J Clin Child Adolesc Psychol. Author manuscript; available in PMC 2020 November 01.

Published in final edited form as:

J Clin Child Adolesc Psychol. 2019 ; 48(6): 934–946. doi:10.1080/15374416.2019.1666400.

Real-time monitoring of suicide risk among adolescents: Potential barriers, possible solutions, and future directions

Evan M. Kleiman, Ph.D.,

Department of Psychology, Rutgers, The State University of New Jersey

Catherine R. Glenn, Ph.D.,

Department of Clinical & Social Sciences in Psychology, University of Rochester

Richard T. Liu, Ph.D.

Department of Psychiatry and Human Behavior, Alpert Medical School of Brown University, Bradley Hospital

Abstract

Recent advances in real-time monitoring technology make this an exciting time to study risk for suicidal thoughts and behaviors among youth. Although there is good reason to be excited about these methods, there is also reason for caution in adopting them without first understanding their limitations. In this manuscript, we present several broad future directions for using real-time monitoring among youth at risk for suicide focused around three broad themes: novel research questions, novel analytic methods, and novel methodological approaches. We also highlight potential technical, logistical, and ethical challenges with these methodologies as well as possible solutions to these challenges.

Real-time monitoring (also called ambulatory assessment) broadly refers to the study of people in their natural environment using a range of technology like smartphones and wearable devices (Trull & Ebner-Priemer, 2013). Real-time monitoring can involve active assessment of self-reported constructs (also called Ecological Momentary Assessment, Experience Sampling, or intensive longitudinal monitoring) or passive assessment of behavior through sensors on smartphones or wearable devices. Real-time monitoring technology has existed for nearly 20 years (Barrett & Barrett, 2001) and lower-tech paper-based methods have existed for over 30 years (Csikszentmihalyi & Larson, 1987). In just the past few years, however, there has been a marked increased interest in using real-time monitoring in clinical psychology. This increase is certainly due, in part, to the increased availability of smartphones and wearable devices and the software to use them for real-time monitoring. As shown in Figure 1, there has been an exponential rise in the number of available real-time monitoring apps for both iOS and Android phones, with just two apps available for either platform in 2013 to 21 available apps for iOS and 18 available for Android as of 2019.

Corresponding author: Evan M. Kleiman, Department of Psychology, Rutgers, The State University of New Jersey, Tillett Hall, Room 627, 53 Avenue E, Piscataway, NJ 08854, evan.kleiman@rutgers.edu.

There has been particular interest in using these real-time monitoring technologies to study the everyday lives of people at risk for suicide. Supporting this, a quick search of PsycInfo shows nearly a 10-fold increase in the number of studies mentioning smartphones and suicide from the past five years (*n*=48) compared to the 10 years prior (*n*=5). Moreover, in 2018–2019 alone, NIMH released five Funding Opportunity Announcements or Notices of Special Interest that specifically mention real-time monitoring and suicide (National Institute of Mental Health, 2018a, 2018a, 2018b, 2019b, 2019a). Advancing our ability to monitor and assess risk for suicidal thoughts and behaviors (STBs) in youth is particularly critical. Adolescence is a time full of frequent transitions (Lenz, 2001; Patton & Viner, 2007). Risk for STBs increases substantially during this time, beginning around age 12. By age 18, more than 1 in 10 youth have had suicidal thoughts at some point (Nock et al., 2013). STBs among youth are an increasing problem over time. One study found that the proportion of admissions due to STBs at children's hospitals in the United States nearly tripled from 2008 to 2015 (Plemmons et al., 2018). Beyond the importance of studying STBs among youth, doing so using real-time monitoring is especially worthwhile because of their fluency with technology and their near ubiquitous use of it (95% of adolescents age 13–17 have access to a smartphone; Pew Research Center, 2018).

Taken together, in recent years real-time monitoring technology has become more accessible and interest in using this technology to study STBs, particularly among youth, has increased substantially. Thus, this is an excellent time to take stock of what we have learned so far and expand on what we can learn in the future using real-time monitoring to study STBs. Accordingly, this paper has three main goals. The first goal is to provide a brief review of the current state of the research using real-time monitoring to study STBs among adolescents. The second goal is to discuss the unexplored areas and unanswered questions about STBs among youth that can be addressed using real-time monitoring. The third goal is to discuss the challenges that can arise when using real-time monitoring to study STBs among adolescents. Before going further, however, it is important to acknowledge several decisions we made in the preparation of this manuscript. First, we deliberately place more focus on future directions than on current literature because there are several pre-existing reviews specifically on using real-time monitoring to study suicidal thoughts and behaviors (Kleiman & Nock, 2018) and non-suicidal self-injury (Rodríguez-Blanco, Carballo, & Baca-García, 2018). Moreover, the state of the literature is moving quite quickly, thus a review could quickly become outdated, whereas the future directions we provide here are intended to provide a broad roadmap for years to come. Second, although we remain highly optimistic about the ability of advanced methodology to help us better predict and prevent STBs among adolescents, we dedicate considerable space in this paper to the challenges associated with doing so. Many papers already accurately extol the virtues of the methodology, but few discuss the challenges of using it that must be overcome.

Current State of real-time monitoring research

The majority of research that has been conducted using real-time monitoring within the context of STBs has been conducted on adults. Thus, the following section, which reviews the current state of real-time monitoring research on adolescents, is relatively brief and covers two areas: (1) research showing that real-time monitoring is feasible in adolescent samples and (2) research describing the real-time occurrence of STBs. Although it would be advantageous to replicate in adolescent samples all work that has been done in adult samples, we discuss below specific areas where replication is particularly needed (e.g., because such work would set the stage for other real-time monitoring work in adolescents).

Feasibility of measuring STBs in youth

It does not matter how promising or novel a research methodology is if it is not feasible to conduct research using it. Thus, the most basic question regarding real-time monitoring methodology is whether it is feasible to use in adolescent samples. Although there have been only a small handful of feasibility studies on suicidal adolescents, there have been many studies in clinical samples of adolescents that demonstrate that this work is generally feasible. One meta-analysis of 42 studies of clinical and non-clinical samples of adolescents using EMA or EMA + wearables found an average compliance rate of 78.3%. They found no differences in compliance rate by study length, sample severity, or whether or not a wearable was also used with EMA. The only significant predictor of compliance was sampling frequency where studies with lower sampling rates (~2–3 times per day) had higher compliance than those with higher rates (Wen, Schneider, Stone, & Spruijt-Metz, 2017). It should be noted, however, that only one of the 42 studies in this meta-analysis had suicidal participants (Nock, Prinstein, & Sterba, 2009). Since this meta-analysis, several other feasibility studies in suicidal adolescents have been published. One study suggested that adolescents will complete daily surveys about suicide risk (Czyz, King, & Nahum-Shani, 2018) about 70% of the time, however, this may not perfectly translate to more than once a day. Another study shows that suicidal adolescent inpatients are generally highly compliant in research studies that ask them to use wrist-worn biosensors (Kleiman et al., 2019).

Although these studies generally support that participants will be compliant with study protocols, there is little research suggesting how to maintain or improve compliance rates. In adolescents, there is a particular need to evaluate what types of incentive schedules are most likely to increase compliance. For example, given the research showing that younger adolescents have a weaker future orientation than older adolescents and young adults (Steinberg et al., 2009), younger adolescents in particular may be more likely to participate in a study where compensation is given weekly instead of once at the end of a study (especially if that study has a long follow-up period). Other recent work focuses on developing algorithms to determine the contexts under which someone is most likely to complete a survey on their smartphone (Aminikhanghahi, Schmitter-Edgecombe, & Cook, 2019). This technology is particularly exciting due to its ability to increase compliance rates; however, it may do so at the risk of bias in when surveys are sent. For example, if adolescents are more likely to respond to a survey when calm, the algorithm may miss sending surveys when an adolescent is distressed, even if this is the time period researchers are most interested in.

Describing the real-time occurrence of suicidal thoughts and behaviors

One of the most apparent and unique benefits of real-time monitoring is that it enables researchers to gain a basic understanding of the phenomenology of STBs as they occur in the real world. This is important on the most basic level: we must first be able to describe our phenomenon of interest before we explain it, predict it, or prevent it. Real-time monitoring gives us the tools to do this.

