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The Behavioral Assessment Screening Tool for Mobile Health ($BAST_{mHealth}$): Development and Compliance in Two Weeks of Daily Reporting in Chronic Traumatic Brain Injury

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Abstract

Objectives: To develop and evaluate the feasibility of a short form of the Behavioral Assessment Screening Tool ($BAST_{mHealth}$) for high frequency *in situ* self-reported assessment of neurobehavioral symptoms using mobile health technology for community-dwelling adults with traumatic brain injury (TBI).

Design: Prospective, repeated measures study of mHealth assessment of self-reported neurobehavioral symptoms in adults with and without a lifetime history of TBI over a two-week period.

Setting: Community

Participants: Community-dwelling adults with (n=52) and without (n=12) a lifetime TBI history consented to the study.

Interventions: Not applicable

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Main Outcome Measures: $BAST_{mHealth}$ subscales (2-items each): Negative Affect, Fatigue, Executive Function, Substance Abuse, Impulsivity; Feasibility measured via compliance (assessments assigned/assessments completed) and participant-reported usability.

Results: We developed the 10-item $BAST_{mHealth}$ as a screener for high frequency *in situ* self-reported assessment of neurobehavioral symptoms leveraging mHealth. Compliance for two-weeks of $BAST_{mHealth}$ supports its feasibility. Fifty-six of 64 participants (87.5%) who completed baseline assessments completed the two-weeks of daily assessments; all 8 participants who did not complete EMA had a history of TBI. Overall compliance was 81.4% (496 completed of 609 assigned assessments) among all 52 participants with TBI and 96.7% (494 completed of 511 assigned assessments) among the 44 who completed any daily measures, compared to 91.8% (135 completed of 147 assigned assessments) among those with no TBI history. Participants thought the daily surveys were easy to understand and complete and the number of prompts were reasonable.

Conclusions: Conducting daily high frequency *in situ* self-reported assessment of neurobehavioral symptoms using the $BAST_{mHealth}$ is feasible among individuals with and without a lifetime history of TBI. Developing and evaluating self-reported assessments for community-based assessment is a critical step towards expanding remote clinical monitoring systems to improve post-TBI outcomes.

Keywords

traumatic brain injury; measurement; neurobehavioral; mHealth; ecological momentary assessment; experience sampling method

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Neurobehavioral consequences of traumatic brain injury (TBI) often become chronic and adversely affect community participation, health, and quality of life.[1-5] Long-term clinical monitoring for these problems could facilitate better symptom management and improve health and function post-TBI.[6-8] To provide a measurement tool for monitoring these problems, informed by persons with lived experience and designed specifically to be captured remotely, we developed the Behavioral Assessment Screening Tool (BAST) and validated it as a self-reported neurobehavioral symptom screener for adults with chronic TBI.[9-13] The BAST is a 38-item measure, developed using patient-centered outcome techniques,[9,14] with strong evidence for content validity[9,11] and a multidimensional factor structure with excellent internal consistency reliabilities.[10] The five subscales, or symptom domains, derived from the BAST are Negative Affect, Executive Dysfunction, Fatigue, Impulsivity, & Substance Abuse.[10] Items about experiencing symptoms or behaviors in the past two weeks are rated on a 5-point frequency scale, ranging from never to very often. Previous Rasch analysis of the BAST indicated that its subscales were unidimensional and that items covered and differentiated between a range of symptom frequency levels.[12]

Collecting repeated neurobehavioral symptoms in real time and in an individual’s natural environment (e.g., community), an approach integral to Ecological Momentary Assessment (EMA)[15] and the Experience Sampling Methods (ESM),[16] allows clinicians to assess multiple fluctuating symptoms and behaviors over time in diverse community-based populations (see Supplement A for further discussion of different sampling methods and considerations). This type of high frequency *in situ* assessment reduces errors associated with recall bias or poor recall by focusing on specific moments or behaviors that occur in day-to-day life.[15] It also captures self-reports across waking hours of a typical week to create an overall picture of a person's daily experience.[16] The increasing ubiquity of smartphones presents new opportunities for even more efficient electronic and *in situ* symptom tracking in a variety of medical populations, including TBI.[17-23]

