Journal of Affective Disorders 250 (2019) 163–169

Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com/locate/jad

Research paper

Short-term prediction of suicidal thoughts and behaviors in adolescents: Can recent developments in technology and computational science provide a breakthrough?

Nicholas B. Allen[a,b,*], Benjamin W. Nelson[a,b], David Brent[c], Randy P. Auerbach[d,e]

[a] Department of Psychology, University of Oregon, Eugene, Oregon, United States
[b] Center for Digital Mental Health, University of Oregon, Eugene, Oregon, United States
[c] Department of Psychiatry, University of Pittsburgh, Pittsburgh, PA, United States
[d] Department of Psychiatry, College of Physicians and Surgeons, Columbia University, New York City, United States
[e] Division of Clinical Developmental Neuroscience, Sackler Institute, New York City, United States

ARTICLE INFO

Keywords:
Suicide prediction
Suicide prevention
Smart phones
Wearable computing
Smart home technology
Machine learning

ABSTRACT

Background: Suicide is one of the leading causes of death among adolescents, and developing effective methods to improve short-term prediction of suicidal thoughts and behaviors (STBs) is critical. Currently, the most robust predictors of STBs are demographic or clinical indicators that have relatively weak predictive value. However, there is an emerging literature on short-term prediction of suicide risk that has identified a number of promising candidates, including (but not limited to) rapid escalation of: (a) emotional distress, (b) social dysfunction (e.g., bullying, rejection), and (c) sleep disturbance. However, these prior studies are limited in two critical ways. First, they rely almost entirely on self-report. Second, most studies have not focused on assessment of these risk factors using intensive longitudinal assessment techniques that are able to capture the dynamics of changes in risk states at the individual level.

Method: In this paper we explore how to capitalize on recent developments in real-time monitoring methods and computational analysis in order to address these fundamental problems.

Results: We now have the capacity to use: (a) smartphone, wearable computing, and smart home technology to conduct intensive longitudinal assessments monitoring of putative risk factors with minimal participant burden and (b) modern computational techniques to develop predictive algorithms for STBs. Current research and theory on short-term risk processes for STBs, combined with the emergent capabilities of new technologies, suggest that this is an important research agenda for the future.

Limitations: Although these approaches have enormous potential to create new knowledge, the current empirical literature is limited. Moreover, passive monitoring of risk for STBs raises complex ethical issues that will need to be resolved before large scale clinical applications are feasible.

Conclusions: Smartphone, wearable, and smart home technology may provide one point of access that might facilitate both early identification and intervention implementation, and thus, represents a key area for future STB research.

Introduction

Suicide is a leading cause of death across all age groups (Turecki and Brent, 2016) and is the second leading cause of death among adolescents (CDC, 2017). This is likely to be an underestimate as many cases are not reported or do not present for care. In addition to deaths, 16% of high school students report seriously considering suicide each year, and 8% make one or more suicide attempt (CDC, 2017). Despite these alarming statistics, little is known about factors that confer imminent risk for suicide in this (or any other) age group. A recent meta-analysis showed that in the past 50 years, we have not appreciably improved our ability to predict which individuals are most likely to die by suicide (Franklin et al., 2017), and the question of *when* they might be at greatest risk is even more challenging (Millner et al., 2017). Doubtlessly, part of the problem stems from the fact that research has continuously tested variants of the same risk indicators with a heavy reliance on medical records, demographics, clinical interviews, and patient self-report questionnaires. Furthermore, much of this

* Corresponding author.
E-mail address: nallen3@uoregon.edu (N.B. Allen).

https://doi.org/10.1016/j.jad.2019.03.044
Received 26 July 2018; Received in revised form 4 March 2019; Accepted 5 March 2019
Available online 06 March 2019

research has tested these measures in isolation, rather than incorporating multiple risk variables that may have additive and interacting effects (Walsh et al., 2017). Only a few studies have focused on imminent suicide risk (Glenn and Nock, 2014), and moreover, these studies are often conducted with group level data, which may not generalize to the individual (Fisher et al., 2018). This is a particular challenge given the fact that risk processes for suicide are likely to be highly idiosyncratic. Taken together, it is clear that there is a critical need to improve the short-term prediction of suicide risk, and to develop innovative approaches and techniques in order break out of our pattern of stasis.

The ability to intervene precisely at critical moments in a person's life—such as during acute risk for suicidal actions—could dramatically reduce loss of life from suicide. Much of what we do in the clinical consulting room is designed to equip patients with the coping skills necessary to face crises that occur outside of the clinician's presence. Indeed, many of the most effective suicide prevention programs are effective exactly because they provide barriers to harmful behaviors *at the critical moment of action* (Yip et al., 2012). Moreover, even if attempts are not fully prevented, interrupting attempts before actions become lethal can also have life-saving benefits. An example is the use of blister packaging for medications commonly used in suicide attempts, where placing a minor barrier to lethal action at the moment of action can divert people away from the attempt and save lives (Yip et al., 2012). "Just-in-time" adaptive interventions delivered via mobile health applications have also demonstrated the potential benefit of low-intensity, high-impact interventions when they are delivered in a timely fashion (Nahum-Shani et al., 2014; 2016). However, to apply such techniques to suicide, we need to solve the prediction problem—to determine not only *who* may need an intervention, but also *when* an intervention would be ideally timed.

In order to have a real public health impact, methods of predicting short-term suicide risk must be reliable, feasible, scalable, and affordable. Given the large proportion of individuals experiencing mental health crises who do not receive treatment (Thornicroft et al., 2016), prediction methods should ideally have the potential to reach those not currently in traditional mental health care. Current methods for predicting suicidal thoughts and behaviors (STBs), such as clinical monitoring and screening usually fail on most, if not all, of these criteria. Currently, our most common predictors of STBs are general demographic or clinical indicators with relatively weak predictive value that are of little use in short-term prediction (Glenn and Nock, 2014). The goal of this paper is to explore the potential of new consumer technology (i.e., mobile, wearable, and smart home computing) for moving past traditional methods to identify new real-time predictors of STBs in high-risk individuals.