Several studies have leveraged real-time monitoring technology in order to describe STBs. Most of these studies have been in adults, however, we describe them here to serve as an example for doing similar work in adolescents. Two studies in adults at acute risk for suicide (e.g., suicidal adult inpatients) have shown that suicidal thinking is highly variable over just a few hours (Hallensleben et al., 2017; Kleiman et al., 2017). Initial work in adolescents using a daily diary study also showed this considerable variability (Czyz, Horwitz, Arango, & King, 2019). This research is important for at least two reasons. First, it shows that suicidal thinking can change rapidly, suggesting that intense suicidal thinking may be episodic and confirming retrospective research on this topic (Bagge, Littlefield, Conner, Schumacher, & Lee, 2014). Second, it shows that real-time monitoring is useful to study STBs. Intensive longitudinal monitoring is only useful if the factors being monitored change substantially over the frequency in which they are being monitored. If, for example, STBs varied over days or weeks, it would not be necessary to measure them every few hours. In the future, it is important to replicate the findings regarding the variability in suicidal thinking that have been seen in adults and in daily diary studies. Although it is likely that we would see such variability across age groups, we should not treat this assumption as fact. Indeed, as noted above, this high level of variability over a short period of time is one of the key reasons why real-time monitoring is so useful to study suicidal thinking. But, if there were not as much variability, there would also be less novelty and necessity in using a technology, the main advantage of which is that it can capture variability over a short time period. It could even be that we may see more within-person variability among adolescents compared to adults given the age differences found in constructs that could lead to such variability like emotion regulation and emotion reactivity (Silvers et al., 2012).

Broad unanswered questions and exciting future directions

In the sections below, we describe broad future directions that can be taken using real-time monitoring in youth. Additionally, and where appropriate, we discuss specific barriers to each future direction. We categorize the future directions in three areas reflecting different steps in the research process: (1) novel research questions, (2) novel analyses, and (3) novel methodological advances. It is possible that the first two areas could be addressed with pre-existing real-time monitoring data, whereas the third section provides a roadmap for future studies of real-time monitoring of STBs among youth.

Novel research questions

Characterizing the “crisis state” before a suicide attempt

Considerable retrospective work suggests that, for many adolescents, a suicide attempt is preceded by a period of brief, but intense, suicidal thinking. For example, nearly 70% of adolescents in one retrospective study reported that thoughts of suicide began just 30 minutes before their most recent suicide attempt (Negron, Piacentini, Graae, Davies, & Shaffer, 1997). Several proposed clinical diagnoses such as the Suicide Crisis Syndrome

(Schuck, Calati, Barzilay, Bloch-Elkouby, & Galynker, 2019) and Acute Suicidal Affective Disturbance (Rogers, Chu, & Joiner, 2019) also include aspects of episodic crisis-like states of intense suicidal thinking (in addition to other states, e.g., agitation) appearing imminently before suicidal behavior. Despite the theoretical support, retrospective empirical work, and earlier calls to do so (Glenn & Nock, 2014), there has been no prospective work exploring the minutes and hours right before a suicide attempt. Real-time monitoring is uniquely suited to characterize the time before a suicide attempt because it can capture the hypothesized rapid increases in suicidal thinking, agitation, and other affect states in a way not possible with other methods (e.g., because real-time monitoring is less suspectable to recall bias; Shiffman et al., 1997).

There are at least two barriers to our ability to capture suicidal behaviors in real-time. First, suicidal behaviors are low-base rate, infrequent occurrences, even among those at high risk. Studies of adolescents hospitalized for a suicide attempt (a high risk group) report rates of a repeat suicide attempt over the 6 months after discharge ranging from 7% to 18% (Goldston et al., 1999; King et al., 1995; Prinstein et al., 2008; Yen et al., 2013). Thus, characterizing the time right before suicidal behaviors would require capturing a large enough group of high-risk individuals, during a high-risk period (e.g., post-hospitalization), over a long enough time period for sufficient suicidal behaviors to be captured. Second, the time before a suicide attempt is indeed characterized by intense distress through suicidal thinking or agitation. This means that we are trying to characterize a time period where people may be less willing or able to complete a smartphone-based assessment of their current state. Supporting the idea that these barriers have contributed to our lack of information on the time before a suicide attempt, work has been done characterizing a related phenomenon, non-suicidal self-injury, which does not have such barriers (Andrewes, Hulbert, Cotton, Betts, & Chanen, 2017) because it occurs more frequently than suicide attempts.

Verifying how well our theories hold up in everyday life and generating new theories

There are well over a dozen theories of suicide (Lester, 1994). Nearly all of these theories either explicitly or implicitly propose a process that should play out over a short period of time (e.g., days, hours). For example, both Beck’s (Wenzel & Beck, 2008) and Alloy and Abramson’s (Abramson et al., 2000) theories of suicide propose trait-like dispositions (i.e., cognitive vulnerabilities) that confer risk for suicide only when activated by the occurrence of stressors in everyday life, leading to suicide-relevant cognitions and then suicidal thoughts or behaviors. Joiner’s interpersonal theory proposes that suicidal desire arises out of the combination of beliefs that one is a burden to others and does not belong to a social group, as well as hopelessness about these beliefs (Van Orden et al., 2010). All three of these factors (burdensomeness, belongingness, hopelessness) are likely state-like and should vary over short periods.

Although many of these theories have support in adolescent samples, this support comes from either retrospective studies or prospective studies with long follow-up periods (e.g., months) that cannot capture the short-term changes proposed in the theories (Burke et al., 2016; Horton et al., 2016). Thus, it is surprising that despite proposing these real-time processes (e.g., the real-time activation of a cognitive vulnerability), there have been no studies to date testing whether these predictions hold up when assessed at the frequency they are expected to vary in. This is especially important because it may be that these theories work well to explain suicide risk over the time scale measured, but not when measured in real time. In line with this idea, some real-time monitoring studies in adults have tested components of the interpersonal theory and generally found inconsistent support for it (Hallensleben et al., 2019; Kleiman et al., 2017). If our theories are not supported using real-time methodology, it does not mean that these theories are wrong. Rather, it may mean that these theories explain the more distal or static components of suicide risk and should be modified to incorporate prediction of proximal risk. Indeed, theories of suicide may be most useful if they can identify both distal and proximal predictors of suicide risk. One such example is the ideation-to-action framework, which aims to model the dynamic progression from suicidal thoughts, a relatively distal predictor of suicidal actions, to the most proximal predictors of suicidal actions (Klonsky, Saffer, & Bryan, 2018). Beyond the modification of existing theory, there may also be room for the generation and testing of new theories using real-time monitoring data.

Novel Analyses

Identifying new risk factors using machine learning

Machine learning has received considerable attention in recent years for its promise to help identify new risk factors or new combinations of existing risk factors. Given that suicide risk is a multi-faceted construct, it is unlikely than any single risk factor will predict risk for STBs among all adolescents. Thus, there is great promise for methods that can identify particularly "risky" combinations of risk factors (Kleiman & Anestis, 2015). Some work suggests that machine learning can possibly help identify new theories by finding patterns in the data not easily detectable by humans alone (Yarkoni & Westfall, 2017).