Though using mobile health (mHealth) technology for *in situ* assessment in chronic TBI is an emerging practice,[17,18,20,24,25] it too often relies on self-reported measures that were initially designed and validated to be completed with a trained clinician or rater, are typically domain-specific (e.g., mood), and often have single questions that are too long to easily read on a smartphone screen without scrolling.[17,18,26] Thus, these measures do not effectively translate to community-based high frequency assessment on smartphones. Remote screening via mHealth requires an easy, relatively brief, and comprehensive assessment to maximize the likelihood of complete and valid responses to high frequency repeated assessments. Leveraging mHealth to improve healthcare delivery requires rigorous research to develop and validate every aspect of an mHealth system, including the assessment used. The *Standards for Educational and Psychology Testing*[27] stipulate that users of an assessment tool have the responsibility to demonstrate validity evidence for that tool in the specific population and the specific context in which the tool is being used.

Though the BAST meets the requirements for a psychometrically strong self-reported neurobehavioral symptom assessment for long-term clinical monitoring in chronic TBI, a short-form version of the BAST is needed to be compatible with high frequency *in situ* self-reported assessments. Therefore, to address this need, the purpose of the current study was two-fold: first, to create a 10-item short-form of the BAST (the $BAST_{mHealth}$) that can be used for high frequency *in situ* self-reported assessment of neurobehavioral symptoms; and second, to determine the feasibility of collecting the $BAST_{mHealth}$ for high frequency *in situ* self-reported assessment of neurobehavioral symptoms among community-dwelling adults with chronic TBI.

Method

Developing the $BAST_{mHealth}$

Rasch analysis provides item-level and person-level information about measurement tools that can be used to inform selection of items for a short-form version of a validated measure.[28] It functions on the premise that people experiencing more severe or more frequent overall symptoms in a unidimensional symptom domain are more likely to endorse certain items than people experiencing less severe or less frequent symptoms. This can be observed, for example, in person-item maps generated by Rasch analysis, as we previously presented for four of the five subscales of the BAST.[12] While others have used Rasch analysis to establish short forms for various outcomes for individuals with chronic pain,[29-32] self-assessment of work or school performance,[33,34] psychological disorders,[35,36] and functional and emotional outcomes in cardiac rehabilitation,[37,38] there is no standard approach for how to select specific items based on Rasch analysis outputs. In the absence of standard guidance, we employed a mixed approach to item selection based on item fit statistics (Infit/Outfit MSNQ closest to 1 is the best fit), visual examination of person-item maps and keyforms to determine item coverage across response options, and consideration of the purpose of the $BAST_{mHealth}$ for clinical monitoring to identify likely problems in each symptom domain that would require further clinical evaluation of severity and interference in daily life. We selected two items from each of the five BAST subscales (symptom domains), with the *a priori* goal of having one item capturing the highest end of the symptom-spectrum and the other item to capture more moderate symptom frequency. With further testing, this could allow for both identification of clinical symptoms requiring immediate intervention and monitoring of prodromal symptoms that may require further evaluation. Rasch person-item maps also differentiate where different responses across the BAST response scale (1-5) fall on the overall spectrum of symptom frequency, so when selecting the two items for each subscale, we also chose items with a good spread across response options that did not cover the same region of the continuum of symptom frequency. Our Rasch analysis of the BAST, upon which selection of the $BAST_{mHealth}$ items was based, was previously described.[12] Relevant item fit statistics and person-item map logits are presented in Table 1, where items selected for each $BAST_{mHealth}$ subscale are highlighted. Rasch-generated keyforms, which we used to identify how well responses to items covered the range of symptom frequency, are presented in Supplemental Figures A-D, with detailed explanations for the rationale behind item selection. Item difficulty for the $BAST_{mHealth}$ indicates the probability of that item being endorsed at that response level by individuals with more severe symptoms. For Substance Abuse, Rasch analysis was not previously performed,[12] so we instead selected one item as a single screen for alcohol abuse and a second as a single screen for drug abuse, with the determination that *any* endorsement (≥2=rarely) would be a flag for clinical follow-up. These items were “I needed alcohol to get through my day” and “I needed drugs to get through my day.”

