Original Paper

Smartphone Keystroke Biomarkers as Predictors of Adverse Neuropsychiatric Sequelae After Trauma in Trauma Survivors: Prospective Observational Cohort Study

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Abstract

Background: Adverse posttraumatic neuropsychiatric sequelae are common after trauma. Early identification of individuals at risk for these outcomes could enable the deployment of preventive interventions to survivors at greatest risk. Smartphone keystroke biomarkers show promise in identifying individuals with neuropsychiatric symptoms; however, to our knowledge, no research has examined whether they can be used to identify symptoms in the aftermath of trauma.

Objective: This study evaluates whether passively collected keystroke data from smartphone use in daily life could identify individuals with high symptom levels, as well as worsening or recovery of symptoms, after trauma exposure.

Methods: Data from a diverse cohort of individuals presenting to 27 emergency departments after trauma were analyzed. Inclusion criteria were presenting to the emergency department within 72 hours of trauma, age 18-75, and the ability to speak and read English. Exclusion criteria were solid organ injury, significant hemorrhage, operative intervention, or likely admission for over 72 hours. Participants installed an app that passively collected keystroke data during use of any app on their smartphone, beginning in the emergency department. Participants also completed serial symptom assessments over 8 weeks after trauma exposure.

Results: A total of 3445 patients met study criteria, provided informed consent, and completed assessments in the emergency department. Of these, 1072 (mean age 40, SD 13; 616/1072, 57.46%, women; 565/1072, 52.71% non–Hispanic Black) installed the app on their Android smartphone and completed the 8-week assessment and were therefore included in analyses. Keystroke biomarkers related to typing speed, identified using bivariate linear mixed models controlling for false discovery rates, were associated with elevated pain, reexperiencing, and mental fatigue (absolute values of rs=0.22-0.25, Ps=.02). Separate change-of-operation and scrolling keystroke biomarkers were associated with increased reexperiencing symptoms (r=0.18, *P*=.047) and mental fatigue (rs=0.18-0.19, Ps=.031-.047). Further, changes in specific keystroke biomarkers were associated with worsening or recovery of pain (rs=0.07-0.10, Ps=.02), somatic symptoms (rs=0.02, Ps=.02), mental fatigue (rs=0.02-0.04, Ps=.02), sleep disturbance (absolute rs=0.07-0.09, Ps=.02), reexperiencing (rs=0.02-0.04, Ps=.02), and hyperarousal (rs=0.02-0.04, Ps=.02).

Conclusions: In general, slower typing and scrolling speeds were associated with higher symptom levels, with small to medium effect sizes. Keystroke data passively collected via smartphone use may help identify individuals with significant or changing posttraumatic symptoms. Future research should continue to explore these keystroke biomarkers and whether they can be leveraged to connect vulnerable trauma survivors to appropriate services. Overall, these results add to the literature, indicating that passively collected keystroke data may help identify individuals with neuropsychiatric symptoms or changes and are, to our knowledge, the first to test whether keystroke biomarkers are useful in the aftermath of trauma. This represents a critical period during which preventive interventions could be deployed to reduce the long-term burden of trauma-related sequelae.

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KEYWORDS

trauma; keystroke; posttraumatic stress; pain; somatic symptoms; sleep; mHealth

Introduction

Problem

Approximately 9 in 10 Americans experience at least one traumatic stressor during their lifetimes [1]. Most individuals recover naturally; however, adverse posttraumatic neuropsychiatric symptoms (APNSs) are common and morbid [2]. Common APNS domains include pain and other somatic symptoms; depression and anxiety; posttraumatic stress (PTS) symptoms such as reexperiencing, avoidance, and hyperarousal; as well as sleep disruption and nightmares. APNSs are associated with negative consequences, including emotional distress, functional impairments [3,4], and reduced quality of life [5,6].

The vast majority of individuals experience some level of pain or mental health symptoms, particularly PTS, in the immediate aftermath of trauma exposure [7-9]. For most, these symptoms resolve naturally on their own [7,9], whereas for others they become chronic and debilitating conditions [7]. Certain traumas, such as sexual assault, result in a higher risk for specific APNS [10,11]. Despite this, even after "minor" traumas, such as motor vehicle collision (MVC) without serious injury, a large proportion of survivors develop persistent APNSs. Up to half develop persistent pain [8,12-21], and approximately a quarter develop chronic PTS symptoms [22]. Unfortunately, many trauma survivors do not receive trauma-related services outside of emergency care [23]. This is particularly true for individuals who identify as racially minoritized or have lower levels of education and income [24], who are also at higher risk for trauma exposure [25-27]. However, early treatments for such disorders [28,29] could help avoid decades of suffering for trauma survivors, underscoring the importance of identifying at-risk survivors.

Review of Relevant Scholarship

Nearly 9 in 10 Americans own a smartphone, up from 4 in 10 just 10 years ago [30]. Apps can passively collect data in daily life, including user keystroke behavior. Keystroke patterns may help identify individuals' risk for mental and physical health problems, including APNSs. Smartphone keystroke behavior data are particularly appealing because they do not require any additional device (eg, wearable), making them feasible to collect given the ubiquity of smartphone use. Research in this area is in nascent stages but suggests that keystroke behavior data, alone [31-33] or in combination with other smartphone data [34], are useful for identifying increased depressive symptoms and cognitive functioning/impairments [35,36] among individuals with depression and bipolar disorder, as well as among healthy controls and military veterans [37]. Furthermore, keystroke dynamics can identify individuals with fine motor impairments [38]. This area of research has tremendous promise, as smartphone use is ubiquitous and could be leveraged to screen for and monitor APNSs in the aftermath of trauma, and to connect those in need to further assessment or care. Although studies have used other types of passively sensed data to detect PTS-related symptoms [39], no large-scale study, to our knowledge, has evaluated the predictive utility of smartphone keystroke behavior for APNSs after trauma.

Hypotheses, Aims, and Objectives

Given the potential of keystroke behavior data to identify and predict APNSs, the goal of this study was to use longitudinal keystroke data collected from an app installed on participants' smartphones after trauma exposure to predict APNS outcomes. Specifically, the aims were to test whether keystroke data collected from smartphone use in daily life in a socioeconomically and racially diverse population of trauma survivors presenting to emergency departments (EDs) after traumatic stress exposure can predict risk for, and recovery from or worsening of, APNSs. Individuals with lower socioeconomic status and those identifying with racially/ethnically minoritized groups are at relatively high risk for trauma exposure [25,27] and may experience difficulties accessing appropriate care after the ED visit [23], making them an important sample for targeting preventive interventions. Research Domain Criteria [40]–defined APNSs (ie, pain, reexperiencing, avoidance, hyperarousal, mental fatigue, sleep disturbance, somatic symptoms, nightmares, depression, anxiety) were assessed in the 8 weeks after trauma exposure (a critical period for the development of chronic symptoms) [7]. We hypothesized that it would be possible to derive and validate keystroke behaviors associated with each APNS outcome (ie, trait biomarkers stable over time), and that changes in such behaviors could accurately predict worsening of or recovery from APNSs over time (ie, state symptoms measured at the current assessment and subject to fluctuation) as well as trait symptoms (stable over time). To enhance rigor and replicability, journal article reporting standards were used in this study [41].

Methods

Study Design and Setting

Data for these analyses were obtained from the AURORA (Advancing Understanding of Recovery After Trauma) study, a prospective observational cohort study of a diverse sample of trauma survivors recruited from EDs across the United States in the early aftermath of trauma. Most EDs were part of academic medical centers and concentrated in the Northeast and Midwest of the United States. The full methodology of the AURORA study has been published elsewhere [2]. AURORA enrollment began in September 2017 and continued through June 30, 2020. Individuals were eligible to participate if they presented to 1 of 27 EDs within the national AURORA network. Participants were recruited from EDs and followed using a variety of remote follow-up procedures, including smartphone-based surveys that collected self-reported APNS data over 8 weeks after trauma exposure, and an app that collected keystroke data (SonderMind; formerly Mindstrong).