Although there is great promise in using machine learning to help advance our understanding of suicide risk among adolescents, as with any new scientific endeavor, skepticism is appropriately warranted. Some recent empirical work and commentaries related to machine learning in suicide present a positive outlook (Allen, Nelson, Brent, & Auerbach, 2019; Torous & Walker, 2019) whereas others take an appropriately less optimistic view (Belsher et al., 2019). Here, we present a more balanced view of the positives and negatives of machine learning, in line with still other recent commentaries (Dwyer, Falkai, & Koutsouleris, 2018; Kessler, 2019). There are several problems to acknowledge. The first problem is overfitting, which occurs when models prioritize prediction of already-known cases in training data rather than generalizability to future data. This is a problem well known within statistics and computer science (Dietterich, 1995), and addressed in some areas of psychology (e.g., screening for pediatric bipolar disorder; Youngstrom, Halverson, Youngstrom, Lindhiem, & Findling, 2018) but possibly less frequently acknowledged within suicide research. Overfitting is especially problematic for creating algorithms to predict suicide risk because of the costs associated with a false positive (e.g., someone may be given an intervention for suicide risk despite not needing one) and especially high cost associated with a false negative (e.g., someone at risk may die by suicide) (Gianfrancesco, Tamang, Yazdany, & Schmajuk, 2018). The second problem is the lack of machine learning models appropriate for real-time monitoring data. Most extant studies using machine learning within the context of suicide among adolescents use medical record data to predict future suicide events (Walsh, Ribeiro, & Franklin, 2018). Real-time monitoring data are far more complex (because they involve time-varying data, collected at hundreds or thousands of datapoints) and this can create problems with complexity that existing machine learning models are not able to address. The third problem involves clinical utility. Even if a model identifies a new predictor of STB risk, it does not mean that this predictor will actually contribute to the prediction of STBs in a clinically meaningful way (Franklin et al., 2017). This is a topic that is becoming better understood in other areas of research (e.g., medicine; Emanuel & Wachter, 2019; Shah, Milstein, & Bagley, 2019). Despite these potential issues, there is of course, great promise in this area due to the large number of statisticians focused on expanding the science of machine learning (Dwyer et al., 2018).

Moving beyond nomothetic analytic approaches to idiographic and subgroup models

Because real-time monitoring involves repeated sampling of an individual over time, it allows researchers to gain a deep understanding of an individual in ways not possible with other methodologies. Real-time monitoring makes it possible to move from group-level nomothetic models to idiographic, person-centered models. The use of idiographic models in suicide research is not necessarily new, as calls for such work have existed for more than 15 years (Leenars, 2002). What is new, however, is our ability to collect data that are well-suited for idiographic analyses. Supporting the use of idiographic models is the idea that what is true about a group is rarely true about all members of it (referred to as the ecological fallacy; Piantadosi, Byar, & Green, 1988). Illustrating this, Fisher, Medaglia, and Jeronimus (2018) found across four repeated-measures studies that although individuals' means often aligned well with the overall group mean, the variability around that mean differed considerably. This means that we could miss crucial pieces of information about the individual if we apply to them only what we know from the group. The idiographic approach is especially promising for its ability to create individually-tailored interventions that can "trigger" an intervention (e.g., on the smartphone) based on other data (e.g., wearable monitor, prior smartphone responses) in a way that is specific to the individual (Fisher & Boswell, 2016) delivered just-in-time when the intervention is needed (i.e., using just-in-time adaptive interventions [JITAIs]; Nahum-Shani et al., 2018).

The first challenge is that the individual variability not accounted for by group-level models may reflect poor internal validity instead of poor generalizability from groups to individuals (Schwartz, 1994). For example, some trait-level factors (e.g., difficulty using technology) that only occur in a minority of adolescents could contribute to discrepancies between group and individual models in ways that are not meaningful. The second challenge is that even the data that are collected using real-time monitoring may not actually represent the individual. Data that are collected over a particularly stressful (e.g., beginning of a school year), not stressful (e.g., the middle of summer break), or otherwise atypical period may not generalize to other periods. This would mean collecting data over a long enough period of time to capture a range of periods. A longer monitoring period, of course, presents additional logistical challenges for compliance and retention. The third challenge, articulated well by

Wright et al. (in press) is that a personalized model does not allow for information learned about one adolescent to be generalized to others. This lack of generalizability would present problems for understanding psychopathology (e.g., what is a typical level of agitation?) and treatment (e.g., needing to "start from scratch" for each new client).

To summarize, nomothetic models can suffer from poor group-to-individual generalizability and idiographic models can suffer from poor individual-to-group generalizability. Thankfully, there exist a variety of analytic techniques that can maximize the benefits of both approaches while minimizing their drawbacks. We present two such options here. The first approach involves the class of analyses that can create subgroups of individuals based off of their responses, such as mixture models (latent class analysis, latent profile analysis; McCutcheon, 1987; Nagin, 2005). There has been promise using these methods with real-time monitoring data of suicidal adults (Kleiman et al., 2018) and cross-sectional data among adolescents (Thullen, Taliaferro, & Muehlenkamp, 2016). Subgroups present a "middle ground" between nomothetic and idiographic models, possessing some benefits of both (e.g., generalizability to other individuals) while still having some tradeoffs (e.g., individuals are likely more similar to a subgroup than the entire population, but there are still likely important differences between the individual and the subgroup). The second approach is the Group Iterative Multiple Model Estimation (GIMME; Gates & Molenaar, 2012) which allows estimation of both individual- and subgroup-level effects. GIMME was initially designed for fMRI analysis, but has some promise for use in analyses using real-time monitoring data (Wright et al., in press). Because it was designed for a different type of time-series analyses, this leads to a few important limitations to acknowledge. First is the requirement that there cannot be any constants with an individual (e.g., if an adolescent [accurately] reported a rating of 0 on a measure of suicidal thinking at every time point, they would need to be removed from the analyses). Second, GIMME assumes that data are evenly spaced and data from most real-time monitoring studies are (by design) unevenly spaced due to surveys being delivered at random intervals. Like other advanced statistical methods discussed here, however, there is hope that in the near future extensions of these models will be developed than can better handle the types of data that come from real-time monitoring studies.

Understanding the role of time in suicidal thoughts and behaviors

Nearly all real-time monitoring studies published to date have used multi-level modeling (also called hierarchical linear modeling, linear mixed-effect modeling, random coefficient modeling, and others). These analyses are certainly appropriate for the types of data that are typically collected using real-time monitoring (where there are multiple measurements from the same participant). However, multi-level models are among the most basic types of analyses that can be done on these data. Real-time monitoring data are almost always also time-series data in the sense that the data collected are indexed by some sort of time variable. Most traditional multi-level modeling approaches cannot take advantage of time-series data, which means there is still much to learn about the nature of time in suicide risk. Understanding the nature of time in suicide risk has many possible benefits, including the ability to explore the time course of suicidal thinking, which is still unknown.

What is the time course of suicidal thinking?—Although it is unlikely that the length of an episode of suicidal thinking is the same from one adolescent to the next, or even from one episode to the next, establishing an understanding of the length of time episodes of suicidal thinking may last could be useful for determining the frequency of assessment (e.g., to capture the episode; Dormann & Griffin, 2015) or windows for intervention. One of the earliest real-time monitoring studies of suicidal thinking among adolescents supports the idea that episodes of suicidal thinking are likely brief. This study found that more than half of all episodes of suicidal thinking that was reported lasted 30 minutes or less (Nock et al., 2009). One way to explore the time course of suicidal thinking is through the use of autoregressive models, which can be used to understand how prior ratings of a variable predict future ratings of the same variable (Hytti, Takalo, & Ihalainen, 2006). This would be particularly useful to determine the length of an episode (e.g., by determining at what point the relationship between current and prior ratings disappears). Several types of autoregressive models exist, including basic autoregression, which can determine the relationship between current ratings of a variable and all prior ratings of it; autoregressive integrated moving average (ARIMA), which also takes into account the error associated with prior measurements; and vector autoregression, which can include multiple variables. Like GIMME, autoregressive models were not designed with real-time monitoring data in mind. They were originally designed to be applied to economic data (Dickey & Fuller, 1981), which, unlike real-time monitoring data, are evenly spaced in time.

Are there cyclical patterns in risk for STBs?—It is possible that suicidal thinking may vary as a function of time and thus there may be cyclical patterns that could be useful to explore. There are several different time scales which would merit exploration. Within a day, there is a body of work on diurnal variation in psychopathology among adolescents (e.g., anxiety and depression symptoms) and it may also be that such variation occurs in suicidal thinking or other suicide risk factors (Granger et al., 2003). Within a week, there may be variation from weekdays to weekends. Within a month, for females, there may be variations around the menstrual cycle (Saunders & Hawton, 2006). Spectral density analysis is particularly useful for studying these types of cycles, but like the other analyses mentioned thus far, has not been designed with some of the peculiarities of real-time monitoring data in mind (Stoica & Moses, 2005).