Design and Participants

We conducted a prospective, repeated measures study with participants randomized to one of three sampling frequency groups for self-reporting neurobehavioral symptoms over a two-week period. We administered the $BAST_{mHealth}$ via a link to an electronic database sent via text message to conduct high frequency *in situ* self-reported assessment over a 2-week period in adults with and without a lifetime history of TBI. The three sampling frequency groups were: daily random time, daily scheduled time, and every other day scheduled time (all between 9am and 8pm with scheduled times chosen by participants), though one aim of this study was overall feasibility, so we report compliance and usability in the sample overall.

Potential participants were English-speaking adults living in the community. They were recruited from the investigators’ previous studies and from a University Acquired Brain Injury Research Registry via email that included a link to a RedCap® database. This link was also posted publicly to social media to recruit both those with and without lifetime TBI history, allowing for direct comparison of compliance among those with TBI to those without. After participants provided informed consent (e-consent), they were directed to complete questionnaires, including an electronic modification of the Ohio State University TBI Identification Method (OSU-TBI)[39,40] to identify presence and severity of lifetime TBI history, provide basic demographic information, and complete the full BAST to assess baseline neurobehavioral symptom frequency. After completing these baseline surveys, study staff contacted participants to review expectations for the two-weeks of data collection and to answer their questions. Text messages with links to surveys were sent at scheduled times, with a reminder sent after one hour if participants had not completed assessments. If participants missed a day, they were instructed not to go back and fill out the missed survey. Participants were compensated upon completion of the study, with partial compensation if they completed baseline but not daily $BAST_{mHealth}$ measures. All study procedures were approved by the University's Institutional Review Board.

Measures

Participant demographics included age, gender, race/ethnicity, and education. Injury-related information derived from the OSU-TBI included TBI history (severity, >1 TBI), age at first injury, and time since most recent TBI. We measured compliance as the percent of completed daily assessments. Usability for the $BAST_{mHealth}$ was evaluated with seven items, developed originally for another post-TBI mHealth study[41] and adapted for this study. Items were related to ease of use, user understanding, reasonableness of the number of prompts, and interference in daily activities. Participants rated their agreement with each statement (i.e., item) on a 5-point agreement scale (1=Disagree, 5=Agree).

To measure baseline neurobehavioral function, participants completed the full BAST measure, comprising five subscales with average scores indicating more symptoms or experiences with higher frequency in that domain over the past two weeks (1=never, 2=rarely, 3=sometimes, 4=often, 5=very often).[9,10] Participants then completed the 10-item $BAST_{mHealth}$ repeatedly over two weeks, with items evaluated on the same response scale with reference to the past 48 hours. For both versions of the BAST, higher scores indicate more problems/symptoms in that domain (Executive Function items are reverse-scored).

Data analysis

We used descriptive and summary statistics of baseline measures to characterize our sample. We examined correlations between the BAST subscale scores and the $BAST_{mHealth}$ subscales scores using Spearman's rho correlation coefficients and differences in all BAST subscales scores based on history of TBI using independent samples t-tests and Cohen's d effect sizes. We calculated compliance as the percentage of completed daily surveys (total complete/total assigned) for the overall sample, broken down by history of TBI, and within person (median and range). Based on average compliance in a meta-analysis of adult EMA of health behaviors and psychological constructs,[42] we set a threshold for establishing feasibility at 80% compliance. For usability, we present the percentage of agreement responses for all items assessing usability. All data analyses were conducted using SPSSv26™ for Windows.

Results

Participant Characteristics

Sixty-four participants consented and completed baseline assessments (n=52 with TBI history, n=12 without TBI history). Average participant age was 42.4 years (SD=13.8), 68.8% were women, and 76.6% had a college degree. Racial and ethnic identities were non-Hispanic White (79.7%), non-Hispanic Black (6.5%), Hispanic White (7.8%), and Asian (6.5%). Of those with a history of TBI (n=52), 32.7% has more than 1 lifetime TBI (average age at first injury was 27.5 years, SD=13.2), range 7-69 years) and worst lifetime injuries were mild without loss of consciousness (23.1%), mild with loss of consciousness (42.3%), and moderate-severe (34.6%). Time since most recent TBI averaged 7.9 years (SD=9.2).