Theories of suicidal thoughts and behaviors: relevance to short-term prediction

Despite the existence of a number of well-supported theoretical approaches that delineate risk for STBs across all age groups, they have not yet translated into improved short-term prediction of STBs. That said, promising risk factors from Shneidman's *Psychache Theory* (e.g., emotional distress; Shneidman, 1993), Joiner's *Interpersonal Theory of Suicide* (Van Orden et al., 2010), and Mann's *Diathesis-Stress Theory of Suicidal Behavior* (Mann et al., 1999) offer frameworks within which to make predictions regarding proximal risk processes for STBs – including in youth populations. Specifically, Shneidman proposed that *Psychache*, or mental pain (i.e., emotional distress), is a transdiagnostic predictor of suicidal behavior (Shneidman, 1993; Troister et al., 2013; Troister and Holden, 2012; Verrocchio et al., 2016) and may provide a strong motivation to engage in suicidal behavior (Ma et al., 2016). Consistent with this, a recent study used a timeline follow-back approach to assess near-term affect prior to suicide attempts and found that acute emotional distress—namely feelings of self-dissatisfaction, hostility, loneliness, or fear—increased in the 6 h preceding a suicide attempt (Bagge et al., 2017; Millner et al., 2017). Moreover, the findings highlighted acute peaks in distress 1–2 h prior to the attempt, which provides important preliminary empirical support for the link between rapid increases in emotional distress and suicide attempts. Similarly, Ecological Momentary Assessment (EMA) research in high-risk groups has found that emotional distress (e.g., loneliness, hopelessness) covaried with suicidal ideation (Kleiman et al., 2017). These studies are broadly consistent with previous studies linking increases in negative affect with suicidal thoughts (Nock et al., 2009) and suicide deaths (Hendin et al., 2001). Therefore, Shneidman's theoretical model and the extant literature strongly suggest that real time monitoring of emotional distress is likely to be important for any approach to short-term prediction of STBs as one of the motivations for suicide has been proposed to relate to an attempt to escape distress (Klonsky et al., 2016).

Joiner's *Interpersonal Theory of Suicide* (Van Orden et al., 2010) posits that suicidal acts result from interactions among acquired capacity for suicide, thwarted belongingness, and perceived burdensomeness (Ma et al., 2016). In a test of this theory, Bagge et al. (2013) also used a timeline follow-back approach and found that increased risk of attempting suicide was associated with the occurrence of a negative life events in the 48 h prior to the attempt—particularly interpersonal life events involving a romantic partner. This is consistent with prior research that found 78% of patients with a recent suicide attempt reported a conflict with a spouse, lover, or family member preceding their attempt (Hall et al., 2011). Among youth, Stewart et al. (2017a) recently demonstrated that when comparing the occurrence of stress among suicide ideators and attempters, interpersonal stress, but not non-interpersonal domains, differentiated the groups, further highlighting the importance of probing the association between interpersonal processes and suicide attempts (Stewart et al., 2019). Among psychiatrically hospitalized youth, Stewart et al. (2017a) also showed that peer victimization (e.g., reputational and overt victimization) was associated with past suicide attempts. Integrating these findings with Joiner's interpersonal theory underscore the importance of probing disturbances in social relationships to improve the short-term prediction of STBs.

Finally, Mann's *Diathesis-Stress Theory of Suicidal Behavior* (Mann et al., 1999) views suicidal behavior as a convergence between the experience of distress and the tendency to act. Although Mann refers to a wide range of biologically-based diatheses, one potential diathesis that shows dynamic change across time is sleep disturbance. Furthermore, sleep disturbance is a well-established risk factor for STBs itself, and also potentiates the effect other risk factors (e.g., emotional distress, social dysfunction; Goldstein and Walker, 2014; Tarokh et al., 2016). In prior research, Goldstein and colleagues found that sleep disturbance, particularly insomnia in the previous week, was associated with adolescent suicide, even after controlling for depression severity (Goldstein et al., 2008). Similarly, Hall et al. (1999) found that insomnia was associated with severe suicide attempts, again highlighting the link between sleep disturbance and suicide. In a recent study using EMA techniques, Littlewood et al. (2018) found that daily measures of short sleep duration and poor sleep quality predicted next day suicidal ideation. In regards to treatment, a more recent study of veterans with insomnia, found that after treatment with cognitive behavioral therapy for insomnia, there was a 65% reduction in participants' odds for suicidal ideation (Trockel et al., 2015). As we note below, there is an opportunity to move beyond traditional self-report based sleep disturbance assessments by using digital technology sensing methods to assess sleep patterns to determine whether the detection of real-time fluctuations in sleep improves short-term STB prediction.

Real-time monitoring and short-term prediction of suicidal thoughts and behaviors with mobile and wearable computing

While the onset of suicidal ideation and selection of suicide methods

often occur years prior to an attempt, the proximal steps to suicide often occur within a week, and mostly within hours, prior to the attempt (Millner et al., 2017). Thus, it is imperative to probe risk processes that occur over the day preceding a suicide attempt, as this may afford key insights about why individuals *plan* and *attempt* suicide. Presently, existing research aimed at detecting short-term risk for STBs is limited in a number of critical ways. First, it relies almost entirely on self-report data, and moreover, often uses retrospective recall techniques, which may not be sensitive to psychological and behavioral processes that are rapidly changing, may be poorly recalled when not in an acute state of risk, and may even be outside of one's conscious awareness (e.g., Stewart et al., 2017b). Second, most studies have not focused on assessment of these risk factors using intensive longitudinal assessment methods, which is a major fundamental limitation of extant STB research. Those that have used real time assessment techniques such as EMA, involve considerable participant burden (thereby limiting the scalability and application in clinical assessment), and still rely primarily on self-report data.

Intensive longitudinal assessment, using mobile computing (Harari et al., 2016; Insel, 2017; Lind et al., 2018) and wrist-worn smart watches and fitness monitors (i.e., wearables) (Sano et al., 2018) may be transformative technologies that can improve our short-term prediction of suicidal behavior and thus, our capacity to provide timely and effective intervention at scale to high-risk individuals (Torous et al., 2018; Vahabzadeh et al., 2016; See Lind et al., 2018, for detailed description of the type of data that can be collected using smart phone based passive sensing methods). The temporal precision with which these data can be collected provide unprecedented opportunities to evaluate processes derived from key theoretical models and prior empirical research; especially as they apply to youth. Current mobile technologies are able to passively record key variables that are plausibly related to risk domains drawn from theoretical models of suicide, including communicative language (e.g., in social media communications; Jashinsky et al., 2014), social withdrawal, and sleep (Bernert et al., 2015). Also, and perhaps most critically, these technologies provide continuous, unobtrusive, and ecologically valid measurement of these variables, allowing for the assessment of individualized baselines and sensitive detection of deviations from these baselines that may clarify the pathway to suicide. This is critical for the short-term prediction of STBs, as very often suicidal acts are impulsive (Auerbach et al., 2017; Rimkeviciene et al., 2015) and represent a response to rapid changes in the person's internal or external environment that can be easily missed by less frequent assessments (such as those associated with clinical or outreach consultations—which are presently the gold-standard of care) or even more frequent EMA methods.