How do relationships between suicide risk factors and STBs change over time?—It may that the relationship between risk factors for STBs and STBs vary over time in a meaningful way. For example, there may be periods of time (e.g., after certain types of events) that the relationship between two variables becomes stronger. Techniques such as time-varying effect modeling (TVEM; Tan, Shiyko, Li, Li, & Dierker, 2012) are useful in these cases because they can model the change in the relationship between variables as a function of time. Unlike the other methods mentioned in this section, TVEM has been developed for use with repeated measures data like the type collected in real-time monitoring studies (Shiyko, Lanza, Tan, Li, & Shiffman, 2012). To date, however, TVEM has not been used specifically in real-time monitoring studies of suicide.

Novel Methodology

Moving beyond self-report data

The majority of the studies referenced here use only active monitoring of self-report data. Such data are an advancement over prior self-report studies that retrospectively assess a construct of interest. However, there is much to be gained by expanding our real-time assessment beyond self-report to other streams of data that can objectively reflect the behavior we are interested in studying. In the sections below, we talk about two methods to objectively measure behavior that may be related to suicide risk: wearable devices and passive sensing. These technologies are especially useful because they do not require individuals to report how they are thinking and feeling at a time when it might be difficult to engage in more active reporting.

Wearable devices—Much like other real-time monitoring methodology, research-grade wearable devices have been available for quite some time (Thorpy et al., 1995). In the past few years, however, interest in using these devices in real-time assessment has escalated markedly. This is likely due in part to the increased accessibility of research-grade devices that can be worn unobtrusively, usually on the wrist, but sometimes elsewhere on the body (e.g., a patch on the shoulder). For example, high quality actigraphy devices that can measure sleep and related factors can be purchased for ~$750. This increased interest has almost certainly also been due to the recent proliferation of consumer-grade wearable devices (e.g., Fitbit) that are easier to use than research-grade devices and are more aesthetically appealing, which is especially important for adolescents. Although a thorough review of the technical specifications of wearable devices is outside of the scope of this paper, we provide here a brief overview of features common in wearable devices. These devices usually contain a variety of sensors that can assess factors such as movement (via an accelerometer or gyroscope), temperature (via a thermopile or thermometer), heart rate (via a photoplethysmograph), and measures of autonomic arousal (via electrodermal activity). These data streams can then be converted into behavioral indices of constructs of interest. For example, accelerometry data can be used to passively detect sleep.

Suicidal thoughts (and to an extent, suicidal behaviors), are not observable using passive monitoring. There is no currently known physiological signature that corresponds to suicidal thinking. Thus, passive monitoring alone is not sufficient to study STBs. The most advantageous way to use wearable devices to study STBs is to pair the objective behavioral data collected using a wearable device with the subjective data collected from EMA. Some studies in adults have begun to do this. One study that combined EMA data with actigraphy to show how sleep corresponded to next-day reports of suicidal thinking (Littlewood et al., 2019). This would be particularly useful in terms of developing new risk detection algorithms that could trigger interventions based on data from a wearable monitor.

There are several issues that researchers who wish to use wearable devices in their studies should acknowledge. First, there is relatively consistent support that wearable devices are able to accurately detect sleep among adolescents, relative to both medical-grade polysomnography and to other wearable devices (Baron et al., 2018; Ridgers et al., 2018). There is less research on other sensors, and the research that does exist (e.g., on heart rate sensors on wrist-worn devices) raises some concern for whether these devices are sufficiently accurate for most researchers' needs (Parak & Korhonen, 2014). Second, technological limitations (e.g., battery capacity, location of sensors) means many tradeoffs in sampling quality relative to typical laboratory devices. For example, the Empatica E4, a research-grade wearable device, measures skin conductance at 4hz, which is ½5th of the rate recommended for laboratory studies (Figner & Murphy, 2010). Third, many commercial devices do not provide to researchers the level of data that would be needed to study STBs. As noted in prior real-time monitoring research, suicide risk and related factors change over hours or less (Kleiman et al., 2017; Nock et al., 2009). This means that the type of data collected should match this frequency (e.g., minute-to-minute heart rate, skin conductance measured ever 250 milliseconds). Some of the most consumer-friendly wearable devices do not provide these data. For example, although Fitbit devices are some of the most consumer-friendly devices and although Fitbit has an excellent reputation for providing research data, the data that are provided are never at this granular of a level. Finally, the data files that are produced from these devices are large and potentially noisy. For example, collecting accelerometer data measured at 32hz (a relatively low frequency) for four weeks would lead to over 11 million rows of data per participant. Managing and cleaning data files this large requires analytic methods that do not necessarily keep pace with the development of the monitoring technology. However, like several other areas discussed thus far, the increased interest into these methods will likely lead to the creation of new tools to work with the data they produce.

Passive sensing—Another route to supplement self-report data collection is through "passive sensing," or harnessing the data that are passively collected by sensors used in everyday life, such as the GPS or text message logs from an adolescent's smartphone (Mohr, Zhang, & Schueller, 2017). These streams of data are exciting because they allow large amounts of data to be collected with essentially no burden to the participant (e.g., because the logs will be recorded on the phone no matter what). These data can then be used as part of a *digital phenotyping* framework where behavioral indices can be created from the passive data streams (Insel, 2017). For example, constructs relevant to suicide like social connection could be assessed through the number of texts made or the number of places visited assessed via GPS. Of particular relevance to youth is the ability to passively detect and quantify interactions on social media, given the importance of social media to most adolescents (Best, Manktelow, & Taylor, 2014). There has been relatively little research in this area, most of which has been done on small samples (the median sample size of studies in one review of passive sensing studies was 15; Cornet & Holden, 2018). This work has not yet been conducted on suicidal populations or adolescents. Thus, as echoed by others (Torous et al., 2018), passive sensing is a novel way to improve our ability to understand the everyday lives of adolescents at risk for suicide.

Despite the clear promise of these data, there are many pitfalls to acknowledge. First, and possibly most important, many of the potential streams of passive data that can be collected are of a highly personal and identifiable nature. For example, even one GPS sample can easily tell where a participant lives or goes to school. A call log can give away someone's friends or family. This means that extra care should be taken to secure these data and to make sure participants and their parents are informed of the risk associated with collecting these data. Many apps capable of this sort of sensing use methods to obscure information (e.g., encrypting or "hashing" phone numbers) but this could reduce its utility (e.g., it would not be possible to tell the actual phone number dialed if the number has been encrypted). Second, because so few studies have used passive data to better understand constructs of interest, there is not a particularly large base of knowledge in how to work with these data. Of course, given the popularity of these data, it will likely not be long until more advanced analytic techniques are developed. Third, the passive data that are collected may not capture all possible ways a behavior could manifest. This is especially true for adolescents. Even though, as noted earlier, smartphone use is nearly ubiquitous for adolescents, the ways in which adolescents use their smartphones shifts rapidly. For example, if passive sensing technologies cannot capture all methods of communication, researchers could erroneously conclude that such communication never happened. This is particularly true for passive sensing of social media given that the popularity of social media platforms can change considerably from year to year. Fourth, there are technological limitations to this approach such as a lack of available data on some platforms (e.g., the security settings on all Apple smartphones prevents researchers from accessing the call logs) to missing data as a result of smartphones turning off sensors to conserve battery (e.g., it is common for smartphones to turn off the GPS when not in use). Finally, for both smartphone passive sensing and wearable sensors, there are issues with compatibility across devices. Any risk algorithm generated with passive data would be specific to that configuration of manufacturer, model, and operating system (Harari et al., 2016; Mohr et al., 2017; Stisen et al., 2015).