$BAST_{mHealth}$ Feasibility

Fifty-six participants (87.5%) completed the two-weeks of $BAST_{mHealth}$ measures, resulting in an overall compliance (measured as number of assessment completed/number assigned) of 81.4% among all 64 participants and 95.6% (96.7% in TBI survivors; 91.8% in those with no TBI history) among the 56 who completed repeated measures (see Table 2). Overall, 79.7% of participants met the threshold of completing 80% of their assigned assessments; among those who participated at all (Completers), 91.1% met the >80% threshold. Summaries of within person compliance are provided in Table 2. Participants thought the daily surveys were easy to understand and complete and the number of prompts were reasonable; no one agreed that completing daily surveys interrupted their daily activities (see Table 3).

$BAST_{mHealth}$ Validity

Participants reported a range of neurobehavioral symptom frequency at baseline (see Table 4), with symptoms occurring most often in Fatigue and Negative affect domains, followed by Executive Function and Impulsivity, and least often in Substance Abuse. Notably, the higher scores for all participants compared to just the subset of those who completed two-week assessments indicates that those who did *not* go on to complete repeated measures were also experiencing more frequent neurobehavioral symptoms. Average scores across the two-weeks indicated a similar pattern of neurobehavioral symptom frequency, except for Executive Function (average scores were slightly lower for $BAST_{mHealth}$ compared to the full BAST across all subscales but higher for Executive Function), and BAST and BASTmHealth subscales scores were significantly correlated within all subscales (see Table 4).

Comparison of BAST and $BAST_{mHealth}$ scores between those with and without TBI indicates that neurobehavioral symptoms in the domains of Negative Affect, Executive Function, and Fatigue were all more frequent in those with TBI (see Table 4), with large effect sizes. Differences were not statistically significant for Impulsivity (which still had a medium effect size) or Substance Abuse, likely because these symptoms were endorsed far less frequently in both groups. One notable exception is the $BAST_{mHealth}$ Negative Affect subscale, for which scores in persons with TBI were notably lower compared to the full BAST, and which did not show statistical differences between those with and without TBI (though the effect size was still large). Given the heterogeneity of emotions that the Negative Affect subscale covers, the $BAST_{mHealth}$ Negative Affect subscale may require more than 2 items to be sufficiently sensitive.

Discussion

Opportunities to conduct efficient and effective remote clinical monitoring abound with the proliferation of mHealth technology. Consistent with previous studies, we found excellent overall compliance and high usability with remote self-reporting of neurobehavioral symptoms after TBI.[17] Though, also consistent with EMA studies in other populations, some participants in this study never started daily assessments, bringing down the overall compliance.[43,44] In our sample, these individuals all had a lifetime history of TBI and may have been those experiencing more frequent symptoms, so future efforts should be made to understand barriers to compliance and identify approaches to promote active symptom-tracking in these individuals. However, among those who did complete daily measures, participants with a lifetime history of TBI demonstrated better compliance than those without a TBI history. This finding may indicate that those with TBI have more intrinsic motivation to complete symptom tracking that is related to their injury experiences, though it may also be that those without a history of TBI have less time to respond to high frequency *in situ* self-reported assessments because they are more active in other areas of their lives. Whatever the reason, this is an important finding as it addresses concerns that individuals with TBI may struggle more than those without in complying with self-reported assessments.

Unlike previous studies, our neurobehavioral symptoms measure was specifically developed for *in situ* high frequency self-reported assessment. The BAST was developed using patient-centered outcomes techniques, ensuring accessibility of language (low literacy), simplicity, and high relevance to the lived experience of individuals with TBI.[9,11,14] The BAST is completed independently, in the absence of a clinician or trained rater,[10,12,13] mirroring how EMA or ESM items are collected. Based on previous Rasch analysis of the BAST,[12] we identified items specific for the $BAST_{mHealth}$ that, together, covered a wide range of symptom frequency.[28] Choosing the two items with the highest factor loadings, a commonly employed method for developing short forms, may not accurately reflect the range of symptom frequency in a symptom domain and may largely overlap, rather than complement, one another. Hence, the rigorous methods we took to develop the $BAST_{mHealth}$ described herein provide an evidence-based assessment for advancing high frequency *in situ* self-reported assessment for clinical monitoring in chronic TBI.

