing mode on IKD

As expected, typing mode was found to be a significant predictor of typing speed, with one handed typing being much slower (b = -0.014, t = 7.50, p < .0001) and more variable (b = .0056, t = 6.65, p < .0001) than two-handed typing. Typing mode also exhibited an effect on typing accuracy (defined as distance (in pixel) of touch from key center referred to as finger-touch distance). We show that typing with one hand will have less average finger-touch location (b = −0.45, p < .0001), as it is the slower typing mode than two-handed typing.



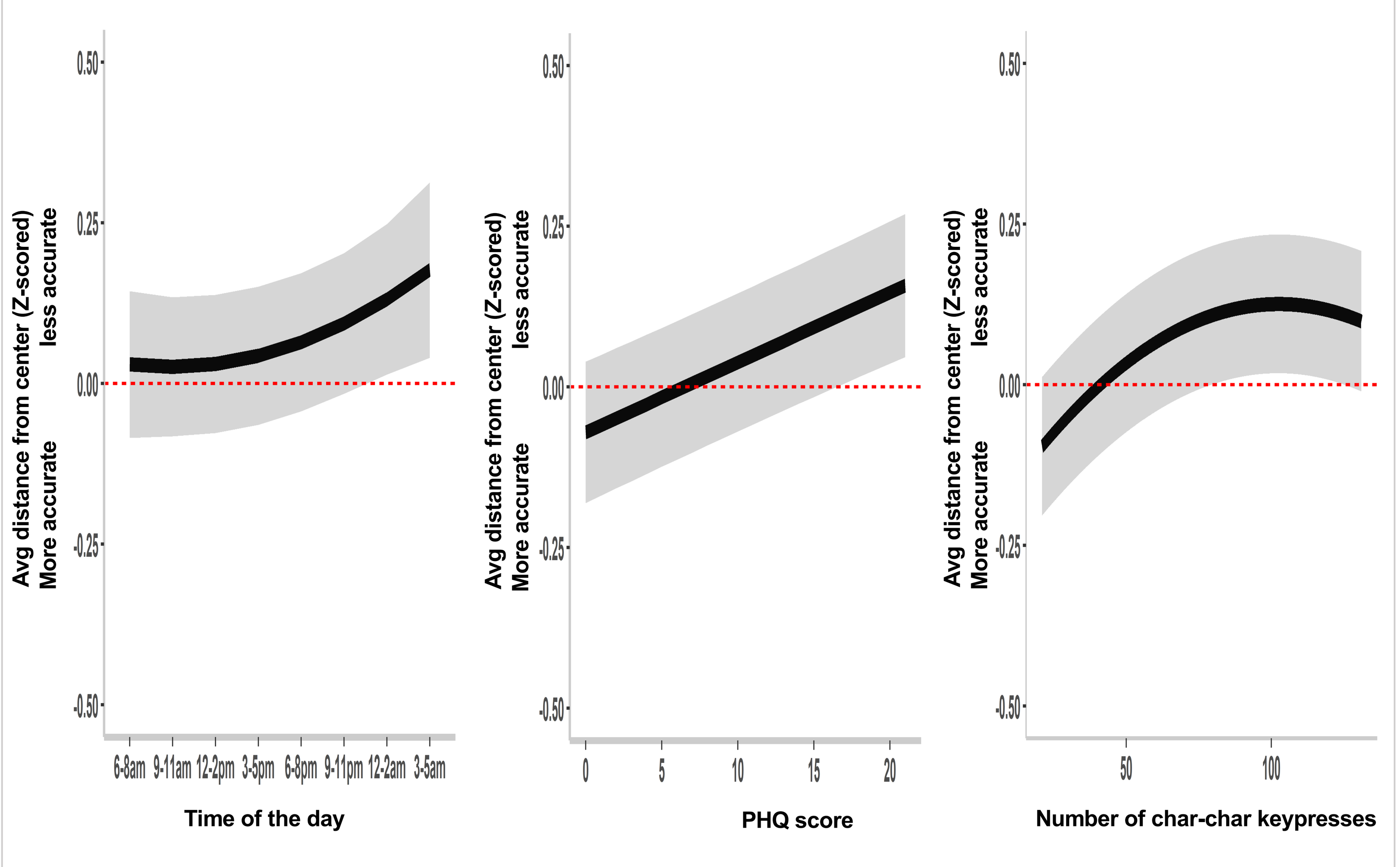
Effects of typing mode on IKD

We report a positive linear effect for age on median IKD (b = 0.069, t = 14.9, p < .0001) and MAD IKD (b = 0.028, t = 13.9, p < .0001), such that older users typed slower and more variably. Results supported a 2nd order polynomial effect of diurnal patterns, with fastest (1st order, b = 1.31, t = 5.77, p < .0001; 2nd order, b = 2.76, t = 14.15, p <.0001) and least variable (1st order, b = 0.68, t = 6.14, p < 0.0001; 2nd order, b = 1.33, t = 13.68, p < .0001) typing speed occurring midday.



Effects of typing mode on IKD

We found that elevated depressive symptoms (higher PHQ score) relate to higher average finger-touch distance (b = 0.23, p < 0.001), and this average distance increases linearly by time-of-day (1st order, b = 27.47, p < .0001; 2nd order, b = 12.94, p >.05). We found an overall increase in typing speed variability (b = .0013, t = 3.74, p = .00018) in users reporting elevated depressive symptoms (i.e., higher PHQ), potentially driven by the shorter median IKD (b = -.002, t = -3.83 , p =.00013) which measures pure typing, and longer pauses, probed by the long IKD (b =.014, t = 6.08 , p <.0001).



Abbreviations

PHQ – Patient Health Questionnaire

IKD – Inter-Key Delay

MAD – Median absolute deviation

1. University of Illinois at Chicago 2. DePaul University 3. University of Utah 4. Sage Bionetworks 5. University of California at San Diego