Capturing critical transition periods

Adolescence involves many transitions from one stage to the next (Lenz, 2001; Patton & Viner, 2007). These transitions may be critical periods where suicide risk emerges and thus there could be value in capturing, in real time, what sorts of changes happen during these transitions. To date, nearly all real-time monitoring studies of suicide risk have not explicitly focused on an explicit period. Those that have (all of which are relatively new studies as of the writing of this paper) focus on the period of time immediately after discharge from inpatient psychiatric care. Although the transition out of inpatient psychiatric care is one of the highest risk periods for suicide (Chung et al., 2017), there are many other critical periods as well that should be explored. For example, there is some support for the idea that adolescents (and adults) are at greater risk for suicide during the spring compared to other seasons (Shinsugi, Stickley, Konishi, Ng, & Watanabe, 2015; Sun et al., 2011). As noted by others, however, it is not well understood *why* the suicide rate is higher during spring (Ajdacic-Gross, Bopp, Ring, Gutzwiller, & Rossler, 2010). Real-time monitoring could be useful in this case as it could capture specific changes from season-to-season as they actually occur, which may provide insight into the processes that occur as the seasons change. Other important critical periods to explore in future research include the transition from the school year to summer or from one school to the next (e.g., middle school to high school) and changes throughout the course of puberty (Dervic, Brent, & Oquendo, 2008). Finally, there has been no specific study of the pubertal transition where STBs drastically increase (Nock et al., 2013).

One challenge with capturing these critical periods is that they would require long monitoring periods (and this is likely one of the reasons why such work has not yet been conducted; Liu & West, 2016). For example, to compare real-time data from one season to the next could require an entire year of real-time monitoring data. Doing this would be quite burdensome on the researcher and participants and would likely lead to issues in retention. At the extreme, an overly-burdensome study protocol could lead to biased attrition (Miller & Wright, 1995), where adolescents with less-severe suicide risk are more likely to complete the study. One solution to this may be collecting real-time monitoring data for short periods separated by longer intervals. For example, Weinstein, Mermelstein, Hedeker, Hankin, & Flay (2006) collected real-time monitoring data for one week every six months in order to capture the transition from one grade to the next.

Understanding the ethical implications of conducting real-time monitoring studies in youth

Suicide research is unlike nearly any other area of research in psychology because of the ethical imperative to keep participants safe when we learn that they are at risk for suicide. This issue is hardly new within the study of suicide, and has been discussed at length in reference to studies that assess suicide only once, or once every week, month, etc. (Fisher, Pearson, Kim, & Reynolds, 2002; Pearson, Stanley, King, & Fisher, 2001). Real-time monitoring provides a unique challenge, however. Whereas traditional online studies may ask about suicide risk averaged over weeks or months at one time point (or multiple points with long spans in between assessments), real-time monitoring studies ask multiple times per day about levels of suicidal desire, intent, ability to keep oneself safe, etc. at that very moment. Moreover, some real-time monitoring apps also allow the collection of GPS data. Taken together, this means that real-time monitoring studies of suicide risk assess risk as it is happening, many times per day, and records not just *when* someone is at risk but *where* someone is at risk. As we detail below, these important differences make it challenging to manage suicide risk in the same way as we would in traditional studies. We intentionally provide here no specific recommendations for dealing with suicide risk monitoring in real-time monitoring studies, because there is likely not one correct answer or best practice for any research study. The optimal way to handle suicide risk monitoring in a real-time monitoring study depends upon many factors.

Existing guidelines (Michaels, Chu, Silva, Schulman, & Joiner, 2015) and common practice for managing risk in traditional online studies generally involve setting thresholds (e.g., scores above a certain level on a measure of suicidal ideation) for “moderate” or “high” risk. When risk is moderate, participants receive some sort of passive intervention (e.g., list of local treatment providers). When risk is “high”, an active intervention is engaged (e.g., calling for further risk assessment and safety planning). There are at least two reasons why these traditional approaches, as is, would not translate to feasible risk management strategies in real-time monitoring studies. First, although we refer to this technology as “real-time monitoring”, it is important to note that this refers to *assessing* constructs as they occur in real time. It does not refer to *receiving* data in real time. Most real-time monitoring apps are designed to store data on participants’ phones until a stable connection (usually via Wifi) is available. This means that there could be a gap of hours or days between an adolescent reporting that they are at high risk and someone on the research team having access to those data. Second, risk monitoring protocols that involve immediately contacting the participant might not be scalable even to small-scale real-time monitoring studies. For example, even running 10 participants at a time, with six prompts per day would yield up to 420 responses each week. If even 2% of these responses are “high risk,” this would require 84 separate active interventions per week. This would mean that active protocols would require a large staff that would not be feasible in most cases. Moreover, many of these interventions would be false positives. As noted earlier, 7–18% of adolescents during the highest risk time for STBs (i.e., suicidal inpatients in the time immediately after discharge from inpatient care) will attempt suicide (Goldston et al., 1999; King et al., 1995; Prinstein et al., 2008). Even the adolescents who do attempt suicide would likely also report false positives on the surveys that did not immediately precede a potential suicide attempt. These false positives (i.e., contacting the participant or their parent when contact is not needed) may lead to participants becoming unwilling to respond to the study, or to purposely underreporting their level of suicide risk. It could also lead to increased burden on parents (and clinicians, depending on the nature of the risk assessment protocol). Ultimately, this would mean that by adding appropriate risk monitoring procedures, we are no doubt changing the phenomenon we are trying to observe while adding additional burden to study participants and their parents. Thus, any risk assessment protocol should be designed in a way that takes into account participant safety, risk of false positives, accuracy of responses, and burden on participants and their parents.

Conclusion

Recent advances in smartphones and wearable devices make real-time monitoring more feasible than ever before. This is especially true for adolescents who are already familiar with this technology. Real time monitoring is particularly promising because it can give us an opportunity to observe the everyday lives of youth at risk for STBs which will help us better understand what it is about their experiences that lead to increased risk for STBs. Given the clear promise of using real-time monitoring to explore STBs among adolescents, the goals of this manuscript were: (1) to provide an overview of the current status of using real-time monitoring to study STBs among youth, (2) to discuss future directions using real-time monitoring, and (3) to clarify the potential challenges using this technology. The existing literature that uses real-time monitoring to study STBs primarily establishes good feasibility and provides some initial description of what STBs look like in everyday life. The future directions we discuss build on this initial research in terms of identifying of new research questions, promoting innovative analytic methods of new or existing data, and highlighting novel methodological approaches. Despite these exciting new directions, there are real barriers to using this methodology that must also be recognized in terms of logistics (e.g., getting adolescents to complete real-time monitoring during critical periods), technical barriers (e.g., current mathematical models may not be ideal for our needs), and ethics (e.g., ensuring participant safety).

Acknowledgements

Research reported in this publication was supported by the National Institute of Mental Health (R21MH115293 [EMK], RF1MH120830 [RTL], R01MH115905 [RTL]) and the American Foundation for Suicide Prevention (YIG-1-054-16 [CRG])

References

Abramson LY, Alloy LB, Hogan ME, Whitehouse WG, Gibb BE, Hankin BL, & Cornette MM (2000). The hopelessness theory of suicidality In Joiner TE & Rudd MD (Eds.), Suicide science: Expanding the boundaries (pp. 17–32). New York, NY, US: Kluwer Academic/Plenum Publishers.