The availability of a brief measure of neurobehavioral symptoms, which can be completed repeatedly and conveniently in real time by the person with TBI, has important clinical implications. Subjective report of function is an important component of assessing outcomes after TBI and of diagnosing co-morbid mental health conditions and/or cognitive and emotional symptoms that could be early warning signs of dementia. Health providers, such as physicians and neuropsychologists, typically rely on retrospective patient and/or family member reports when making diagnoses and treatment decisions. These retrospective reports are subject to bias and may represent the single worst episodes of problems rather than typical daily functioning. The $BAST_{mHealth}$ could be assigned to people with TBI to complete for two weeks before their health appointments, and the results could be provided to their health care providers to offer them insight into the patient's typical neurobehavioral functioning in their everyday environments, facilitating accurate diagnosis and treatment plans. The ability to compare functioning at different times of day or different days throughout the week could assist health care professionals with monitoring patterns that could guide treatments, such as whether negative affect is more common in the evenings or on weekdays. The inclusion of items that measure common symptoms that may occur less frequently could assist with early identification of symptoms that may worsen and trigger serial monitoring of these symptoms in the person's daily environment. These types of assessment have the potential to empower persons with TBI and their care partners to take control of monitoring these symptoms and their correlates, which can be the first step to effective self-management.

Study Limitations

Most participants (76.6%) in our study had at least an undergraduate degree, and all had completed high school, so results may not generalize to the those with less education. Similarly, as participants were recruited entirely online, our sample was skewed towards more technology-literate individuals, so the high compliance in this study may not generalize to individuals less comfortable using mHealth technology or those with severe cognitive impairment post-TBI. While overall compliance was high, 8 participants (12.5%) did not complete repeated measures, despite repeated contact attempts by study personnel. These participants all had a history of TBI and reported more frequent neurobehavioral symptoms at baseline, so may represent those most in need of long-term monitoring and intervention. Future studies should examine strategies to increase buy-in among participants, which would likely improve compliance with remote symptom-monitoring. While use of Rasch analysis to develop the $BAST_{mHealth}$ was a strength, it is possible that the specific items best able to differentiate persons who reported on the full BAST with reference to the 'past two weeks' would not be the same items best able to differentiate those reporting on symptoms over the 'past 48 hours.' This may explain the lack of statistically significant differences found in those with and without TBI for the $BAST_{mHealth}$ Negative Affect subscale. Adding an additional one to two items to this subscale, given the diversity of emotions captured by the full BAST Negative Affect subscale, may be necessary. Further work is needed to validate the Substance Abuse subscale of the $BAST_{mHealth}$ as these items were not yet included in the full BAST version used herein. Effectiveness of the BAST and the $BAST_{mHealth}$ in the context of a larger remote symptom monitoring protocol still needs to be tested.

Conclusions

Developing and evaluating self-reported assessments for community-based high frequency *in situ* self-reported assessment, like that used in EMA or ESM, is a critical step towards expanding remote clinical monitoring systems to monitor and improve post-TBI outcomes. To that end, we developed and piloted the $BAST_{mHealth}$, a short version of the well-validated BAST, for high frequency *in situ* self-reported assessment of chronic neurobehavioral symptoms after TBI. Conducting mHealth-based assessment using the $BAST_{mHealth}$ is feasible for community-based symptoms post-TBI. The $BAST_{mHealth}$ could be integrated into mHealth platforms to provide clinicians with detailed and ecologically valid information about a person's typical neurobehavioral functioning in their everyday environments, which could in turn trigger further clinical evaluation as needed and facilitate more effective and personalized interventions. Future testing is needed to validate the psychometrics of the $BAST_{mHealth}$ in a larger sample, determine its responsiveness to change, and identify symptom frequency or level of change in symptom frequency that should trigger further evaluation and/or intervention.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Conflicts of Interest and Sources of Funding:

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List of abbreviations

BAST	Behavioral Assessment Screening Tool
EMA	Ecological Momentary Assessment
ESM	Experience Sampling Method
mHealth	Mobile Health
MSNQ	mean-square
OSU-TBI	Ohio State University TBI Identification Method
TBI	Traumatic Brain Injury