Theoretical models of STBs, such as those described above, and recent empirical findings, suggest ways in which passive mobile sensing technology may be used to: (1) differentiate suicide *attempters* and suicide *ideators* (thereby more objectively and accurately identifying high-risk individuals) (Auerbach et al., 2015; Stewart et al., 2017c), (2) improve short-term prediction of youth STBs, (3) inform testing and refinement of leading theoretical models, (4) collect intensive longitudinal data using current consumer mobile devices, and (5) provide additional services at critical moments of action. Table 1 describes domains of variables that can be collected by mobile and wearable computing devices that relate to theoretical models and mobile sensing data and features extracted from mobile sensing.

For example, *Emotional distress* can be measured using acoustic voice data, communicative language (e.g., via social media, text messaging), heart rate, facial expression, and music choice. *Social dysfunction* can be measured through natural language processing of the content of online communication, patterns (i.e., frequency, duration) of online communication, and geographic movement. Sleep patterns can be quantified through mobile and wearable sensing using actigraphy, heart rate, light sensors, and diurnal patterns of device use.

Adolescents and digital technology: a special opportunity?

We have already made clear that adolescence is a critical phase of life for the emergence of suicidal thoughts and behaviors, and indeed for mental disorders more generally (Kessler et al., 2005). There are also reasons suggesting that the opportunity to apply mobile and wearable technology to understanding short-term risk factors for STBs is particularly propitious amongst adolescents. Technological innovations, especially smartphones and online social networks, are especially influential in the daily lives of adolescents (Bell et al., 2015; Madden et al., 2013; Shapiro and Margolin, 2014). The current cohort of adolescents are often referred to as “digital natives”— and they use digital communication extensively to enhance their social relationships by sharing intimacy, displaying affection and arranging social activities (Yau and Reich, 2018). Moreover, the ways in which current technologies facilitate social communication mesh with the primary developmental tasks of adolescence, which include exploring and learning about peer, romantic, and sexual relationships (Dahl et al., 2018). Social media in particular provides almost ubiquitous access to peer interaction (Shapiro and Margolin, 2014), and does so in a way that is relatively free of parental monitoring (another appealing aspect of social media for adolescents; Smetana et al., 2006). This creates unprecedented opportunities for positive social connection and support, but it also intensifies adolescents’ exposure to negative social encounters. Indeed, in a recent review, Odgers proposed that the use of social media acts as an “amplifier” of offline strengths and vulnerabilities—often enhancing the lives of those who are popular and confident, and increasing vulnerability amongst those who are at risk (Odgers, 2018). Not surprisingly young people experiencing mental health problems highly value accessing mental health information and support online (Lal et al., 2018). In short, adolescents use digital technology in ways that are distinct from older people. In particular they are more likely to use these technologies for intimate and socially risky forms of communication, which may include direct request for support during mental health and other crises. As such, the behavior that can be accessed via mobile phone sensors may well be more reflective of psychological states and interpersonal needs during adolescence than they are at other phases of life, creating a particular opportunity to utilize these approaches to track psychologically significant processes, especially those related to distress (*psychache*) and interpersonal models of vulnerability.

Smart home devices in the prediction of STBs

Another promising avenue afforded by recent developments in consumer technology is the potential use of smart home technology (i.e., internet connect devices in the home including cameras, “smart” speakers, and internet connected home appliances; sometimes also referred to as “internet of things” or IOT devices), for furthering our understanding of risk processes that typically occur in the home (Nelson and Allen, 2018). Like mobile and wearable computing, collection of behavioral data via smart home technology also provides a set of tools that can create unique opportunities. For example, similar to mobile and wearable computing devices, smart home methods collect data in a way that is *continuous, passive, intensively longitudinal,* and *multimodal* (e.g., facial expression, acoustical qualities of voice, interpersonal behaviors, language). However, smart home approaches have some unique advantages that are distinct from those associated with mobile and wearable approaches, including that they provide data from a *third-person observational perspective* (i.e., they can observe behavior from a vantage point away from the person themselves, such as with cameras) that preserves *ecological validity* by taking place outside of the laboratory and within participants’ own homes (Nelson and Allen, 2018). Moreover, smart home approaches can connect to home devices (i.e., a gun safe, medicine cabinet, or refrigerator) that may provide information about risky behaviors, which are known

Table 1
Continuity among theoretical constructs, risk domains, and passive sensing.

Theoretical Model	Risk Domain	Digital Sensing Data	Example Features
Psychache Theory (Shneidman)	Emotional distress	Acoustic voice; Sentiment in communicative language (e.g., via social media, text messaging); Facial expression (selfies); Music choice.	Fundamental frequency of voice; Positive or negative sentiment in language; Sad or anxious facial expression; Change in music selection.
Interpersonal Theory of Suicide (Joiner)	Social dysfunction (e.g., thwarted belongingness, perceived burdensomeness)	Self-relevant and social content in communicate language; Patterns of online communication (frequency, diversity of online contacts); Geographic movement.	Negative self-sentiment in language; Bullying or social rejection; Reduction in frequency of social contacts; Reduction in diversity of social contacts; Decrease in time spent outside of home.
Diathesis-Stress Model of Suicide (Mann)	Sleep disturbance (biological diathesis)	Actigraphy; Light Sensor, Diurnal Patterns of phone Use.	Time in bed; Total sleep time; Sleep onset latency; Wake after sleep onset; Morningness/Eveningness.

Note. Digital sensing data can be collected from a range of devices (e.g., smart phones) and methods (e.g., keyboard input, voice input, GPS location data, photography, etc.).

contributors to suicide behaviors (Stewart et al., 2017). As the majority of suicide attempts occur in the home (Kellermann et al., 1992), home based monitoring technology may have particular relevance for addressing this issue. Utilizing smart home technologies in tandem with EMA methods (Kleiman et al., 2017) would allow for the collection of observed facial, speech, and behavioral data as well as experiential data on affective states that could allow for a greater understanding of short-term risk processes and have great clinical significance by detecting those who are likely to attempt suicide, thereby facilitating timely intervention at moments of greatest risk. Given the significance of home environments for close interpersonal relationships, and salience of interpersonal processes in risk for STBs, smart home assessment may be especially relevant to understanding interpersonal risk processes—particularly those linked to STBs.

Although it is likely that smart home data collection is relevant to many age groups, some aspects of these methodologies may be particularly applicable to adolescents. For example, adolescence is a period of life associated with increases in family conflict (Collins and Laursen, 2004; Laursen et al., 1998) and family conflict is also associated with suicide risk (Pineda and Dadds, 2013). Prior efforts to study interpersonal behaviors in families have used designs such as laboratory conflict resolution paradigms, questionnaires, and recruiting families to stay in specially designed research homes equipped with recording devices (Gottman, 1979, 2011, Sheeber et al., 2000). In a recent paper, Nelson and Allen (2018) have described how smart home technology could be applied to understanding interpersonal dynamics in the home, including family conflict, in ways that have a number of methodological advantages over prior approaches. Given the salience of family conflict during adolescence, and its relevance to STBs, these techniques may provide unique, developmentally targeted, opportunities to study these processes in real time, and in real contexts amongst families of at-risk adolescents.