Ajdacic-Gross V, Bopp M, Ring M, Gutzwiller F, & Rossler W (2010). Seasonality in suicide – A review and search of new concepts for explaining the heterogeneous phenomena. Social Science & Medicine, 71(4), 657–666. 10.1016/j.socscimed.2010.05.030 [PubMed: 20573433]

Allen NB, Nelson BW, Brent D, & Auerbach RP (2019). Short-term prediction of suicidal thoughts and behaviors in adolescents: Can recent developments in technology and computational science provide a breakthrough? Journal of Affective Disorders, 250, 163–169. 10.1016/j.jad.2019.03.044 [PubMed: 30856493]

Aminikhanghahi S, Schmitter-Edgecombe M, & Cook DJ (2019). Context-aware delivery of ecological momentary assessment. IEEE Journal of Biomedical and Health Informatics. 10.1109/JBHI.2019.2937116

Andrewes HE, Hulbert C, Cotton SM, Betts J, & Chanen AM (2017). An ecological momentary assessment investigation of complex and conflicting emotions in youth with borderline personality disorder. Psychiatry Research, 252, 102–110. 10.1016/j.psychres.2017.01.100 [PubMed: 28259033]

Bagge CL, Littlefield AK, Conner KR, Schumacher JA, & Lee H-J (2014). Near-term predictors of the intensity of suicidal ideation: An examination of the 24 h prior to a recent suicide attempt. Journal of Affective Disorders, 165, 53–58. 10.1016/j.jad.2014.04.010 [PubMed: 24882177]

Baron KG, Duffecy J, Berendsen MA, Cheung Mason I, Lattie EG, & Manalo NC (2018). Feeling validated yet? A scoping review of the use of consumer-targeted wearable and mobile technology to measure and improve sleep. Sleep Medicine Reviews, 40, 151–159. 10.1016/j.smrv.2017.12.002 [PubMed: 29395985]

Barrett LF, & Barrett DJ (2001). An introduction to computerized experience sampling in psychology. Social Science Computer Review, 19(2), 175–185. 10.1177/089443930101900204

Belsher BE, Smolenski DJ, Pruitt LD, Bush NE, Beech EH, Workman DE, … Skopp NA (2019). Prediction models for suicide attempts and deaths: A systematic review and simulation. JAMA Psychiatry, 76(6), 642–651. 10.1001/jamapsychiatry.2019.0174 [PubMed: 30865249]

Best P, Manktelow R, & Taylor B (2014). Online communication, social media and adolescent wellbeing: A systematic narrative review. Children and Youth Services Review, 41, 27–36. 10.1016/j.childyouth.2014.03.001

Burke TA, Connolly SL, Hamilton JL, Stange JP, Abramson LY, & Alloy LB (2016). Cognitive Risk and Protective Factors for Suicidal Ideation: A Two Year Longitudinal Study in Adolescence. Journal of Abnormal Child Psychology, 44(6), 1145–1160. 10.1007/s10802-015-0104-x [PubMed: 26597963]

Chung DT, Ryan CJ, Hadzi-Pavlovic D, Singh SP, Stanton C, & Large MM (2017). Suicide rates after discharge from psychiatric facilities: A systematic review and meta-analysis. JAMA Psychiatry 10.1001/jamapsychiatry.2017.1044

Cornet VP, & Holden RJ (2018). Systematic review of smartphone-based passive sensing for health and wellbeing. Journal of Biomedical Informatics, 77, 120–132. 10.1016/j.jbi.2017.12.008 [PubMed: 29248628]

Csikszentmihalyi M, & Larson R (1987). Validity and reliability of the Experience-Sampling Method. The Journal of Nervous and Mental Disease, 175(9), 526–536. [PubMed: 3655778]

Czyz EK, Horwitz AG, Arango A, & King CA (2019). Short-term change and prediction of suicidal ideation among adolescents: A daily diary study following psychiatric hospitalization. Journal of Child Psychology and Psychiatry, 60(7), 732–741. 10.1111/jcpp.12974 [PubMed: 30246870]

Czyz EK, King CA, & Nahum-Shani I (2018). Ecological assessment of daily suicidal thoughts and attempts among suicidal teens after psychiatric hospitalization: Lessons about feasibility and acceptability. Psychiatry Research, 267, 566–574. 10.1016/j.psychres.2018.06.031 [PubMed: 30031317]

Dervic K, Brent DA, & Oquendo MA (2008). Completed Suicide in Childhood. Psychiatric Clinics of North America, 31(2), 271–291. 10.1016/j.psc.2008.01.006 [PubMed: 18439449]

Dickey DA, & Fuller WA (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057–1072. 10.2307/1912517

Dietterich T (1995). Overfitting and undercomputing in machine learning. ACM Computing Surveys, 27(3), 326–327. 10.1145/212094.212114

Dormann C, & Griffin MA (2015). Optimal time lags in panel studies. Psychological Methods, 20(4), 489–505. 10.1037/met0000041 [PubMed: 26322999]

Dwyer DB, Falkai P, & Koutsouleris N (2018). Machine learning approaches for clinical psychology and psychiatry. Annual Review of Clinical Psychology, 14(1), 91–118. 10.1146/annurev-clinpsy-032816-045037

Emanuel EJ, & Wachter RM (2019). Artificial intelligence in health care: Will the value match the hype? JAMA, 321(23), 2281 10.1001/jama.2019.4914 [PubMed: 31107500]

Figner B, & Murphy RO (2010). Using skin conductance in judgment and decision making research In Kuehberger A & Ranyard R (Eds.), A handbook of process tracing methods for decision research. New York, NY: Psychology Press.

Fisher AJ, Medaglia JD, & Jeronimus BF (2018). Lack of group-to-individual generalizability is a threat to human subjects research. Proceedings of the National Academy of Sciences, 115(27), E6106–E6115. 10.1073/pnas.1711978115

Fisher AJ, & Boswell JF (2016). Enhancing the personalization of psychotherapy with dynamic assessment and modeling. Assessment, 23(4), 496–506. 10.1177/1073191116638735 [PubMed: 26975466]

Fisher CB, Pearson JL, Kim S, & Reynolds CF (2002). Ethical issues in including suicidal individuals in clinical research. IRB: Ethics and Human Research, 24(5), 9 10.2307/3563804

Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, … Nock MK (2017). Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research. Psychological Bulletin, 143, 187–232. 10.1037/bul0000084 [PubMed: 27841450]

Gates KM, & Molenaar PCM (2012). Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. NeuroImage, 63(1), 310–319. 10.1016/j.neuroimage.2012.06.026 [PubMed: 22732562]

Gianfrancesco MA, Tamang S, Yazdany J, & Schmajuk G (2018). Potential biases in machine learning algorithms using electronic health record data. JAMA Internal Medicine, 178(11), 1544–1547. 10.1001/jamainternmed.2018.3763 [PubMed: 30128552]

Glenn CR, & Nock MK (2014). Improving the short-term prediction of suicidal behavior. American Journal of Preventive Medicine, 47(3), S176–S180. 10.1016/j.amepre.2014.06.004 [PubMed: 25145736]

Goldston DB, Daniel SS, Reboussin DM, Reboussin BA, Frazier PH, & Kelley AE (1999). Suicide attempts among formerly hospitalized adolescents: A prospective naturalistic study of risk during the first 5 years after discharge. Journal of the American Academy of Child & Adolescent Psychiatry, 38(6), 660–671. 10.1097/00004583-199906000-00012 [PubMed: 10361783]

Granger DA, Shirtcliff EA, Zahn–Waxler C, Usher B, Klimes–Dougan B, & Hastings P (2003). Salivary testosterone diurnal variation and psychopathology in adolescent males and females: Individual differences and developmental effects. Development and Psychopathology, 15(2), 431–449. 10.1017/S0954579403000233 [PubMed: 12931836]

Hallensleben N, Glaesmer H, Forkmann T, Rath D, Strauss M, Kersting A, & Spangenberg L (2019). Predicting suicidal ideation by interpersonal variables, hopelessness and depression in real-time. An ecological momentary assessment study in psychiatric inpatients with depression. European Psychiatry: The Journal of the Association of European Psychiatrists, 56, 43–50. 10.1016/j.eurpsy.2018.11.003 [PubMed: 30530103]

Hallensleben N, Spangenberg L, Forkmann T, Rath D, Hegerl U, Kersting A, … Glaesmer H (2017). Investigating the dynamics of suicidal ideation: Preliminary findings from a study using ecological momentary assessments in psychiatric inpatients. Crisis, 1–5. 10.1027/0227-5910/a000464 [PubMed: 28256167]

Harari GM, Lane ND, Wang R, Crosier BS, Campbell AT, & Gosling SD (2016). Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. Perspectives on Psychological Science, 11(6), 838–854. 10.1177/1745691616650285 [PubMed: 27899727]

Horton SE, Hughes JL, King JD, Kennard BD, Westers NJ, Mayes TL, & Stewart SM (2016). Preliminary examination of the interpersonal psychological theory of suicide in an adolescent clinical sample. Journal of Abnormal Child Psychology, 44(6), 1133–1144. 10.1007/s10802-015-0109-5 [PubMed: 26667025]