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Table 1

BAST item-level properties

Subscale Items	Infit MNSQ	Outfit MNSQ	Logits Above Mean (0) by Response Category	
			4=Often	5=Very often
Negative affect				
Thoughts got stuck in my head	1.26	1.35	1-2	3-4
I felt guilty	1.23	1.28	2-3	3-4
I got mad easily	1.23	1.20	2-3	4-5
Couldn't let go	1.13	1.10	0-1	2-3
I did not enjoy activities that are usually important to me.	0.90	0.93	2-3	3-4
Anxious	0.92	0.90	1-2	3-4
Worried	0.89	0.84	1-2	2-3
Stressed	0.88	0.84	0-1	2-3
Depressed	0.86	0.81	2-3	3-4
Overwhelmed	0.71	0.81	0-1	2-3
Executive (Dys)Function *				
I started activities on my own	0.95	0.95	0-1	3-4
Finished activities started	0.74	0.75	0-1	3-4
Planned ahead	1.18	1.14	0-1	2-3
Able to adapt	0.83	0.83	1-2	2-3
I was organized	0.95	0.95	0-1	2-3
Understood effect on others	1.13	1.14	1-2	2-3
Followed through	0.73	0.76	2-3	-
Generate multiple solutions	1.26	1.24	1-2	1-2
Able to pay attention	0.99	1.01	-	1-2
Thought about others' feelings	1.18	1.18	1-2	1-2
Fatigue				
Needed a nap/rest	1.21	1.23	1-2	2-3
Too tired for physical activities	1.23	1.22	1-2	3-4
I felt too tired to finish tasks that required thinking	1.00	1.03	2-3	3-4
I had low energy	0.81	0.87	1-2	2-3
I felt tired	0.66	0.61	0-1	1-2
Impulsivity				
I took unnecessary risks	0.96	0.97	1-2	2-3
I acted rudely	0.93	0.92	1-2	3-4
Inappropriate sexual comments	1.39	1.40	1-2	2-3
Reacted without thinking	0.97	0.96	-	0-1
Did unsafe things	0.76	0.81	1-2	2-3

NOTE. Highlighted items are those selected for the BAST$_{\text{mHealth}}$. Items are shortened in the table to convey general meaning, but the full BAST is available for public use at https://eprovide.mapi-trust.org. Selected items, highlighted in gray, are presented fully here.

*Executive Function responses are reverse scored prior to Rasch analysis, so 3=Sometimes, 4=Rarely, 5=Never. Logits >Mean=0 indicate above average severity strata in that symptom domain; used to select screening items. Logits < Mean of 0 indicate less than average severity in that symptom domain, so are not presented here.

Table 2

Compliance rates for $BAST_{mHealth}$ over 2 weeks

	Overall Compliance in the Sample	Mean ± SD and Range of Individual Participant Compliance	Number and Percent of Participants >80% Compliance Threshold
Participants with a lifetime history of TBI (n=52)	496 of 609 assessments	81.6% (SD=3.6%)	41
	81.4%	0%-100%	78.8%
Only completers with lifetime history of TBI * (n=44)	494 of 511 assessments	96.1% (10.4%)	41
	96.7%	42.9%-100%	93.2%
Participants without a lifetime history of TBI (n=12)	135 of 147 assessments	92.9% (10.1%)	10
	91.8%	71.4%-100%	83.3%

*Completers=participants who completed >2 daily measures. n=1 participant completed 2 measures; n=7 participants did not complete any daily measures. All adults without a lifetime history of TBI were completers.

Table 3

Usability and satisfaction of the $BAST_{mHealth}$ repeated surveys

	Disagree			Agree	
Survey Item	**1**	**2**	**3**	**4**	**5**
Completing the daily surveys was easy.	0	0	0	20.8	79.2
I understood how the daily survey notifications would work.	0	0	6.3	20.8	72.9
I understood the questions that were asked.	0	0	2.1	20.8	77.1
It was fun completing the daily surveys.	0	0	31.3	35.4	33.3
The number of prompts was reasonable.	0	0	4.2	20.8	75.0
The number of prompts was annoying.	58.3	29.2	10.4	2.1	0
Completing daily surveys interrupted my daily activities.	60.4	31.3	8.3	0	0
I would be willing to complete daily short surveys like I did in this study to track my symptoms and experiences.	0	4.2	6.3	25.0	64.6

NOTE. N=48 participants completed this survey. Values are row percentages. Grayed cells indicate negatively framed questions, so disagreement indicates a more positive response.