As noted above, sleep disturbance is related to risk for STBs and is another example of a salient set of home-based behaviors that may be tracked and potentially modified using smart home technology. As with family conflict, there are developmental issues that make sleep a particularly salient target during adolescence, as biological, environmental, and behavioral aspects of adolescent development often result in compromised sleep, and poor sleep has in turn shown strong associations with depression, anxiety, and suicide (Blake et al., 2018; Kearns et al., 2018). Consumer wearable devices such as actigraphy sensors are now commonly used to capture behavioral sleep data (Marino et al., 2013). While smart home technologies cannot yet capture all physiological data that can be acquired in a full sleep polysomnograph, new methods utilizing RF signals via WiFi can now be used to index respiration, heart rate (Adib et al., 2015; Zhao et al., 2016), and sleep stages (Zhao et al., 2017) even in the absence of wearable sensors, therefore providing novel data that could be used to advance understanding of STBs.

Collectively, the use of passive sensing data holds enormous promise to improve the short-term prediction of STBs. Doubtlessly, identifying *when* an individual will make a suicide attempt represents the *holy grail* of suicide research. However, by leveraging the native technology that people are using every day, it affords a unique opportunity to assess risk states, and ultimately, provides a critical window to intervene.

Using machine learning to analyze digital health data

Smartphone, wearable, and smart home technologies all provide multimodal longitudinal data that may offer the possibility of discovering new predictors though data driven techniques such as machine learning (ML). This is particularly relevant to the high volume, and high dimensionality, of data that can be obtained using digital sensing of behavior, which lends itself to ML approaches. For example, past studies have utilized ML on retrospective data to predict suicide attempts (Delgado-Gomez et al., 2012; Mann et al., 2008). More recently, research has applied ML techniques to improve suicide prediction. Specifically, ML analyses of military administrative data and medical records identified about half of all post-Army discharge suicide deaths (Kessler et al., 2017); yet, the fact that accurately detecting only half the cases constitutes an impressive achievement is testament to the challenges inherent in prediction of suicide risk. In another recent study, ML was used to analyze functional magnetic resonance imaging neural signatures of death- related and life-related concepts amongst suicide ideators and controls and found that they were able to predict which ideators went to have an attempt with 94% classification accuracy (Just et al., 2017). In addition, recent research has applied ML techniques to electronic health records and researchers were able to predict future suicide attempts with 79% precision (Walsh et al., 2017). In the realm of digital data, recent research has utilized ML approaches on public Twitter posts in order to classify “unique linguistic profiles” that may signal suicide risk (Burnap et al., 2017; O'Dea et al., 2017), and more recently Du et al. (2018) found that deep learning models of Twitter data performed better than more traditional ML approaches (e.g., Support Vector Machine, Extra Trees) in identifying suicide related Tweets. Despite these promising findings, attempts to apply ML techniques to suicide prediction are still in their infancy, and most do not utilize the kinds of data that will facilitate short-term prediction of suicidal thoughts and behaviors (i.e., those that predict not only who might be at risk, but when a suicide attempt is likely to occur).

Ethical considerations for technological measurement of suicide risk

The collection of behavioral data through mobile, wearable, and smart home based technologies—particularly among adolescents—is an especially complex issue because of the personal and highly identifiable nature of the data being collected (e.g., Carter et al., 2015; Kelly et al., 2013; Nebeker et al., 2016; Nelson and Allen, 2018; Pisani et al., 2016;

Torous and Nebeker, 2017; Torous and Roberts, 2017), which creates unique ethical and legal issues that should proactively be taken into consideration. For example, a recent study found that research participants can be uniquely identified with only four smartphone location data points (De Montjoye et al., 2013). Therefore, due to the highly identifiable characteristics of digital health data, these data will require novel methods to protect not only participant data, but also that of third-parties (Nebeker et al., 2016; Torous and Nebeker, 2017). It is important to note that simply removing subject names, dates of birth, addresses, and other common variables that are de-identified in research settings will be insufficient to anonymize participants when digital health data is being used. For example, in an anonymized dataset of medical billing records of 2.9 million individuals released by the Australian government, researchers were able to de-anonymize and find individual health history by integrating the anonymized dataset with public information (Culnane et al., 2017). Similarly, researchers have been able to correctly identify Twitter users in a large database with 96.7% accuracy solely based on applying ML to users' metadata (Perez et al., 2018).

There are a number of potential methods for data encryption and automated identity recognition via facial or voice data that would allow for achieving greater confidentiality of participant and third-party data. For example, prior to data storage, highly identifiable data such as video, picture, and voice data could be scanned by automated facial and speech recognition software in order to match collected data with participants facial and audio samples (Hansen and Hasan, 2015; Jain and Li, 2011; Turk and Pentland, 1991). Prior to humans viewing this data, any data that did not match that of the target participant would be automatically deleted prior to being saved to an encrypted and HIPAA protected cloud service. Lastly, the collection of highly identifiable digital health data creates some challenges when trying to adhere to Open Science guidelines, particularly those surrounding open datasets. In a simple scenario, only data that participants have specifically authorized to be shared on open data repositories would be made available to other researchers. Another option might be to provide an open science database that researchers could only access through an interface that precludes the ability to look at raw data in order to preserve participant data protections, while allowing for research findings to be reproducible.

An ethical challenge that is particularly relevant to studies of those at risk for suicide is to establish appropriate balance between privacy and safety when a life-threatening event is at stake (Coppersmith et al., 2018). For example, what kind of duty of care should be afforded to participants who provide data that may indicate risk, and what threshold of certainty in prediction should be applied to such a response? Given the ubiquitous and intensive nature of the data collection there are a number of somewhat unique challenges here. First, research has not yet provided us with algorithms that can use passive sensor data to predict suicide risk with acceptable sensitivity and specificity to engender a clinical response. For example, phrases that may be considered to indicate high risk on face value but that are often used colloquially, such as entering the words "*I can't stand it anymore*" or "*I want to kill myself*" into one's mobile phone, are likely to result in a large number of false positives until research can provide decision rules that clarify the cases when this is, and is not, likely to be indicative of risk. Such false positive could result in clinical responses that take resources from more genuinely urgent cases. A second challenge is the time frame of the response, as few research studies have the systems required to process and respond to such indices in real time (in part because, as outlined above, accurate prediction algorithms do not yet exist). Finally, if a study is geographically diverse (as might be required to obtain the number to participants to provide adequate power to conduct prospective prediction study of STBs) the task of mounting an effective response to a high-risk situation might be especially challenging in locations that are distal to the study team and/or have limited local resources. Although these challenges are not insurmountable, they do need to be carefully considered by teams planning this type of research.