Participants and Sample Size

Participants were recruited if they presented to an ED within the AURORA network after experiencing qualifying traumatic events (ie, MVC, physical assault, sexual assault, fall >10 ft, or mass casualty incidents). Participants were included if they presented within 72 hours of the trauma, were aged 18-75, and were able to speak and read English. Individuals were excluded if they had a solid organ injury grade >1 per the American Association for the Surgery of Trauma, significant hemorrhage, required operative intervention, or were likely to be admitted for >72 hours. A total of 3445 patients met these criteria, provided informed consent, and completed ED assessments. Of the 3445 patients enrolled at baseline, 2626 remained enrolled for at least 67 days or completed 90% or more of the week 8 survey and did not become pregnant or incarcerated. Of the 2626 participants, 1072 were included in this analysis because they had an Android operating system on their device, had keystroke data, and completed APNS measures. Only Android users were included because iOS users could opt out of the passive collection of keyboard behaviors, resulting in a lack of keystroke data (of note, Android users could also opt out of the app portion of the study while still participating in the overall study, if desired). See Tables S1 and S2 in Multimedia Appendix 1 for a comparison of Android versus iOS users. In brief, there were no clinically significant differences between Android and iOS users; however, Android users were, on average, 7 years older, less likely to be women, more racially and ethnically diverse, less educated, more likely to have been married, and more likely to have experienced traumas other than an MVC. Purposive sampling was used to recruit trauma survivors presenting at EDs, and the sample size for the parent study was determined based on power analysis for its aims [2].

Participants were, on average, 40 (SD 13) years of age (Table 1), with a slight majority being women (616/1072, 57.46%). Most participants self-identified as non–Hispanic Black (565/1072, 52.71%), followed by non–Hispanic White (353/1072, 32.93%), Hispanic (114/1072, 10.63%), and other (34/1072, 3.17%). Most reported having some college education (457/1072, 42.63%), a total annual family income of less than US $35,000 (653/1072, 60.91%), and being single/never married (578/1072, 53.92%).

Table 1. Sample demographic and trauma characteristics of trauma survivors participating in an observational cohort study (N=1072).

Characteristics	Values
Age (years), mean (SD)	39.4 (12.6)
Female, n (%)	616 (57.46)
Total family income (US $), n (%)	
≤19K	348 (32.46)
19,000-35,000	305 (28.45)
35,001-50,000	129 (12.03)
>50,000	174 (16.23)
Race, n (%)	
Hispanic	114 (10.63)
Non–Hispanic White	353 (32.93)
Non–Hispanic Black	565 (53.71)
Non–Hispanic other	34 (3.17)
Education status, n (%)	
High school or less	422 (39.37)
Some college	457 (42.63)
College or more	189 (17.63)
Marital status, n (%)	
Married	245 (22.85)
Separated, divorced, widowed, or annulled	238 (22.20)
Never been married	578 (53.92)
Trauma type, n (%)	
Motor vehicle collision	772 (72.01)
Physical assault	118 (11.01)
Sexual assault	4 (0.37)
Fall	83 (7.74)
Nonmotorized collision	21 (1.96)
Animal-related	20 (1.87)
Other (including poisoning, burns, mass trauma exposure)	54 (5.04)

Assessments and Data Sources

APNS Data Collection and Preparation

Sociodemographic characteristics measured in the ED were assessed via survey items [2]. Following the ED visit, participants completed a rotating battery of smartphone-based questionnaires consisting of brief assessments of 10 common APNS domains: pain [42], depression and anxiety symptoms [43], sleep [44], nightmares [45], somatic symptoms [46], difficulty with concentration/thinking/fatigue (mental fatigue) [46], and reexperiencing, avoidance, and hyperarousal [47]. Each survey item was administered at 6 time points within the first 8 weeks after trauma exposure using the app. Survey items, and the study day on which each item was administered, are presented in Table S3 in Multimedia Appendix 1.

These survey items were used as indicator variables to develop measurement models for each APNS domain, and factor scores for each symptom were computed for each participant at every time point. Joint measurement models that included all 6 time points within the first 8 weeks after trauma exposure were developed to define each symptom domain. Temporal correlations among these indicator variables were introduced to improve model fit when temporal autocorrelations were not fully explained by the joint measurement model. Model fit indices (eg, Comparative Fit Index, Tucker-Lewis Index, standardized root mean square residual) were used to evaluate the fit of each measurement model [48].

Keystroke Data Collection

Longitudinal keystroke behavior data were collected from an app installed on participants' phones after trauma exposure (SonderMind; formerly Mindstrong). Keystroke data were collected from any smartphone use across apps and were not limited to study-specific interactions or the use of any specific app. Naturally occurring typing was captured, and users did not receive prompts to type. Typing word content was also collected and is reported in a separate manuscript [24]. Several aspects of keystroke behavior were collected: typing speed (the time elapsed between typing one character [or making one action] and the next); change of operations (switching from one process [eg, typing characters] to another [eg, deleting]); and scrolling (in any context, the distance scrolled in a list before clicking on an item). The data were processed within the app; thus, only the features reported in this manuscript were available for analysis.

Ethical Considerations

The AURORA study protocol was approved by the Institutional Review Board (approval number 17-0703) at the University of North Carolina at Chapel Hill. All participants provided informed consent at the time of enrollment during their ED visit. All data reported are fully deidentified and anonymous. Participants were compensated for their involvement as follows: US $60 for the ED assessment, US $30 for app installation, and US $5 per serial assessment. No identification of individual participants or users in any images in the manuscript or multimedia appendices is possible. Shared data from the AURORA study are deidentified, with no patient identifiers included.

Data Analysis: Keystroke Feature Extraction

The passive data collection app collected 41 features derived from participants' interactions with their smartphones. Each feature had 23 signals, resulting in a total of 943 possible feature variables. Analyses began by pairing keystroke features with APNS data. Daily keystroke feature variables were merged with each of the 10 APNS constructs, whereby keystroke data collected on the same day or the day before the flash survey day were retained. The means of the keystroke feature variables across the 2 days were used to summarize the data in relation to the relevant APNS construct.

Second, within- and between-person correlations of keystroke features with each of the 10 APNS constructs were calculated. The top 50 variables with the highest absolute correlation values (either within- or between-persons) that were statistically significant (adjusted *P* value <.05, controlling for false discovery rate) were selected.

Third, the aggregated data were randomly divided into 2 equal parts: 1 for biomarker identification and 1 for validation. A bivariate linear mixed model approach was used to model the cross-sectional and longitudinal associations with each of the 10 APNS constructs. Feature variables that had significant associations (either cross-sectional or longitudinal) with any of the APNS constructs were then validated using the same bivariate linear mixed model in the remaining 50% of the data. Multiple testing was controlled by adjusting *P* values with a false discovery rate for the identification step and a Bonferroni correction for the validation step.

Fourth, we conducted an additional analysis for features that passed the identification and validation steps. For state biomarkers, we evaluated how accurately they predicted the direction of change in the corresponding APNS constructs (eg, worsening vs recovery).

Missing values for these 10 APNS constructs ranged from 250 out of 2438 (10.25%) to 285 out of 2554 (11.16%) during the first week after enrollment and from 1251 out of 2547 (49.12%) to 1479 out of 2438 (60.66%) around 6 months after enrollment. To explore the potential impact of missing data, we evaluated correlations between main outcomes (eg, posttraumatic stress disorder and pain) at different time points (eg, before trauma, 2 weeks, and 8 weeks after trauma) and completion rates of 4 main tasks (eg, watch wearing, flash survey, neurocognitive tests, and full surveys). All correlations were weak (<0.1; see Table S8 in Multimedia Appendix 1), suggesting that missing data were not driven by these outcomes. Thus, missing data for these APNS construct scores were considered missing at random and were imputed using the joint measurement model.