Table 4

Neurobehavioral symptoms (BAST/BAST$_{mHealth}$) of the study sample

BAST Subscales	Full Sample (n=64) BAST Full	Completers (n=56) BAST Full	Completers (n=56) BAST 2-items	Completers (n=56) BAST$_{mHealth}$	BAST vs BAST$_{mHealth}$ ±
Negative affect					
All	3.09 (0.9)	2.99 (0.9)	2.52 (1.0)	2.02 (0.7)	.619*, .815*
Persons *with* TBI only	3.23 (0.9)	3.14 (0.9)	2.61 (1.0)	2.06 (0.7)	.593*, .794*
Persons *without* TBI only	2.47 (0.6)	2.47 (0.6)	2.13 (0.9)	1.90 (0.7)	.786†, .864*
Differences in those with and without TBI	*P*=.007, d=.86	*P*=.014, d=.81	*P*=.150, d=.93	*P*=.516, d=.70	
Executive function					
All	2.28 (0.6)	2.28 (0.7)	2.38 (0.8)	2.54 (0.8)	.744*, .770*
Persons *with* TBI only	2.39 (0.6)	2.40 (0.7)	2.51 (0.8)	2.68 (0.8)	.696*, .780*
Persons *without* TBI only	1.81 (0.4)	1.81 (0.4)	1.83 (0.5)	2.06 (0.3)	.792†, .350
Differences in those with and without TBI	*P*=.004, d=.60	*P*=.004, d=.61	*P*=.003, d=.79	*P*<.001, d=.75	
Fatigue					
All	3.36 (1.0)	3.31 (1.0)	3.38 (1.1)	2.80 (1.0)	.763*, .762*
Persons *with* TBI only	3.56 (1.0)	3.52 (1.0)	3.56 (1.1)	2.98 (1.0)	.707*, .700*
Persons *without* TBI only	2.52 (0.6)	2.52 (0.6)	2.58 (0.7)	2.13 (0.4)	.590†, .759†
Differences in those with and without TBI	*P*<.001, d=.94	*P*<.001, d=.93	*P*=.007, d=1.00	*P*<.001, d=.92	
Impulsivity					
All	2.06 (0.7)	2.01 (0.6)	2.18 (0.8)	1.57 (0.5)	.653*, 580*
Persons *with* TBI only	2.12 (0.7)	2.08 (0.6)	2.25 (0.8)	2.12 (0.7)	.614*, .547*
Persons *without* TBI only	1.77 (0.5)	1.77 (0.5)	1.88 (0.6)	1.33 (0.3)	.735†, .732†
Differences in those with and without TBI	*P*=.094, d=.65	*P*=.107, d=.58	*P*=.146, d=.71	*P*=.056, d=.49	
Substance abuse					
All	1.27 (0.6)	2.01 (0.6)	n/a	1.24 (0.5)	.427*, n/a
Persons *with* TBI only	1.25 (0.6)	1.16 (0.4)	n/a	1.27 (0.6)	.495*, n/a
Persons *without* TBI only	1.36 (0.4)	1.36 (0.4)	n/a	1.16 (0.5)	.427, n/a
Differences in those with and without TBI	*P*=.551, d=.58	*P*=.093, d=.36	n/a	*P*=.535, d=.54	

NOTE. Completers=participants who completed >2 daily measures. BAST 2-items=The 2 items from each subscale of the BAST mHealth completed as part of the full BAST at baseline. Differences in BAST scores between those with and without TBI were assessed via independent samples *t* tests. Effects sizes are Cohen's d.

± Spearman's ρ correlations between BAST$_{mHealth}$ and the BAST dull subscale, BAST 2-item.

* *P*<.001.

† *P*<.05.