One resource for researchers, IRBs, and industry partners dealing with the myriad ethical issues surrounding the collection and use of digital health data comes from the Connected and Open Research Ethics (CORE) initiative that was recently designed and launched to develop ethical practices in digital research (Torous and Nebeker, 2017). This initiative, launched in 2016, contains members from over 10 countries with expertise spanning bioethics, privacy, technology, and research ethics and provides a digital platform of shared knowledge and resources (e.g., approved IRBs and consents) regarding the use of passive sensing technology in research studies (The Regents of the University of California, 2016), while also providing a means for researchers to ask and answer questions related to the ethics of digital health data. In other words, CORE encourages sound digital health research practices by tapping into a transdisciplinary network of researchers to crowdsources resources to help guide research design and implementation.

Future directions

The ultimate goal of this work is to translate these findings into actionable steps that clinicians and patients can take to reduce distress and save lives. In this review, we wish to highlight the opportunity to develop robust, automated, and scalable methods for predicting transitions in clinical status that are associated with increased suicidal risk—especially proximal to the suicide attempt. However, before we can achieve this goal, a number of critical research agendas must be addressed. Each of these are complex and demanding topics that will require considerable investment of effort and funding. These include (but are not limited to):

1. Can we use technology assisted methods to predict short term (i.e., over days, hours, or minutes) changes in suicide risk status? If so, can this be achieved with sufficient sensitivity and specificity to be clinically useful?
2. In what populations is this possible (e.g., general population, psychiatric populations, those at high risk for STBs such as previous attempters or those in current treatment for STBs)?
3. Can we develop normative models of prediction that can be applied to individuals, or do we need to develop individual specific (ideographic) models to achieve adequate prediction? If ideographic models are necessary, how can we collect enough baseline data on each person to develop such models?
4. How do we balance duty of care against privacy given the intrusive nature of the data collection permitted by digital technology?
5. If we are able to track behavior and predict changes in risk status, what kinds of "just-in-time" interventions are helpful (and not harmful) during psychologically sensitive states such as periods of high risk for suicidal behavior? (See Noterdame et al., 2018 for a description of such a system). How can such interventions be tailored to individuals?

As noted, these questions are complex and will require considerable interdisciplinary research efforts from teams with expertise in a variety of disciplines including psychiatry, psychology, computer and biomedical engineering, data science, human computer interaction, behavior change, and public health. Indeed, the aspiration to predict suicidal thoughts and behaviors specifically may ultimately turn out to be less tractable than the prediction of a broader category of events associated with mental health crisis states (e.g., increases in symptoms and or disability, and decreases in functioning). Thus, we may have to design automated clinical response systems that remain relatively broad in their focus until careful assessment of the individual can be conducted. Another important future direction will be conducting focus groups with patients, parents, and clinicians to find out how they would prefer to be notified of risk and what actions they would find useful and acceptable in response to this change in risk status. For example,

signatures associated with changes in risk status could be identified during an initial period of care, after which the clinician could provide feedback to the patient on triggers and early warning signs. The clinician and patient can then discuss the time course and talk about actions that can be taken so that resources and support can be matched to the patent's individual needs. Perhaps a young person who is experiencing a lot of emotional pain, might get pushed prompts to use distress tolerance skills (e.g., Kennard et al., 2019). Alternatively, a teen feeling socially disconnected or rejected might benefit from a text or phone call to help manage the crisis. Such person-centered—or precision medicine-oriented interventions—would revolutionize clinical care. In this review wish aim to highlight the fact that smartphone, wearable, and smart home technology may provide the opportunity for important innovations that may facilitate both early identification and intervention, and thus, represents a key area for future STB research.

Conflict of interest

The authors report no conflict in interest.

Contributors

All authors contributed to the writing of this manuscript and approved it for submission.

Dr. Auerbach is member of the American Foundation for Suicide Prevention Advisory Board.

Role of funding source

The project was supported through funding from the National Institute of Mental Health (NIMH) U01 MH116923-01 (NBA, RPA, DB). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or NIMH.

Acknowledgments

None

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jad.2019.03.044.

References

Adib, F., Mao, H., Kabelac, Z., Katabi, D., Miller, R.C., 2015. Smart homes that monitor breathing and heart rate. In: Proceedings of the 33rd annual ACM conference on human factors in computing systems. ACM, pp. 837–846.

Auerbach, R.P., Millner, A.J., Stewart, J.G., Esposito, E.C., 2015. Identifying differences between depressed adolescent suicide ideators and attempters. *J. Affect. Disord.* 186, 127–133. http://doi.org/10.1016/j.jad.2015.06.031.

Auerbach, R.P., Stewart, J.G., Johnson, S.L., 2017. Impulsivity and suicidality in adolescent inpatients. *J. Abnorm. Child Psychol.* 45 (1), 91–103. http://doi.org/10.1007/s10802-016-0146-8.

Bagge, C.L., Glenn, C.R., Lee, H.-J., 2013. Quantifying the impact of recent negative life events on suicide attempts. *J. Abnorm. Psychol.* 122 (2), 359–368. http://doi.org/10.1037/a0030371.

Bagge, C.L., Littlefield, A.K., Glenn, C.R., 2017. Trajectories of affective response as warning signs for suicide attempts. *Clin. Psychol. Sci.* 5 (2), 259–271. http://doi.org/10.1177/2167702616681628.

Bell, V., Bishop, D.V., Przybylski, A.K., 2015. The debate over digital technology and young people. *BMJ* 351.

Bernert, R.A., Kim, J.S., Iwata, N.G., Perlis, M.L., 2015. Sleep disturbances as an evidence-based suicide risk factor. *Curr. Psychiatry Rep.* 17 (3) 15. http://doi.org/10.1007/s11920-015-0554-4.

Blake, M.J., Trinder, J.A., Allen, N.B., 2018. Mechanisms underlying the association between insomnia, anxiety, and depression in adolescence: implications for behavioral sleep interventions. *Clin. Psychol. Rev.* 63, 25–40. https://doi.org/10.1016/j.cpr.2018.05.006.

Burnap, P., Colombo, G., Amery, R., Hodorog, A., Scourfield, J., 2017. Multi-class machine classification of suicide-related communication on Twitter. *Online Soc. Netw. Media* 2, 32–44. http://doi.org/10.1016/j.osnem.2017.08.001.

Carter, A., Liddle, J., Hall, W., Chenery, H., 2015. Mobile phones in research and treatment: ethical guidelines and future directions. *JMIR MHealth UHealth* 3 (4), e95. http://doi.org/10.2196/mhealth.4538.