Of note, due to the large number of highly intracorrelated features associated with various APNSs, results were simplified as follows. For similar signal processing techniques (eg, measures of central tendency such as mean and median; first-, second-, and third-order spectral moments) that were highly intracorrelated with one another (*r*s>0.80), only the signal processing technique variable with the highest correlation with the relevant APNS was retained in the results and tables (eg, if both mean and median frequency were associated with pain, only mean frequency was retained as a predictor when it had the higher correlation with pain). Full results, including all variables, are available in Tables S4-S7 in Multimedia Appendix 1.

Results

Participant Flow and Sociodemographic, Trauma Exposure, and Clinical Characteristics

The final sample consisted of 1072 trauma survivors who used the passive data collection app on their Android smartphones (see Figure S1 in Multimedia Appendix 1). The majority of participants experienced an MVC as their trauma type (772/1072, 72.01%), followed by physical assault (118/1072, 11.01%), fall >10 ft (83/1072, 7.74%), other (54/1072, 5.04%; eg, poisoning, burn, mass trauma), nonmotorized collision (21/1072, 1.96%), animal-related (20/1072, 1.87%), and sexual assault (4/1072, 0.37%).

Derivation of Trait Biomarkers

First, we evaluated whether trait-level keystroke biomarkers could identify individuals experiencing high levels of specific APNS (Table 2) at the trait level (ie, symptoms stable over time). Within- and between-person correlations indicated that a total of 24 unique keystroke biomarkers related to typing speed were associated with pain (Table 2; absolute values of *r*s=0.22-0.25, *P*s=.02; α level set at *P*<.05, applied to Bonferroni-adjusted *P* values for these and all analyses), indicating that, overall, slower character typing speed was associated with higher levels of pain. Additionally, 1 keystroke biomarker was associated with increased reexperiencing symptoms (ie, slower speed when typing the space bar; *r*=0.18, *P*=.047). Finally, 5 scroll-related biomarkers were associated with mental fatigue (*r*s=0.18-0.19, *P*s=.031-.047), indicating that slower scrolling was associated with higher levels of mental fatigue. Correlations between biomarkers and specific APNS were in the small- to medium-effect size range and were statistically significant at $P<.05$ after Bonferroni adjustment.

Table 2. Trait keystroke biomarkers captured via the app and associations with adverse posttraumatic neuropsychiatric sequelae among trauma survivors participating in an observational cohort study.

Construct and theme	Type	Signal processing	Correlation (*r*)	Bonferroni-adjusted *P* value
Pain				
Typing speed[a]	Two characters in a row	SD	0.22	.02
Typing speed	Two characters in a row	Mean log	0.24	.02
Typing speed	Two characters in a row	80th percentile	0.24	.02
Typing speed	Two characters in a row	Total (sum) power	–0.25	.02
Typing speed	Two characters in a row	First spectral moment	–0.25	.02
Typing speed	Two characters	Mean log	0.25	.02
Typing speed	Two characters	10th percentile	0.24	.02
Typing speed	Two characters	Total (sum) power	–0.25	.02
Typing speed	Two characters	Mean frequency	–0.25	.02
Typing speed	Two characters	First spectral moment	–0.25	.02
Typing speed	Two characters	Second spectral moment	–0.25	.02
Typing speed	Two characters	Mean log	0.24	.02
Typing speed	Two characters	50th percentile	0.25	.02
Typing speed	Two characters	Total (sum) power	–0.25	.02
Typing speed	Two characters	First spectral moment	–0.25	.02
Typing speed	Three characters or fewer in a row	Mean log	0.24	.02
Typing speed	Three characters or fewer in a row	50th percentile	0.24	.02
Typing speed	Three characters or fewer in a row	Total (sum) power	–0.25	.02
Typing speed	Three characters or fewer in a row	Second spectral moment	–0.25	.02
Typing speed	More than 3 characters in a row	Mean	0.24	.02
Typing speed	More than 3 characters in a row	Mean log	0.25	.02
Typing speed	More than 3 characters in a row	80th percentile	0.25	.02
Typing speed	More than 3 characters in a row	Total (sum) power	–0.26	.02
Typing speed	More than 3 characters in a row	First spectral moment	–0.26	.02
Reexperiencing				
Change of operations[b]	Character to space	Mean power	–0.18	.047
Mental fatigue				
Scroll[c]	Scroll then click	Mean	0.18	.047
Scroll	Scroll then click	Mean log	0.19	.03
Scroll	Scroll then click	*a* (intercept of linear regression of sorted time differences)	0.18	.047
Scroll	Scroll then click	Total (sum) power	–0.19	.03
Scroll	Scroll then click	Third spectral moment	–0.19	.03

[a]Typing speed is the length of time elapsed from typing 1 character (or making 1 action) to another (higher values=slower typing speed).

[b]Change of operations refers to switching from 1 process (eg, typing characters) to another (eg, deleting; thought to measure task or set shifting).

[c]Scroll refers to the distance scrolled in a list before clicking on the item they are looking for, or the speed in scrolling through a list (thought to measure processing speed). When the keystroke type description includes "characters in a row," this refers to typing several characters in sequence that are not interrupted by a space key press, deletion, or other action. Correlation can be used as a measure of effect size for linear relationships, where a

positive/negative correlation of *r* between variables *X* and *Y* indicates that a 1 SD change in *X* is associated with *r* SD change in *Y* in the same/opposite direction.

Derivation of State Biomarkers

Second, we evaluated whether changes in keystroke behaviors were associated with worsening or recovery of state-level (ie, measured at the current assessment and subject to fluctuations) specific APNS during the initial 8 weeks after trauma using bivariate linear mixed models (Table 3). State-level biomarkers were identified for changes in pain, sleep disturbance, hyperarousal, reexperiencing, somatic symptoms, and mental fatigue. For pain, 18 separate keystroke-related biomarkers were identified (*r*s=0.07-0.10, *P*s=.02; 17 related to typing speed and 1 related to scrolling speed). Overall, slower typing and scrolling speeds were associated with higher levels of pain. For sleep disturbance, 11 state biomarkers related to typing speed were identified, with absolute *r* values ranging from 0.07 to 0.09 (*P*s=.02). Again, slower typing speed was associated with increased sleep disturbance. For somatic symptoms, 19 typing speed–related biomarkers were identified (*r*s=0.02), along with 4 biomarkers associated with mental fatigue (2 related to scrolling speed and 2 related to typing speed; *r*s=0.02-0.04). Overall, slower scrolling and typing speeds were associated with increased somatic symptoms and mental fatigue.

Table 3. State keystroke biomarkers captured via the app and associations with adverse posttraumatic neuropsychiatric sequelae among trauma survivors participating in an observational cohort study.