Hytti H, Takalo R, & Ihalainen H (2006). Tutorial on multivariate autoregressive modelling. Journal of Clinical Monitoring and Computing, 20(2), 101–108. 10.1007/s10877-006-9013-4 [PubMed: 16779623]

Insel TR (2017). Digital phenotyping: Technology for a new science of behavior. JAMA, 318(13), 1215–1216. 10.1001/jama.2017.11295 [PubMed: 28973224]

Kessler RC (2019). Clinical Epidemiological Research on Suicide-Related Behaviors—Where We Are and Where We Need to Go. JAMA Psychiatry, 76(8), 777–778. 10.1001/jamapsychiatry.2019.1238

King CA, Segal H, Kaminski K, Naylor MW, Ghaziuddin N, & Radpour L (1995). A prospective study of adolescent suicidal behavior following hospitalization. Suicide & Life-Threatening Behavior, 25(3), 327–338. [PubMed: 8553413]

Kleiman EM, & Anestis MD (2015). Introduction to the Special Issue: Recent Advances in Suicide Research: Mediators and Moderators of Risk and Resilience. International Journal of Cognitive Therapy, 8(2), 95–98. 10.1521/ijct.2015.8.2.95

Kleiman EM, Millner AJ, Joyce VW, Nash CC, Buonopane RJ, & Nock MK (2019). Feasibility and acceptability of using wearable physiological monitors with suicidal adolescent inpatients. JMIR MHealth and UHealth. 10.2196/13725

Kleiman EM, & Nock MK (2018). Real-time assessment of suicidal thoughts and behaviors. Current Opinion in Psychology, 22, 33–37. 10.1016/j.copsyc.2017.07.026 [PubMed: 30122275]

Kleiman EM, Turner BJ, Fedor S, Beale EE, Huffman JC, & Nock MK (2017). Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. Journal of Abnormal Psychology, 126(6), 726–738. 10.1037/abn0000273 [PubMed: 28481571]

Kleiman EM, Turner BJ, Fedor S, Beale EE, Picard RW, Huffman JC, & Nock MK (2018). Digital phenotyping of suicidal thoughts. Depression and Anxiety, 35(7), 601–608. 10.1002/da.22730 [PubMed: 29637663]

Klonsky ED, Saffer BY, & Bryan CJ (2018). Ideation-to-action theories of suicide: A conceptual and empirical update. Current Opinion in Psychology, 22, 38–43. 10.1016/j.copsyc.2017.07.020 [PubMed: 30122276]

Leenars AA (2002). In defense of the idiographic approach: Studies of suicide notes and personal documents. Archives of Suicide Research, 6(1), 19–30. 10.1080/13811110213125

Lenz B (2001). The transition from adolescence to young adulthood: A theoretical perspective. The Journal of School Nursing, 17(6), 300–306. 10.1177/10598405010170060401 [PubMed: 11804406]

Lester D (1994). A Comparison of 15 Theories of Suicide. Suicide and Life-Threatening Behavior, 24(1), 80–88. 10.1111/j.1943-278X.1994.tb00665.x [PubMed: 8203011]

Littlewood DL, Kyle SD, Carter L-A, Peters S, Pratt D, & Gooding P (2019). Short sleep duration and poor sleep quality predict next-day suicidal ideation: An ecological momentary assessment study. Psychological Medicine, 49(3), 403–411. 10.1017/S0033291718001009 [PubMed: 29697037]

Liu Y, & West SG (2016). Weekly cycles in daily report data: An overlooked issue: Weekly cycles in daily report data. Journal of Personality, 84(5), 560–579. 10.1111/jopy.12182 [PubMed: 25973649]

McCutcheon AL (1987). Latent class analysis. Newbury Park: Sage Publications.

Michaels MS, Chu C, Silva C, Schulman BE, & Joiner T (2015). Considerations regarding online methods for suicide-related research and suicide risk assessment. Suicide and Life-Threatening Behavior, 45(1), 10–17. 10.1111/sltb.12105 [PubMed: 24863047]

Miller RB, & Wright DW (1995). Detecting and correcting attrition bias in longitudinal family research. Journal of Marriage and Family, 57(4), 921–929. 10.2307/353412

Mohr DC, Zhang M, & Schueller SM (2017). Personal Sensing: Understanding Mental Health Using Ubiquitous Sensors and Machine Learning. Annual Review of Clinical Psychology, 13(1), 23–47. 10.1146/annurev-clinpsy-032816-044949

Nagin D (2005). Group-based modeling of development. Cambridge, Mass: Harvard University Press.

Nahum-Shani I, Smith SN, Spring BJ, Collins LM, Witkiewitz K, Tewari A, & Murphy SA (2018). Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key components and design principles for ongoing health behavior support. Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine, 52(6), 446–462. 10.1007/s12160-016-9830-8 [PubMed: 27663578]

National Institute of Mental Health. (2018a). Dysregulation and proximal risk for suicide (R21 clinical trial optional) (No. RFA-MH-19–210). Retrieved from https://grants.nih.gov/grants/guide/rfa-files/rfa-mh-19-210.html

National Institute of Mental Health. (2018b). Products to support applied research towards Zero Suicide healthcare systems (R43/R44 clinical trial optional) (No. PAR-18–269). Retrieved from https://grants.nih.gov/grants/guide/pa-files/par-18-269.html

National Institute of Mental Health. (2019a). Clinical trials to test the effectiveness of treatment, preventive, and services interventions (collaborative R01—Clinical trial required) (No. RFA-MH-18–700). Retrieved from https://grants.nih.gov/grants/guide/rfa-files/RFA-MH-18-700.html

National Institute of Mental Health. (2019b). Notice of special interest to highlight high priority research opportunities on suicide prevention crisis services (No. NOT-MH-19–025). Retrieved from https://grants.nih.gov/grants/guide/notice-files/NOT-MH-19-025.html

Negron R, Piacentini J, Graae F, Davies M, & Shaffer D (1997). Microanalysis of Adolescent Suicide Attempters and Ideators During the Acute Suicidal Episode. Journal of the American Academy of Child & Adolescent Psychiatry, 36(11), 1512–1519. 10.1016/S0890-8567(09)66559-X [PubMed: 9394935]

Nock MK, Green JG, Hwang I, McLaughlin KA, Sampson NA, Zaslavsky AM, & Kessler RC (2013). Prevalence, correlates, and treatment of lifetime suicidal behavior among adolescents: Results from the National Comorbidity Survey Replication Adolescent Supplement. JAMA Psychiatry, 70(3), 300–310. https://doi.org/10.100½013.jamapsychiatry.55 [PubMed: 23303463]

Nock MK, Prinstein MJ, & Sterba SK (2009). Revealing the form and function of self-injurious thoughts and behaviors: A real-time ecological assessment study among adolescents and young adults. Journal of Abnormal Psychology, 118(4), 816–827. 10.1037/a0016948 [PubMed: 19899851]

Parak J, & Korhonen I (2014). Evaluation of wearable consumer heart rate monitors based on photopletysmography. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3670–3673. 10.1109/EMBC.2014.6944419

Patton GC, & Viner R (2007). Pubertal transitions in health. The Lancet, 369(9567), 1130–1139. 10.1016/S0140-6736(07)60366-3

Pearson JL, Stanley B, King CA, & Fisher CB (2001). Intervention research with persons at high risk for suicidality: Safety and ethical considerations. The Journal of Clinical Psychiatry, 62(Suppl25), 17–26.

Pew Research Center. (2018). Teens, social media & technology 2018. Retrieved from Pew Research Center website: http://assets.pewresearch.org/wp-content/uploads/sites/14/2018/05/31102617/PI_2018.05.31_TeensTech_FINAL.pdf

Piantadosi S, Byar DP, & Green SB (1988). The ecological fallacy. 12.