Collins, W., Laursen, B., 2004. Changing relationships, changing youth. *J. Early Adoles.* 24, 55–62. http://dx.doi.org/10.1177/0272431603260882.

Coppersmith, G., Leary, R., Crutchley, P., Fine, A., 2018. Natural language processing of social media as screening for suicide risk. *Biomed. Inform. Insights* 10, 1178222618792860.

Culnane, C., Rubinstein, B.I.P., Teague, V., 2017. Health data in an open world. Retrieved. http://arxiv.org/abs/1712.05627.

Dahl, R.E., Allen, N.B., Wilbrecht, L., Suleiman, A.B., 2018. Importance of investing in adolescence from a developmental science perspective. *Nature* 554 (7693), 441–450.

De Montjoye, Y.A., Hidalgo, C.A., Verleysen, M., Blondel, V.D., 2013. Unique in the crowd: the privacy bounds of human mobility. *Sci. Rep.* 3, 1–5. http://doi.org/10.1038/srep01376.

Delgado-Gomez, D., Blasco-Fontecilla, H., Sukno, F., Socorro Ramos-Plasencia, M., Baca-Garcia, E., 2012. Suicide attempters classification: toward predictive models of suicidal behavior. Neurocomputing 92, 3–8. http://doi.org/10.1016/j.neucom.2011.08.033.

Du, J., Zhang, Y., Luo, J., Jia, Y., Wei, Q., Tao, C., Xu, H., 2018. Extracting psychiatric stressors for suicide from social media using deep learning. *BMC Med. Inf. Decis. Making* 18 (2) 43.

Fisher, A.J., Medagliab, J.D., Jeronimusd, B.F., 2018. Lack of group-to-individual generalizability is a threat to human subjects research. In: Proceedings of the National Academy of Sciences, , 201711978.

Franklin, J.C., Ribeiro, J.D., Fox, K.R., Bentley, K.H., Kleiman, E.M., Huang, X., Nock, M.K., 2017. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. *Psychol. Bull.* 143 (2), 187–232. http://doi.org/10.1037/bul0000084.

Glenn, C.R., Nock, M.K., 2014. Improving the short-term prediction of suicidal behavior. *Am. J. Prev. Med.* 47 (3), S176–S180. http://doi.org/10.1016/j.amepre.2014.06.004.

Goldstein, A.N., Walker, M.P., 2014. The role of sleep in emotional brain function. *Annual Rev. Clinic. Psychol.* 10, 679–708. http://doi.org/10.1146/annurev-clinpsy-032813-153716.

Goldstein, T.R., Bridge, J.A., Brent, D.A., 2008. Sleep disturbance preceding completed suicide in adolescents. *J. Consult. Clin. Psychol.* 76 (1), 84–91. http://doi.org/10.1037/0022-006X.76.1.84.

Gottman, J., 1979. *Marital interaction: experimental investigations*. New York. Academic Press, New York.

Gottman, J., 2011. The science of trust: emotional attunement for couples. W. W. Norton & Company.

Hall, R.C.W., Platt, D.E., Hall, R.C.W., 1999. Suicide risk assessment: a review of risk factors for suicide in 100 patients who made severe suicide attempts: evaluation of suicide risk in a time of managed care. *Psychosomatics* 40 (1), 18–27. http://doi.org/10.1016/S0033-3182(99)71267-3.

Hansen, J.H.L., Hasan, T., 2015. Speaker recognition by machines and humans: a tutorial review. *IEEE Signal Process. Mag.* 32 (6), 74–99.

Harari, G.M., Lane, N.D., Wang, R., Crosier, B.S., Campbell, A.T., Gosling, S.D., 2016. .Using smartphones to collect behavioral data in psychological science: opportunities, practical considerations, and challenges. *Perspect. Psychol. Sci.* 11 (6), 838–854. http://doi.org/10.1177/1745691616650285.

Hendin, H., Maltsberger, J.T., Lipschitz, a, Haas, a P., Kyle, J., 2001. Recognizing and responding to a suicide crisis. *Suicide Life-Threat. Behav.* 31 (2), 115–128. http://doi.org/10.1111/j.1749-6632.2001.tb05805.x.

Insel, T.R., 2017. Digital phenotyping: technology for a new science of behavior. *JAMA* 318 (13), 1215–1216. http://doi.org/10.1001/JAMA.2017.11295.

Jain, A.K., Li, S.Z., 2011. Handbook of face recognition. Springer, New York.

Jashinsky, J., Burton, S.H., Hanson, C.L., West, J., Giraud-Carrier, C., Barnes, M.D., Argyle, T., 2014. Tracking suicide risk factors through Twitter in the US. *Crisis* 35 (1), 51–59. http://doi.org/10.1027/0227-5910/a000234.

Just, M.A., Pan, L., Cherkassky, V.L., McMakin, D.L., Cha, C., Nock, M.K., Brent, D., 2017. Machine learning of neural representations of suicide and emotion concepts identifies suicidal youth. *Nature Human Behav.* 1 (12), 911–919. http://doi.org/10.1038/s41562-017-0234-y.

Kearns, J.C., Coppersmith, D.D., Santee, A.C., Insel, C., Pigeon, W.R., Glenn, C.R., 2018. Sleep problems and suicide risk in youth: a systematic review, developmental framework, and implications for hospital treatment. *Gen. Hosp. Psychiatry*.

Kellermann, A.L., Rivara, F.P., Somes, G., Reay, D.T., Francisco, J., Banton, J.G., Hackman, B.B., 1992. Suicide in the home in relation to gun ownership. N. Engl. J. Med. 327 (7), 467–472. http://doi.org/10.1056/NEJM199208133270705.

Kelly, P., Marshall, S.J., Badland, H., Kerr, J., Oliver, M., Doherty, A.R., Foster, C., 2013. An ethical framework for automated, wearable cameras in health behavior research. *Am. J. Prev. Med.* 44 (3), 314–319. https://doi.org/10.1016/j.amepre.2012.11.006.

Kennard, B.D., Goldstein, T., Foxwell, A.A., McMakin, D.L., Wolfe, K., Biernesser, C., Brent, D., 2019. As Safe As Possible (ASAP): a brief app-supported inpatient intervention to prevent post-discharge suicidal behavior in hospitalized, suicidal adolescents. *Am. J. Psychiatry*.

Kessler, R.C., Berglund, P., Demler, O., Jin, R., Merikangas, K.R., Walters, E.E., 2005. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the national comorbidity survey replication. *Arch. Gen. Psychiatry* 62 (6), 593–602.

Kessler, R.C., Stein, M.B., Petukhova, M.V., Bliese, P., Bossarte, R.M., Bromet, E.J., Bell, A.M., 2017. Predicting suicides after outpatient mental health visits in the Army Study to Assess Risk and Resilience in Service members (Army STARRS). *Mol. Psychiatry* 22 (4) 544.