Construct and theme	Type	Signal processing	Correlation (*r*)	Bonferroni-adjusted *P* value
Pain				
Typing speed[a]	Two characters in a row	Total (sum) power	–0.07	.02
Typing speed	Two characters in a row	Third spectral moment	–0.09	.02
Typing speed	Two characters	Total (sum) power	–0.07	.02
Typing speed	Two characters	Mean frequency	–0.09	.02
Typing speed	Two characters	Third spectral moment	–0.08	.02
Typing speed	Two characters	Total (sum) frequency	–0.07	.02
Typing speed	Two characters	Mean frequency	–0.09	.02
Typing speed	Two characters	Third spectral moment	–0.09	.02
Typing speed	Consecutive typing events	Mean log	0.08	.02
Typing speed	Consecutive typing events	50th percentile	0.07	.02
Typing speed	Consecutive typing events	Total (sum) power	–0.09	.02
Typing speed	Consecutive typing events	Median frequency	–0.08	.02
Typing speed	Consecutive typing events	Mean frequency	–0.10	.02
Typing speed	Consecutive typing events	Third spectral moment	–0.10	.02
Scroll[b]	Scroll twice to item	Maximum fractal length	–0.09	.02
Typing speed	Three characters or fewer in a row	Mean frequency	–0.07	.02
Typing speed	More than 3 characters in a row	Mean frequency	–0.07	.02
Typing speed	More than 3 characters in a row	Third spectral moment	–0.07	.02
Sleep disturbance				
Typing speed	Two characters in a row	First spectral moment	–0.07	.02
Typing speed	Two characters	Mean log	0.07	.02
Typing speed	Two characters	Second spectral moment	–0.07	.02
Typing speed	Two characters	First spectral moment	–0.07	.02
Typing speed	Consecutive typing events	Mean log	0.08	.02
Typing speed	Consecutive typing events	Total (sum) power	–0.08	.02
Typing speed	Consecutive typing events	Mean frequency	–0.08	.02
Typing speed	Consecutive typing events	Second spectral moment	–0.08	.02
Typing speed	More than 3 characters in a row	Mean	0.08	.02
Typing speed	More than 3 characters in a row	80th percentile	0.08	.02
Typing speed	More than 3 characters in a row	Mean power	–0.09	.02
Hyperarousal				

Construct and theme	Type	Signal processing	Correlation (*r*)	Bonferroni-adjusted *P* value
Typing speed	Character to space	Second spectral moment	–0.07	.02
Typing speed	Two characters in a row	Mean frequency	–0.09	.02
Typing speed	Two characters in a row	First spectral moment	–0.10	.02
Typing speed	Two characters	First spectral moment	–0.09	.02
Typing speed	Consecutive typing events	Second spectral moment	–0.09	.02
Typing speed	More than 3 characters in a row	20th percentile	0.07	.02
Typing speed	More than 3 characters in a row	Total (sum) power	–0.08	.02
Typing speed	More than 3 characters in a row	First spectral moment	–0.08	.02
Typing speed	The second set of at least 5 characters in a row	10th percentile	0.07	.02
Typing speed	The second set of at least 5 characters in a row	80th percentile	0.08	.02
Typing speed	The second set of at least 5 characters in a row	Total (sum) power	–0.08	.02
Typing speed	The second set of at least 5 characters in a row	Mean frequency	–0.07	.02
Typing speed	The second set of at least 5 characters in a row	First spectral moment	–0.08	.02
Reexperiencing				
Typing speed	Character to space	90th percentile	0.07	.04
Typing speed	Character to space	Second spectral moment	–0.08	.02
Typing speed	Character to space	Median frequency	–0.07	.02
Typing speed	Consecutive typing events	Mean log	0.07	.02
Typing speed	Consecutive typing events	Third spectral moment	–0.09	.02
Typing speed	Three characters or fewer in a row	Total (sum) power	–0.09	.02
Typing speed	Four characters or fewer, then space	Mean frequency	–0.07	.02
Somatic symptoms				

Construct and theme	Type	Signal processing	Correlation (r)	Bonferroni-adjusted P value
Typing speed	Two characters in a row	Total (sum) power	–0.08	.02
Typing speed	Two characters in a row	Mean frequency	–0.08	.02
Typing speed	Two characters in a row	Second spectral moment	–0.08	.02
Typing speed	Two characters	Total (sum) power	–0.07	.02
Typing speed	Two characters	Mean frequency	–0.08	.02
Typing speed	Two characters	Third spectral moment	–0.08	.02
Typing speed	Two characters	Median frequency	–0.08	.02
Typing speed	Two characters	Third spectral moment	–0.09	.02
Typing speed	Consecutive typing events	80th percentile	0.07	.02
Typing speed	Consecutive typing events	Total (sum) power	–0.08	.02
Typing speed	Consecutive typing events	Mean frequency	–0.09	.02
Typing speed	Consecutive typing events	Second spectral moment	–0.08	.02
Typing speed	Three characters or fewer in a row	Total (sum) power	–0.06	.04
Typing speed	Three characters or fewer in a row	Second spectral moment	–0.07	.02
Typing speed	More than 3 characters in a row	Mean log	0.07	.02
Typing speed	More than 3 characters in a row	50th percentile	0.07	.02
Typing speed	More than 3 characters in a row	Total (sum) power	–0.09	.02
Typing speed	More than 3 characters in a row	Mean frequency	–0.10	.02
Typing speed	More than 3 characters in a row	Second spectral moment	–0.10	.02
Mental fatigue				
Scroll	Speed of scroll to item	50th percentile	0.06	.04
Scroll	Speed of scroll to item	Median frequency	–0.07	.02
Typing speed	More than 3 characters in a row	Mean frequency	–0.07	.02
Typing speed	More than 3 characters in a row	Third spectral moment	–0.07	.02

[a]Typing speed is the length of time elapsed from typing 1 character (or making 1 action) to another (higher values=slower typing speed).

[b]Scroll refers to the distance scrolled in a list before clicking on the item they are looking for, or the speed in scrolling through a list (thought to measure processing speed). When the keystroke type description includes “characters in a row,” this refers to typing several characters in sequence that are not interrupted by a space key press, deletion, or other action. Correlation can be used as a measure of effect size for linear relationships, where a positive/negative correlation of r between variables X and Y indicates that a 1 SD change in X is associated with r SD change in Y in the same/opposite direction. Regarding PTS, 13 typing speed–related biomarkers were associated with state changes in hyperarousal symptoms (rs=.02-.04), and 7 typing speed–related biomarkers were associated with state changes in reexperiencing symptoms (rs=.02-.04). In general, slower typing speed was associated with elevated PTS. All correlations for state biomarkers were in the small effect size range and were statistically significant at P<.05 after Bonferroni adjustment.

Utility of State Biomarkers

Finally, we examined the potential utility of keystroke biomarkers as screening tools for worsening or improving APNSs after trauma using bivariate linear mixed models (Tables 4 and 5; only statistically significant biomarkers are presented). Worsening and improvement in self-report symptoms were defined as symptom severity at 6 months minus symptom severity in the first week >0 and <0, respectively. High positive predictive values for symptom recovery and negative predictive values for worsening suggest that simple keystroke measures, passively collected via smartphone, may have utility as initial screening tools for mental fatigue, pain, and somatic symptom outcomes among diverse trauma survivors.

Specifically, for identifying worsening PTS symptoms, we found that 11 typing speed–related biomarkers were associated with hyperarousal symptoms, and 7 typing speed–related biomarkers were associated with reexperiencing symptoms. A total of 2 scroll-related and 2 typing speed–related biomarkers were associated with worsening mental fatigue. For pain, 16 typing speed–related and 1 scroll-related biomarker were associated with worsening symptoms. Eleven typing speed–related biomarkers were predictive of worsening sleep. Finally, 19 typing speed–related biomarkers were predictive of worsening somatic symptoms.

Table 4. Prediction of worsening adverse posttraumatic neuropsychiatric symptoms using state keystroke biomarkers captured via the app among trauma survivors participating in an observational cohort study.