Kleiman, E.M., Turner, B.J., Fedor, S., Beale, E.E., Huffman, J.C., Nock, M.K., 2017. Examination of real-time fluctuations in suicidal ideation and its risk factors: results from two ecological momentary assessment studies. *J. Abnorm. Psychol.* 126 (6), 726–738. http://doi.org/http://doi.org/10.1037/abn0000273.

Klonsky, E.D., May, A.M., Saffer, B.Y., 2016. Suicide, suicide attempts, and suicidal ideation. *Annual Rev. Clin. Psychol.* 12, 307–330. http://doi.org/10.1146/annurev-clinpsy-021815-093204.

Laursen, B., Coy, K.C., Collins, W.A., 1998. Reconsidering changes in parent-child conflict across adolescence: a meta-analysis. *Child Dev.* 69, 817–832. http://dx.doi.org/10.2307/1132206.

Lind, M.N., Byrne, M.L., Wicks, G., Smidt, A.M., Allen, N.B., 2018. The effortless assessment of risk states (EARS) tool: an interpersonal approach to mobile sensing. JMIR Mental Health 5 (3) e10334–10. http://doi.org/10.2196/10334.

Littlewood, D.L., Kyle, S.D., Carter, L.A., Peters, S., Pratt, D., Gooding, P., 2018. Short sleep duration and poor sleep quality predict next-day suicidal ideation: an ecological momentary assessment study. *Psychol. Med.* 1–9. https://doi.org/10.1017/S0033291718001009.

Ma, J., Batterham, P.J., Calear, A.L., Han, J., 2016. A systematic review of the predictions of the interpersonal-psychological theory of suicidal behavior. *Clin. Psychol. Rev.* 46, 34–45. http://doi.org/10.1016/j.cpr.2016.04.008.

Mann, J.J., Ellis, S.P., Waternaux, C.M., Liu, X., Oquendo, M.A., Malone, K.M., Currier, D., 2008. Classification trees distinguish suicide attempters in major psychiatric disorders: a model of clinical decision making. *J. Clin. Psychiatry* 69 (1), 23–31. http://doi.org/10.4088/JCP.v69n0104.

Mann, J.J., Waternaux, C., Haas, G.L., Malone, K.M., 1999. Toward a clinical model of suicidal behavior in psychiatric patients. *Am. J. Psychiatry* 156 (2), 181–189. http://doi.org/10.1176/ajp.156.2.181;pageGroup:string:Publication.

Marino, M., Li, Y., Rueschman, M.N., Winkelman, J.W., Ellenbogen, J.M., Solet, J.M., Buxton, O.M., 2013. Measuring sleep: accuracy, sensitivity, and specificity of wrist actigraphy compared to polysomnography. *Sleep* 36 (11), 1747–1755. http://doi.org/10.5665/sleep.3142.

Millner, A.J., Lee, M.D., Nock, M.K., 2017. Describing and measuring the pathway to suicide attempts: a preliminary study. *Suicide Life Threat. Behav.* 47 (3), 353–369. http://doi.org/10.1111/sltb.12284.

Nahum-Shani, I., Smith, S.N., Spring, B.J., Collins, L.M., Witkiewitz, K., Tewari, A., Murphy, S.A., 2016. Just-in-time adaptive interventions (jitais) in mobile health: key components and design principles for ongoing health behavior support. *Ann. Behav. Med.* 52 (6), 446–462. http://doi.org/10.1007/s12160-016-9830-8.

Nahum-Shani, I., Smith, S.N., Witkiewitz, K., Collins, L.M., Spring, B., & Murphy, S.A., (2014). Just-in-time adaptive interventions (JITAIs): aAn organizing framework for ongoing health behavior support. *The Methodology Center Technical Report, 2014*, 14–126.

Nebeker, C., Lagare, T., Takemoto, M., Lewars, B., Crist, K., Bloss, C.S., Kerr, J., 2016. Engaging research participants to inform the ethical conduct of mobile imaging, pervasive sensing, and location tracking research. *Translat. Behav. Med.* 6 (4), 577–586. http://doi.org/10.1007/s13142-016-0426-4.

Nelson, B.W., Allen, N., 2018. Extending the passive sensing toolbox: utilizing smart home technology in psychological science. *Perspect. Psychol. Sci.* 13, 718–733.

Nock, M.K., Prinstein, M.J., Sterba, S.K., 2009. Revealing the form and function of self-injurious thoughts and behaviors: a real-time ecological assessment study among adolescents and young adults. *J. Abnorm. Psychol.* 118 (4), 816–827. http://doi.org/10.1037/a0016948.

Notredame, C.E., Grandgenèvre, P., Pauwels, N., Morgiève, M., Wathelet, M., Vaiva, G., Seguin, M., 2018. Leveraging the Web and social media to promote access to care among suicidal individuals. *Front. Psychol.* 9, 1338.

O'Dea, B., Larsen, M.E., Batterham, P.J., Calear, A.L., Christensen, H., 2017. A Linguistic analysis of suicide-related Twitter posts. *Crisis*. http://doi.org/10.1027/0227-5910/a000443.

Odgers, C.L., 2018. Smartphones are bad for some adolescents, not all. *Nature* 554 (7693), 432–434.

Perez, B., Musolesi, M., Stringhini, G., 2018. You are your metadata: identification and obfuscation of social media users using metadata information. Retrieved from. http://arxiv.org/abs/1803.10133.

Pineda, J., Dadds, M.R., 2013. Family intervention for adolescents with suicidal behavior: a randomized controlled trial and mediation analysis. *J. Am. Acad. Child Adoles. Psychiatry* 52 (8), 851–862.

Pisani, A.R., Wyman, P.A., Mohr, D.C., Perrino, T., Gallo, C., Villamar, J., Brown, C.H., 2016. Human subjects protection and technology in prevention science: selected opportunities and challenges. Prev. Sci. 17 (6), 765–778. http://doi.org/10.1007/s11121-016-0664-1.

Rimkeviciene, J., Ogorman, J., De Leo, D., 2015. Impulsive suicide attempts: a systematic literature review of definitions, characteristics and risk factors. *J. Affect. Disord.* 171, 93–104. http://doi.org/10.1016/j.jad.2014.08.044.

Sano, A., Taylor, S., McHill, A., Phillips, A., Barger, L., Klerman, B., Picard, R., 2018. Identifying objective physiological markers and modifiable behaviors for self-reported stress and mental health status using wearable sensors and mobile phones. *J. Med. Intern. Res.* 20 (6), e210. http://doi.org/10.2196/preprints.9410.

Shapiro, L.A.S., Margolin, G., 2014. Growing up wired: social networking sites and adolescent psychosocial development. *Clin. Child Fam. Psychol. Rev.* 17 (1), 1–18.