Construct and worsening, *n* (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Hyperarousal (N=509)							
263 (51.7)	Typing speed[a]	Character to space	Second spectral moment	0.52	0.48	0.53	0.47
263 (51.7)	Typing speed	Two characters in a row	First spectral moment	0.51	0.49	0.52	0.49
263 (51.7)	Typing speed	Two characters	First spectral moment	0.5	0.5	0.52	0.48
263 (51.7)	Typing speed	Consecutive typing events	Second spectral moment	0.5	0.5	0.52	0.48
263 (51.7)	Typing speed	More than 3 characters in a row	20th percentile	0.51	0.47	0.51	0.47
263 (51.7)	Typing speed	More than 3 characters in a row	Total (sum) power	0.54	0.47	0.53	0.48
263 (51.7)	Typing speed	More than 3 characters in a row	First spectral moment	0.54	0.47	0.53	0.48
263 (51.7)	Typing speed	The second set of at least 5 characters in a row	80th percentile	0.53	0.52	0.59	0.46
263 (51.7)	Typing speed	The second set of at least 5 characters in a row	Total (sum) power	0.51	0.48	0.57	0.43
263 (51.7)	Typing speed	The second set of at least 5 characters in a row	Mean frequency	0.53	0.49	0.58	0.44
263 (51.7)	Typing speed	The second set of at least 5 characters in a row	First spectral moment	0.51	0.48	0.56	0.43
Mental fatigue (N=574)							
160 (27.9)	Scroll[b]	Speed of scroll to item	50th percentile	0.54	0.5	0.3	0.74
160 (27.9)	Scroll	Speed of scroll to item	Median frequency	0.56	0.5	0.3	0.75
160 (27.9)	Typing speed	More than 3 characters in a row	Mean frequency	0.49	0.56	0.3	0.74
160 (27.9)	Typing speed	More than 3 characters in a row	Third spectral moment	0.54	0.55	0.32	0.76
Pain (N=692)							
159 (23.0)	Typing speed	Two characters in a row	Total (sum) power	0.41	0.61	0.24	0.78
159 (23.0)	Typing speed	Two characters in a row	Third spectral moment	0.4	0.6	0.23	0.77
159 (23.0)	Typing speed	Two characters	Total (sum) power	0.39	0.59	0.22	0.77
159 (23.0)	Typing speed	Two characters	Mean frequency	0.36	0.65	0.23	0.77
159 (23.0)	Typing speed	Two characters	Third spectral moment	0.38	0.62	0.23	0.77
159 (23.0)	Typing speed	Two characters	Total (sum) power	0.43	0.62	0.25	0.79
159 (23.0)	Typing speed	Two characters	Mean frequency	0.36	0.62	0.22	0.76
159 (23.0)	Typing speed	Two characters	Third spectral moment	0.41	0.63	0.25	0.78
159 (23.0)	Typing speed	Consecutive typing events	Mean log	0.37	0.65	0.24	0.78
159 (23.0)	Typing speed	Consecutive typing events	50th percentile	0.36	0.64	0.23	0.77
159 (23.0)	Typing speed	Consecutive typing events	Total (sum) power	0.39	0.61	0.23	0.77
159 (23.0)	Typing speed	Consecutive typing events	Mean frequency	0.39	0.62	0.23	0.77
159 (23.0)	Typing speed	Consecutive typing events	Third spectral moment	0.44	0.61	0.25	0.79

Construct and worsening, *n* (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
159 (23.0)	Scroll	Scroll twice to item	Maximum fractal length	0.36	0.59	0.21	0.75
159 (23.0)	Typing speed	Three characters or fewer in a row	Mean frequency	0.44	0.58	0.24	0.77
159 (23.0)	Typing speed	More than 3 characters in a row	Mean frequency	0.42	0.55	0.22	0.77
159 (23.0)	Typing speed	More than 3 characters in a row	Third spectral moment	0.46	0.54	0.23	0.77
Reexperiencing (N=479)							
226 (47.2)	Typing speed	Character to space	90th percentile	0.53	0.48	0.46	0.55
226 (47.2)	Typing speed	Character to space	Second spectral moment	0.55	0.49	0.48	0.56
226 (47.2)	Typing speed	Character to space	Median frequency	0.55	0.54	0.5	0.59
226 (47.2)	Typing speed	Consecutive typing events	Mean log	0.51	0.46	0.46	0.52
226 (47.2)	Typing speed	Consecutive typing events	Third spectral moment	0.5	0.5	0.47	0.53
226 (47.2)	Typing speed	Three characters or fewer in a row	Total (sum) power	0.54	0.51	0.49	0.55
226 (47.2)	Typing speed	Four characters or fewer, then space	Mean frequency	0.56	0.47	0.48	0.56
Sleep (N=487)							
269 (55.2)	Typing speed	Two characters in a row	First spectral moment	0.51	0.49	0.55	0.45
269 (55.2)	Typing speed	Two characters	Mean log	0.51	0.5	0.55	0.45
269 (55.2)	Typing speed	Two characters	Second spectral frequency	0.5	0.48	0.54	0.44
269 (55.2)	Typing speed	Two characters	First spectral frequency	0.53	0.5	0.57	0.47
269 (55.2)	Typing speed	Consecutive typing events	Mean log	0.52	0.52	0.57	0.47
269 (55.2)	Typing speed	Consecutive typing events	Total (sum) power	0.51	0.51	0.56	0.46
269 (55.2)	Typing speed	Consecutive typing events	Mean frequency	0.52	0.51	0.57	0.46
269 (55.2)	Typing speed	Consecutive typing events	Second spectral moment	0.51	0.51	0.56	0.46
269 (55.2)	Typing speed	More than 3 characters in a row	Mean	0.52	0.48	0.56	0.44
269 (55.2)	Typing speed	More than 3 characters in a row	80th percentile	0.5	0.5	0.56	0.44
269 (55.2)	Typing speed	More than 3 characters in a row	Mean power	0.5	0.46	0.54	0.42
Somatic symptoms (N=572)							
130 (22.7)	Typing speed	Two characters in a row	Total (sum) power	0.46	0.54	0.23	0.77
130 (22.7)	Typing speed	Two characters in a row	Mean frequency	0.48	0.57	0.25	0.79
130 (22.7)	Typing speed	Two characters in a row	Second spectral moment	0.45	0.53	0.22	0.77
130 (22.7)	Typing speed	Two characters	Total (sum) power	0.48	0.52	0.23	0.78
130 (22.7)	Typing speed	Two characters	Mean frequency	0.42	0.54	0.21	0.76
130 (22.7)	Typing speed	Two characters	Third spectral moment	0.48	0.53	0.23	0.78
130 (22.7)	Typing speed	Two characters	Median frequency	0.45	0.54	0.22	0.77

Construct and worsening, *n* (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
130 (22.7)	Typing speed	Two characters	Third spectral moment	0.49	0.54	0.24	0.78
130 (22.7)	Typing speed	Consecutive typing events	80th percentile	0.47	0.54	0.23	0.78
130 (22.7)	Typing speed	Consecutive typing events	Total (sum) power	0.48	0.56	0.25	0.79
130 (22.7)	Typing speed	Consecutive typing events	Mean frequency	0.43	0.54	0.22	0.76
130 (22.7)	Typing speed	Consecutive typing events	Second spectral moment	0.47	0.57	0.24	0.79
130 (22.7)	Typing speed	Three characters or fewer in a row	Total (sum) power	0.49	0.56	0.25	0.79
130 (22.7)	Typing speed	Three characters or fewer in a row	Second spectral moment	0.5	0.55	0.25	0.79
130 (22.7)	Typing speed	More than 3 characters in a row	Mean log	0.54	0.55	0.26	0.8
130 (22.7)	Typing speed	More than 3 characters in a row	50th percentile	0.54	0.53	0.25	0.8
130 (22.7)	Typing speed	More than 3 characters in a row	Total (sum) power	0.53	0.54	0.26	0.8
130 (22.7)	Typing speed	More than 3 characters in a row	Mean frequency	0.52	0.57	0.26	0.8
130 (22.7)	Typing speed	More than 3 characters in a row	Second spectral moment	0.54	0.55	0.26	0.8

[a]Typing speed is the length of time elapsed from typing 1 character (or making 1 action) to another (higher values=slower typing speed).

[b]Scroll refers to the distance scrolled in a list before clicking on the item they are looking for, or the speed in scrolling through a list (thought to measure processing speed). When the keystroke type description includes “characters in a row,” this refers to typing several characters in sequence that are not interrupted by a space key press, deletion, or other action.