Sheeber, L., Allen, N., Davis, B., Sorensen, E., 2000. Regulation of negative affect during mother–child problem-solving interactions: adolescent depressive status and family processes. *J. Abnorm. Child Psychol.* 28 (5), 467–479.

Shneidman, E.S., 1993. Suicide as psychache: a clinical approach to self-destructive behavior. *J. Nerv. Ment. Dis.* 181 (3), 145–147. http://doi.org/10.1097/00005053-199303000-00001.

Smetana, J.G., Metzger, A., Gettman, D.C., Campione-Barr, N., 2006. Disclosure and secrecy in adolescent–parent relationships. *Child Dev.* 77 (1), 201–217.

Stewart, J.G., Esposito, E.C., Glenn, C.R., Gilman, S.E., Pridgen, B., Gold, J., Auerbach, R P, 2017c. Adolescent self-injurers: comparing non-ideators, suicide ideators, and suicide attempters. *J. Psychiatr. Res.* 84, 105–112. http://doi.org/10.1016/j.jpsychires.2016.09.031.

Stewart, J.G., Glenn, C.R., Esposito, E.C., Cha, C.B., Nock, M.K., Auerbach, R.P., 2017b. Cognitive control deficits differentiate adolescent suicide ideators from attempters. *J. Clin. Psychiatry* 78 (6), e614–e621. http://doi.org/10.4088/JCP.16m10647.

Stewart, J.G., Shields, G.S., Esposito, E.C., Cosby, E.A, Allen, N.B., Slavich, G.M., Auerbach, R.P., 2019. Life stress and suicide in adolescents. *J. Abnorm. Child Psychol.*.

Stewart, J.G., Valeri, L., Esposito, E.C., Auerbach, R.P., 2017a. Peer victimization and suicidal thoughts and behaviors in depressed adolescents. *J. Abnorm. Child Psychol.* 46 (3), 581–596. http://doi.org/10.1007/s10802-017-0304-7.

Tarokh, L., Saletin, J.M., Carskadon, M.A., 2016. Sleep in adolescence: physiology, cognition and mental health. *Neurosci. Biobehav. Rev.* 70, 182–188. http://doi.org/10.1016/j.neubiorev.2016.08.008.

The Regents of the University of California, 2016. Connected and open research ethics (CORE) platform. Retrieved from. https://thecore.ucsd.edu/.

Thornicroft, G., Chatterji, S., Evans-Lacko, S., Gruber, M., Sampson, N., Aguilar-Gaxiola, S., Kessler, R.C., 2016. Undertreatment of people with major depressive disorder in 21 countries. *Br. J. Psychiatry* 210 (2), 119–124. https://doi.org/10.1192/bjp.bp.116.188078.

Torous, J., Larsen, M.E., Depp, C., Cosco, T.D., Barnett, I., Nock, M.K., Firth, J., 2018. Smartphones, sensors, and machine learning to advance real-time prediction and interventions for suicide prevention: a review of current progress and next steps. *Curr. Psychiatry Rep.* 20 (7), 4–9. http://doi.org/10.1007/s11920-018-0914-y.

Torous, J., Nebeker, C., 2017. Navigating ethics in the digital age: introducing connected and open research ethics (CORE), a tool for researchers and institutional review boards. *J. Med. Intern. Res.* 19 (2), 1–5. http://doi.org/10.2196/jmir.6793.

Torous, J., Roberts, L.W., 2017. The Ethical use of mobile health technology in clinical psychiatry. *J. Nerv. Ment. Dis.* 205 (1), 4–8. http://doi.org/10.1097/NMD.0000000000000596.

Trockel, M., Karlin, B.E., Taylor, C.B., Brown, G.K., Manber, R., 2015. Effects of cognitive behavioral therapy for insomnia on suicidal ideation in veterans. *Sleep* 38 (2), 259–265. http://doi.org/10.5665/sleep.4410.

Troister, T., Davis, M.P., Lowndes, A., Holden, R.R., 2013. A five-month longitudinal study of psychache and suicide ideation: replication in general and high-risk university students. *Suicide Life-Threat. Behav.* 43 (6), 611–620. http://doi.org/10.1111/sltb.12043.

Troister, T., Holden, R.R., 2012. A two-year prospective study of psychache and its relationship to suicidality among high-risk undergraduates. *J. Clin. Psychol.* 68 (9), 1019–1027. http://doi.org/10.1002/jclp.21869.

Turecki, G., Brent, D.A., 2016. Suicide and suicidal behaviour. *Lancet North Am. Ed.* 387 (10024), 1227–1239.

Turk, M.a.M., Pentland, A.A.P., 1991. Face recognition using eigenfaces. *J. Cogn. Neurosci.* 3 (1), 72–86. http://doi.org/10.1109/CVPR.1991.139758.

Vahabzadeh, A., Sahin, N., Kalali, A., 2016. Digital suicide prevention: can technology become a game-changer? *Innovat. Clinic. Neurosci.* 13 (5), 16–20.

Van Orden, K.A., Witte, T.K., Cukrowicz, K.C., Braithwaite, S.R., Selby, E.A., Joiner, T.E, 2010. The Interpersonal theory of suicide. *Psychol. Rev.* 117 (2), 575–600. http://doi.org/10.1037/a0018697.

Verrocchio, M.C., Carrozzino, D., Marchetti, D., Andreasson, K., Fulcheri, M., Bech, P., 2016. Mental pain and suicide: a systematic review of the literature. *Front. Psychiatry* 7, 108. http://doi.org/10.3389/fpsyt.2016.00108.

Walsh, C.G., Ribeiro, J.D., Franklin, J.C., 2017. Predicting risk of suicide attempts over time through machine learning. *Clinic. Psychol. Sci.* 5 (3), 457–469. http://doi.org/10.1177/2167702617691560.

Yip, P.S.F., Caine, E., Yousuf, S., Chang, S.Sen, Wu, K.C.C., Chen, Y.Y., 2012. Means restriction for suicide prevention. *Lancet North Am. Ed.* 379 (9834), 2393–2399. http://doi.org/10.1016/S0140-6736(12)60521-2.

Yau, J.C., Reich, S.M., 2018. Are the qualities of adolescents' offline friendships present in digital interactions? *Adoles. Res. Rev.* 3 (3), 339–355.

Zhao, M., Adib, F., Katabi, D., 2016. Emotion recognition using wireless signals. In: Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking. ACM, pp. 95–108. http://doi.org/10.1145/2973750.2973762.

Zhao, M., Yue, S., Katabi, D., Jaakkola, T.S., Bianchi, M.T., 2017. Learning sleep stages from radio signals : a conditional adversarial architecture. In: International Conference on Machine Learning, pp. 4100–4109.