Table 5. Prediction of recovering adverse posttraumatic neuropsychiatric symptoms using state keystroke biomarkers captured via the app among trauma survivors participating in an observational cohort study.

Construct and recovering, n (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Hyperarousal (N=509)							
246 (48.3)	Typing speed[a]	Character to space	Second spectral moment	0.52	0.48	0.47	0.53
246 (48.3)	Typing speed	Two characters in a row	First spectral moment	0.51	0.49	0.48	0.51
246 (48.3)	Typing speed	Two characters	First spectral moment	0.5	0.5	0.48	0.52
246 (48.3)	Typing speed	Consecutive typing events	Second spectral moment	0.5	0.5	0.48	0.52
246 (48.3)	Typing speed	More than 3 characters in a row	20th percentile	0.53	0.49	0.49	0.53
246 (48.3)	Typing speed	More than 3 characters in a row	Total (sum) power	0.53	0.46	0.47	0.52
246 (48.3)	Typing speed	More than 3 characters in a row	First spectral moment	0.53	0.46	0.47	0.52
246 (48.3)	Typing speed	The second set of at least 5 characters in a row	80th percentile	0.48	0.47	0.41	0.54
246 (48.3)	Typing speed	The second set of at least 5 characters in a row	Total (sum) power	0.52	0.49	0.43	0.57
246 (48.3)	Typing speed	The second set of at least 5 characters in a row	Mean frequency	0.51	0.47	0.42	0.56
246 (48.3)	Typing speed	The second set of at least 5 characters in a row	First spectral moment	0.52	0.49	0.44	0.57
Mental fatigue (N=573)							
413 (72.1)	Scroll[b]	Speed of scroll to item	50th percentile	0.5	0.46	0.7	0.26
413 (72.1)	Scroll	Speed of scroll to item	Median frequency	0.5	0.44	0.7	0.25
413 (72.1)	Typing speed	More than 3 characters in a row	Mean frequency	0.44	0.51	0.7	0.26
413 (72.1)	Typing speed	More than 3 characters in a row	Third spectral moment	0.45	0.46	0.68	0.24
Pain (N=692)							
533 (77.0)	Typing speed	Two characters in a row	Total (sum) power	0.39	0.59	0.76	0.22
533 (77.0)	Typing speed	Two characters in a row	Third spectral moment	0.4	0.6	0.77	0.23
533 (77.0)	Typing speed	Two characters	Total (sum) power	0.41	0.61	0.78	0.23
533 (77.0)	Typing speed	Two characters	Mean frequency	0.35	0.64	0.77	0.23
533 (77.0)	Typing speed	Two characters	Third spectral moment	0.38	0.62	0.77	0.23
533 (77.0)	Typing speed	Two characters	Total (sum) power	0.38	0.57	0.75	0.21
533 (77.0)	Typing speed	Two characters	Mean frequency	0.38	0.64	0.78	0.24
533 (77.0)	Typing speed	Two characters	Third spectral moment	0.37	0.59	0.75	0.22
533 (77.0)	Typing speed	Consecutive typing events	Mean log	0.35	0.63	0.76	0.23
533 (77.0)	Typing speed	Consecutive typing events	50th percentile	0.36	0.64	0.77	0.23
533 (77.0)	Typing speed	Consecutive typing events	Total (sum) power	0.39	0.61	0.77	0.23
533 (77.0)	Typing speed	Consecutive typing events	Mean frequency	0.38	0.61	0.77	0.23
533 (77.0)	Typing speed	Consecutive typing events	Third spectral moment	0.39	0.56	0.75	0.21
533 (77.0)	Scroll	Scroll twice to item	Maximum fractal length	0.41	0.64	0.79	0.25
533 (77.0)	Typing speed	Three characters or fewer in a row	Mean frequency	0.42	0.56	0.76	0.23
533 (77.0)	Typing speed	More than 3 characters in a row	Mean frequency	0.45	0.58	0.78	0.23
533 (77.0)	Typing speed	More than 3 characters in a row	Third spectral moment	0.46	0.54	0.77	0.23

Construct and recovering, n (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Reexperiencing (N=479)							
253 (52.8)	Typing speed	Character to space	90th percentile	0.52	0.47	0.54	0.45
253 (52.8)	Typing speed	Character to space	Second spectral moment	0.51	0.45	0.52	0.44
253 (52.8)	Typing speed	Character to space	Median frequency	0.46	0.45	0.5	0.41
253 (52.8)	Typing speed	Consecutive typing events	Mean log	0.54	0.49	0.54	0.48
253 (52.8)	Typing speed	Consecutive typing events	Third spectral moment	0.5	0.5	0.53	0.47
253 (52.8)	Typing speed	Three characters or fewer in a row	Total (sum) power	0.49	0.46	0.51	0.45
253 (52.8)	Typing speed	Four characters or fewer, then space	Mean frequency	0.53	0.44	0.52	0.44
Sleep (N=487)							
218 (44.8)	Typing speed	Two characters in a row	First spectral moment	0.51	0.49	0.45	0.55
218 (44.8)	Typing speed	Two characters	Mean log	0.5	0.49	0.45	0.55
218 (44.8)	Typing speed	Two characters	Second spectral moment	0.52	0.5	0.46	0.56
218 (44.8)	Typing speed	Two characters	First spectral moment	0.5	0.47	0.43	0.53
218 (44.8)	Typing speed	Consecutive typing events	Mean log	0.48	0.48	0.43	0.53
218 (44.8)	Typing speed	Consecutive typing events	Total (sum) power	0.49	0.49	0.44	0.54
218 (44.8)	Typing speed	Consecutive typing events	Mean frequency	0.49	0.48	0.43	0.54
218 (44.8)	Typing speed	Consecutive typing events	Second spectral moment	0.49	0.49	0.44	0.54
218 (44.8)	Typing speed	More than 3 characters in a row	Mean	0.52	0.48	0.44	0.56
218 (44.8)	Typing speed	More than 3 characters in a row	80th percentile	0.5	0.5	0.44	0.56
218 (44.8)	Typing speed	More than 3 characters in a row	Mean power	0.54	0.5	0.46	0.58
Somatic symptoms (N=572)							

Construct and recovering, n (%)	Theme	Type	Signal processing	Sensitivity	Specificity	Positive predictive value	Negative predictive value
442 (77.3)	Typing speed	Two characters in a row	Total (sum) power	0.46	0.54	0.77	0.23
442 (77.3)	Typing speed	Two characters in a row	Mean frequency	0.43	0.52	0.75	0.21
442 (77.3)	Typing speed	Two characters in a row	Second spectral moment	0.47	0.55	0.78	0.23
442 (77.3)	Typing speed	Two characters	Total (sum) power	0.48	0.52	0.77	0.22
442 (77.3)	Typing speed	Two characters	Mean frequency	0.46	0.58	0.79	0.24
442 (77.3)	Typing speed	Two characters	Third spectral moment	0.47	0.52	0.77	0.22
442 (77.3)	Typing speed	Two characters	Median frequency	0.46	0.55	0.78	0.23
442 (77.3)	Typing speed	Two characters	Third spectral moment	0.46	0.51	0.76	0.22
442 (77.3)	Typing speed	Consecutive typing events	80th percentile	0.46	0.53	0.77	0.22
442 (77.3)	Typing speed	Consecutive typing events	Total (sum) power	0.44	0.52	0.75	0.21
442 (77.3)	Typing speed	Consecutive typing events	Mean frequency	0.46	0.57	0.78	0.24
442 (77.3)	Typing speed	Consecutive typing events	Second spectral moment	0.43	0.53	0.76	0.21
442 (77.3)	Typing speed	Three characters or fewer in a row	Total (sum) power	0.44	0.51	0.75	0.21
442 (77.3)	Typing speed	Three characters or fewer in a row	Second spectral moment	0.45	0.5	0.75	0.21
442 (77.3)	Typing speed	Fewer than 3 characters in a row	Mean log	0.45	0.46	0.74	0.2
442 (77.3)	Typing speed	Fewer than 3 characters in a row	50th percentile	0.47	0.46	0.75	0.2
442 (77.3)	Typing speed	Fewer than 3 characters in a row	Total (sum) power	0.46	0.47	0.74	0.2
442 (77.3)	Typing speed	Fewer than 3 characters in a row	Mean frequency	0.43	0.48	0.74	0.2
442 (77.3)	Typing speed	Fewer than 3 characters in a row	Second spectral moment	0.45	0.46	0.74	0.2

[a]Typing speed is the length of time elapsed from typing 1 character (or making 1 action) to another (higher values=slower typing speed).

[b]Scroll refers to the distance scrolled in a list before clicking on the item they are looking for, or the speed in scrolling through a list (thought to measure processing speed). When the keystroke type description includes “characters in a row,” this refers to typing several characters in sequence that are not interrupted by a space key press, deletion, or other action.

For identifying recovering PTS symptoms, 11 typing speed–related biomarkers were predictive of hyperarousal, and 7 typing speed–related biomarkers were associated with reexperiencing symptoms. Similarly, 2 scroll-related and 2 typing speed–related biomarkers were associated with recovery from mental fatigue. A total of 17 biomarkers (16 typing speed–related and 1 scroll-related) were predictive of recovery from pain. For recovery from sleep disturbance, there were 11 typing speed–related biomarkers. Finally, there were 19 typing speed–related biomarkers associated with recovery from somatic symptoms.

Discussion

Principal Findings

Millions of Americans present to emergency care each year following exposure to a traumatic stressor [49]. Although the majority recover from these events, a significant minority go on to develop chronic APNSs, including PTS, depression, anxiety, sleep disturbance, nightmares, pain, somatic symptoms, and mental fatigue [2]. The ability to identify these individuals and, ultimately, intervene to prevent the development of chronic APNSs would advance public health and reduce substantial personal suffering. Approximately 90% of Americans own a smartphone [30], and data from smartphone use can be collected passively in daily life with minimal effort from the user. This study is, to our knowledge, the first to suggest that such smartphone data may serve as biomarkers for the development of chronic APNSs in the 8 weeks after traumatic event exposure and presentation to emergency care. Further, keystroke data, which index cognitive and motor behavior, may be useful for tracking worsening and recovery of APNSs. Specifically, smartphone data measuring typing and scrolling behaviors during daily life among 1072 trauma survivors who presented for emergency care helped identify those with high levels of pain, reexperiencing, and mental fatigue in the 8 weeks after trauma exposure. In addition, smartphone indicators predicted state changes in pain, somatic symptoms, mental fatigue, sleep disturbance, and PTS (ie, reexperiencing and hyperarousal), including identifying individuals with worsening versus recovering symptoms. Effects were typically in the small- to medium-effect size range. Importantly, the sample was diverse, with more than half identifying as Black and socioeconomically disadvantaged, with a third reporting a total annual family income of less than US $19,000. This contrasts with other studies in the literature using smartphone biomarkers, which tend to include predominantly White, highly educated samples with higher socioeconomic status [33,50].

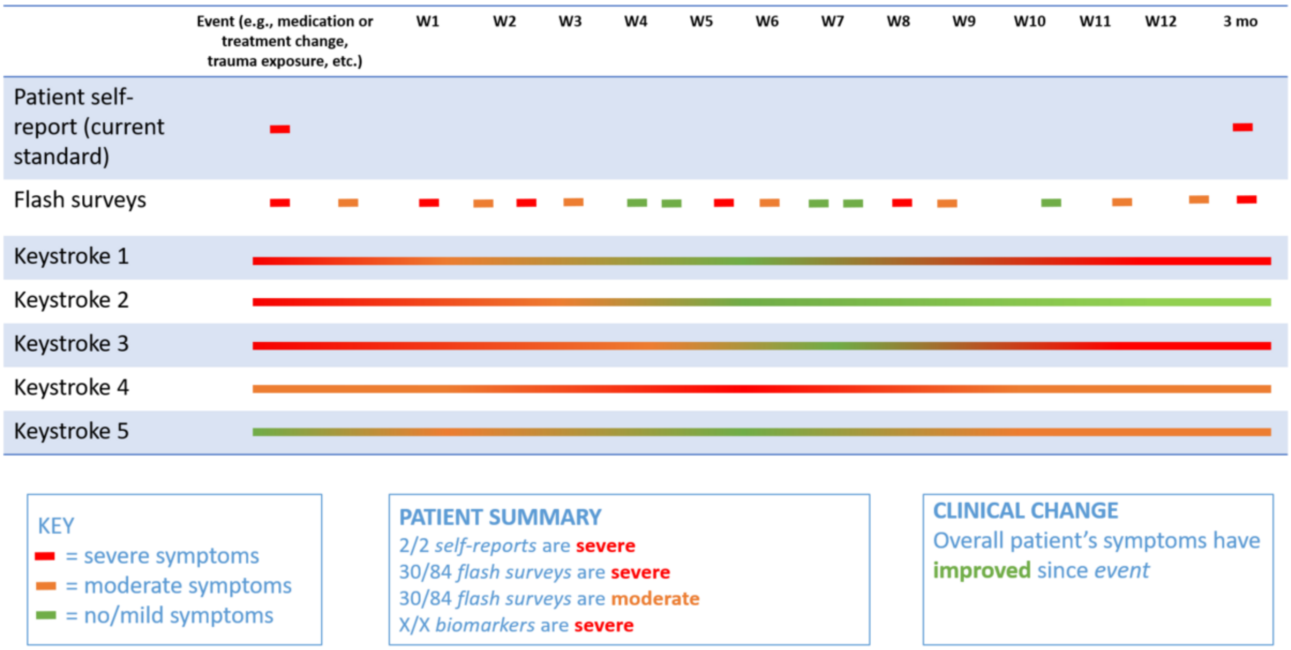
Comparison With Prior Work

Regarding trait biomarkers, our results suggest that 18 keystroke biomarkers could identify individuals with elevated pain in the 8 weeks after trauma exposure. Specifically, individuals with slower typing speeds demonstrated higher levels of pain. Frequency-domain features (eg, total [sum] power, mean frequency, and spectral moments) were the most common signal processing techniques observed in typing speed–related biomarkers, suggesting that these techniques may be particularly useful. Change-of-operation behaviors (eg, time spent switching from typing to pressing the space bar) were associated with reexperiencing symptoms. This is consistent with prior research indicating that PTS symptoms may be associated with difficulties in set shifting [51,52]; however, this is the first study, to our knowledge, to extend such findings to passively collected smartphone data. Finally, scrolling behaviors were associated with mental fatigue, such that longer time spent scrolling to identify desired items was associated with higher levels of mental fatigue. Effects were all in the small- to medium-effect size range. These results are the first to suggest that keystroke biomarkers can identify trauma survivors with pain, PTS symptoms, and mental fatigue. However, the findings are consistent with prior studies in other populations [33], suggesting that keystroke behaviors, including slower typing speeds, can identify individuals with depressive symptoms [37], cognitive impairment [35,36], and pain and clinical disability [50]. These results also align with research indicating that other passively sensed data (eg, sleep and physiological metrics) may serve as potential biomarkers of posttraumatic stress disorder symptoms [39].

State keystroke biomarkers were also identified that could detect within-person changes in APNSs, suggesting improvement or worsening of symptoms. Changes in physical APNSs, such as pain, somatic symptoms, mental fatigue, and sleep disturbance, were predicted by typing and scrolling speed. Changes in mental health–related APNSs (ie, reexperiencing, hyperarousal) were predicted by typing speed. These findings are consistent with prior research indicating that changes in keystroke behaviors can predict within-person changes in mood [31-34]. However, the study findings are, to our knowledge, the first to suggest that keystroke biomarkers can predict worsening or recovery of APNSs among a large sample of trauma survivors followed over the acute posttrauma period.

This study has important clinical implications. Although the sensitivity and specificity of the results indicate that keystroke biomarkers may not be sufficient on their own, they could be useful as part of a suite of heterogeneous biomarkers. The ability to identify individuals at risk for poor outcomes after trauma exposure by leveraging passively collected smartphone data in daily life could facilitate early identification of those at risk for developing APNSs. In turn, such individuals could be connected with appropriate health care services before their symptoms become chronic. More research is needed to determine the most effective preventive interventions after trauma exposure, particularly given the diverse range of potential negative outcomes. However, research has indicated that cognitive behavioral preventive interventions delivered in the early aftermath of trauma may be promising for reducing PTS and related symptoms [28]. Utilizing keystroke biomarkers could also assist in clinical research by identifying and recruiting individuals at risk for APNSs after trauma exposure. Furthermore, the ability to detect state changes in APNSs is particularly valuable. Pending further research, Figure 1 depicts an example of a clinical tool that could be developed to leverage state data from passively collected biomarkers to complement assessments conducted by providers during clinical visits. Ongoing passive data collection indicating state changes in APNSs may ultimately be informative for health care providers and researchers for several reasons. First, providers are often only able to assess changes between appointments, which may occur at long intervals. Second, APNSs are often difficult or impossible to assess “objectively.” Third, APNSs are challenging to report retrospectively with accuracy [53]. Data derived from keystroke biomarkers that capture trajectories of APNSs over time could enhance assessment and improve the ability to evaluate treatment efficacy.

Figure 1. An example of a clinical tool that could be developed to leverage state data from passively collected biomarkers to complement assessments conducted by providers during clinical visits. mo: month; w: week.



Strengths and Limitations

Results of this study should be considered in the context of its strengths and limitations. Strengths include the large sample size of diverse trauma survivors presenting to EDs who were followed prospectively after trauma exposure. Regarding limitations, first, only individuals who presented for emergency care after trauma exposure were included. Many trauma survivors do not seek emergency care, and it is unclear whether these findings generalize to those populations. Second, the majority of the sample consisted of MVC survivors. This is consistent with rates of trauma exposure in the United States, where MVC is one of the most common traumas experienced [1]. However, compared with other trauma types, MVCs may confer a relatively lower risk of developing APNSs [10]. Therefore, results may not generalize to survivors of all trauma types. Third, only Android users were included because iOS users could opt out of keystroke data collection. Although we did not detect differences in clinical symptoms between Android and iOS users, restricting the sample to Android users may affect generalizability. Notably, demographic differences were observed between iOS and Android users; however, these differences suggested that Android users represented a more racially and ethnically diverse sample, which may enhance generalizability. Relatedly, an important consideration in digital phenotyping research is the balance between patient privacy and the potential clinical utility of passively sensed smartphone data. Although substantially more research is needed before keystroke biomarkers can be implemented in clinical settings, further work is also required to ensure the development of secure and trustworthy apps that adequately safeguard private information. Even with such safeguards, some individuals may choose not to use these apps due to privacy concerns. Ethical considerations surrounding these data sources remain ongoing, and the balance of risks and benefits should be discussed with all patients and participants who may use such technologies. Fourth, participants were followed for 8 weeks after trauma exposure to assess APNS outcomes. Research indicates that by this point in the posttrauma period, most individuals with ongoing APNSs will continue to experience chronic symptoms unless they receive treatment [7]. However, future research may benefit from longer follow-up periods after a traumatic event.

Conclusions

Up to 90% of Americans experience a traumatic event at some point in their lives [1], and many go on to develop chronic APNSs [2]. To improve recovery after trauma, it is critical to identify individuals at risk of developing these symptoms. Our findings among 1072 diverse trauma survivors presenting to EDs nationwide indicate the potential utility of passively collected smartphone keystroke data to identify both individuals at risk for developing chronic pain, reexperiencing, and mental fatigue symptoms, as well as state-level worsening or recovery of pain, sleep disturbance, hyperarousal, reexperiencing, somatic symptoms, and mental fatigue in the 8 weeks after trauma exposure. In general, slower typing and scrolling speeds were associated with higher symptom levels, with small- to medium-effect sizes. Keystroke data passively collected via smartphone use in daily life show promise and warrant further research to determine whether they may serve as useful biomarkers for identifying trauma survivors at risk for APNSs. Future research should continue to explore associations between these keystroke biomarkers and APNSs, and assess whether they can be leveraged to connect vulnerable trauma survivors to appropriate health care services, preventive interventions, or both. Overall, these results add to the literature across other conditions indicating that passively collected keystroke data may help identify individuals with neuropsychiatric symptoms or changes. However, to our knowledge, this is the first study to test whether keystroke biomarkers are useful in identifying individuals at risk for neuropsychiatric symptoms in the aftermath of trauma—a critical period during which preventive interventions could be deployed to reduce the long-term burden of trauma-related sequelae.

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Data Availability

Data used in this manuscript are available through the National Institute of Mental Health (NIMH) Data Archive (NDA). The NDA collection for the AURORA (Advancing Understanding of Recovery After Trauma) Project can be found online [54].

Conflicts of Interest

TCN has received research support from the National Institutes of Health (NIH), United States Department of Veterans Affairs (VA), and the Rainwater Charitable Foundation, and consulting income from Otsuka Pharmaceuticals. In the past three years, GDC has received research funding from the National Science Foundation (NSF), the National Institutes of Health, and LifeBell AI, and unrestricted donations from AliveCor Inc, Amazon Research, the Center for Discovery, the Gates Foundation, Google, the Gordon and Betty Moore Foundation, MathWorks, Microsoft Research, NextSense Inc, One Mind Foundation, and the Rett Research Foundation. GDC has a financial interest in AliveCor Inc and NextSense Inc; is also the Chief Technology Officer (CTO) of MindChild Medical; and holds significant stock (all these relationships are unrelated to the current work). LTG receives funding from the National Institute of Mental Health (grant R01 MH121617) and serves on the board of the Many Brains Project; her family also has equity in Intelerad Medical Systems, Inc. CWJ has no competing interests related to this work, although he has been an investigator on studies funded by AstraZeneca, Vapotherm, Abbott, and Ophirex. JLP is president-elect of the Society of Critical Care Medicine. In the past three years, RCK has served as a consultant for Cambridge Health Alliance, Canandaigua VA Medical Center, Holmusk, Partners Healthcare, Inc., RallyPoint Networks, Inc., and Sage Therapeutics; and also holds stock options in Cerebral Inc., Mirah, PYM, and Roga Sciences. KJR has provided scientific consultation for Bioxcel, Bionomics, Acer, and Jazz Pharmaceuticals; serves on Scientific Advisory Boards for Sage, Boehringer Ingelheim, Senseye, and the Brain Research Foundation; and has received sponsored research support from Alto Neuroscience. KCK has served as a paid scientific consultant for the US Department of Justice and Covington & Burling, LLP over the past three years; and receives royalties from Guilford Press and Oxford University Press. SAM has served as a consultant for Walter Reed Army Institute for Research, Arbor Medical Innovations, and BioXcel Therapeutics, Inc.

Multimedia Appendix 1

Additional analysis.
[DOCX File , 513 KB-Multimedia Appendix 1]

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Abbreviations

APNS: adverse posttraumatic neuropsychiatric symptom
AURORA: Advancing Understanding of Recovery After Trauma
ED: emergency department
MVC: motor vehicle collision
PTS: posttraumatic stress

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