Plemmons G, Hall M, Doupnik S, Gay J, Brown C, Browning W, … Williams D (2018). Hospitalization for suicide ideation or Attempt: 2008–2015. Pediatrics, 141(6), e20172426 10.1542/peds.2017-2426 [PubMed: 29769243]

Prinstein MJ, Nock MK, Simon V, Aikins JW,L S, & Spirito A (2008). Longitudinal trajectories and predictors of adolescent suicidal ideation and attempts following inpatient hospitalization. Journal of Consulting and Clinical Psychology, 76(1), 92–103. 10.1037/0022-006X.76.1.92 [PubMed: 18229987]

Ridgers ND, Timperio A, Brown H, Ball K, Macfarlane S, Lai SK, … Salmon J (2018). Wearable activity tracker use among australian adolescents: Usability and acceptability study. JMIR MHealth and UHealth, 6(4), e86 10.2196/mhealth.9199 [PubMed: 29643054]

Rodríguez-Blanco L, Carballo JJ, & Baca-García E (2018). Use of Ecological Momentary Assessment (EMA) in Non-Suicidal Self-Injury (NSSI): A systematic review. Psychiatry Research, 263, 212–219. 10.1016/j.psychres.2018.02.051 [PubMed: 29574356]

Rogers ML, Chu C, & Joiner T (2019). The necessity, validity, and clinical utility of a new diagnostic entity: Acute suicidal affective disturbance. Journal of Clinical Psychology, 75(6), 999–1010. 10.1002/jclp.22743 [PubMed: 30632615]

Saunders KEA, & Hawton K (2006). Suicidal behaviour and the menstrual cycle. Psychological Medicine, 36(7), 901–912. 10.1017/S0033291706007392 [PubMed: 16573848]

Schuck A, Calati R, Barzilay S, Bloch-Elkouby S, & Galynker I (2019). Suicide Crisis Syndrome: A review of supporting evidence for a new suicide-specific diagnosis. Behavioral Sciences & the Law, 37(3), 223–239. 10.1002/bsl.2397 [PubMed: 30900347]

Schwartz S (1994). The fallacy of the ecological fallacy: The potential misuse of a concept and the consequences. American Journal of Public Health, 84(5), 819–824. 10.2105/AJPH.84.5.819 [PubMed: 8179055]

Shah NH, Milstein A, & Bagley SC (2019). Making Machine Learning Models Clinically Useful. JAMA. 10.1001/jama.2019.10306

Shiffman S, Hufford M, Hickcox M, Paty JA, Gnys M, & Kassel JD (1997). Remember that? A comparison of real-time versus retrospective recall of smoking lapses. Journal of Consulting and Clinical Psychology, 65(2), 292–300. 10.1037/0022-006X.65.2.292.a [PubMed: 9086693]

Shinsugi C, Stickley A, Konishi S, Ng CFS, & Watanabe C (2015). Seasonality of child and adolescent injury mortality in Japan, 2000–2010. Environmental Health and Preventive Medicine, 20(1), 36–43. 10.1007/s12199-014-0421-7 [PubMed: 25358906]

Shiyko MP, Lanza ST, Tan X, Li R, & Shiffman S (2012). Using the time-varying effect model (TVEM) to examine dynamic associations between negative affect and self confidence on smoking urges: Differences between successful quitters and relapsers. Prevention Science, 13(3), 288–299. 10.1007/s11121-011-0264-z [PubMed: 22246429]

Silvers JA, McRae K, Gabrieli JDE, Gross JJ, Remy KA, & Ochsner KN (2012). Age-related differences in emotional reactivity, regulation, and rejection sensitivity in adolescence. Emotion, 12(6), 1235–1247. 10.1037/a0028297 [PubMed: 22642356]

Steinberg L, Graham S, O'Brien L, Woolard J, Cauffman E, & Banich M (2009). Age differences in future orientation and delay discounting. Child Development, 80(1), 28–44. 10.1111/j.1467-8624.2008.01244.x [PubMed: 19236391]

Stisen A, Blunck H, Bhattacharya S, Prentow TS, Kjærgaard MB, Dey A, … Jensen MM (2015). Smart devices are different: Assessing and mitigating mobile sensing heterogeneities for activity recognition. Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems - SenSys '15 10.1145/2809695.2809718

Stoica P, & Moses RL (2005). Spectral analysis of signals. Upper Saddle River, N.J: Pearson/Prentice Hall.

Sun J, Guo X, Ma J, Zhang J, Jia C, & Xu A (2011). Seasonality of suicide in Shandong China, 1991–2009: Associations with gender, age, area and methods of suicide. Journal of Affective Disorders, 135(1), 258–266. 10.1016/j.jad.2011.08.008 [PubMed: 21875753]

Tan X, Shiyko MP, Li R, Li Y, & Dierker L (2012). A time-varying effect model for intensive longitudinal data. Psychological Methods, 17(1), 61–77. 10.1037/a0025814 [PubMed: 22103434]

Thorpy M, Chesson A, Derderian S, Kader G, Millman R, Potolicchio S, … Strollo PJ (1995). Practice parameters for the use of actigraphy in the clinical assessment of sleep disorders. Sleep, 18(4), 285–287. [PubMed: 7618028]

Thullen MJ, Taliaferro LA, & Muehlenkamp JJ (2016). Suicide ideation and attempts among adolescents engaged in risk behaviors: A latent class analysis. Journal of Research on Adolescence, 26(3), 587–594. 10.1111/jora.12199 [PubMed: 28581648]

Torous J, Larsen ME, Depp C, Cosco TD, Barnett I, Nock MK, & 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. Current Psychiatry Reports, 20(7), 51 10.1007/s11920-018-0914-y [PubMed: 29956120]

Torous J, & Walker R (2019). Leveraging Digital Health and Machine Learning Toward Reducing Suicide—From Panacea to Practical Tool. JAMA Psychiatry. 10.1001/jamapsychiatry.2019.1231

Trull TJ, & Ebner-Priemer U (2013). Ambulatory Assessment. Annual Review of Clinical Psychology, 9(1), 151–176. 10.1146/annurev-clinpsy-050212-185510

Van Orden KA, Witte TK, Cukrowicz KC, Braithwaite SR, Selby EA, & Joiner TE (2010). The interpersonal theory of suicide. Psychological Review, 117(2), 575–600. 10.1037/a0018697 [PubMed: 20438238]

Walsh CG, Ribeiro JD, & Franklin JC (2018). Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning. Journal of Child Psychology and Psychiatry, 59(12), 1261–1270. 10.1111/jcpp.12916 [PubMed: 29709069]

Weinstein SM, Mermelstein RJ, Hedeker D, Hankin BL, & Flay BR (2006). The time-varying influences of peer and family support on adolescent daily positive and negative affect. Journal of Clinical Child and Adolescent Psychology, 35(3), 420–430. 10.1207/s15374424jccp3503_7 [PubMed: 16836479]

Wen CKF, Schneider S, Stone AA, & Spruijt-Metz D (2017). Compliance With Mobile Ecological Momentary Assessment Protocols in Children and Adolescents: A Systematic Review and Meta-Analysis. Journal of Medical Internet Research, 19(4), e132 10.2196/jmir.6641 [PubMed: 28446418]

Wenzel A, & Beck AT (2008). A cognitive model of suicidal behavior: Theory and treatment. Applied and Preventive Psychology, 12(4), 189–201. 10.1016/j.appsy.2008.05.001

Wright AGC, Gates KM, Arizmendi C, Lane S, Woods WC, & Edershile EA (in press). Focusing personality assessment on the person: Modeling general, shared, and person specific processes in personality and psychopathology. Psychological Assessment.

Yarkoni T, & Westfall J (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. Perspectives on Psychological Science, 12(6), 1100–1122. 10.1177/1745691617693393 [PubMed: 28841086]

Yen S, Weinstock LM, Andover MS, Sheets ES, Selby EA, & Spirito A (2013). Prospective predictors of adolescent suicidality: 6-month post-hospitalization follow-up. Psychological Medicine, 43(5), 983–993. 10.1017/S0033291712001912 [PubMed: 22932393]

Youngstrom EA, Halverson TF, Youngstrom JK, Lindhiem O, & Findling RL (2018). Evidence-based assessment from simple clinical judgments to statistical learning: evaluating a range of options using pediatric bipolar disorder as a diagnostic challenge. Clinical Psychological Science, 6, 243–265. 10.1177/2167702617741845 [PubMed: 30263876]

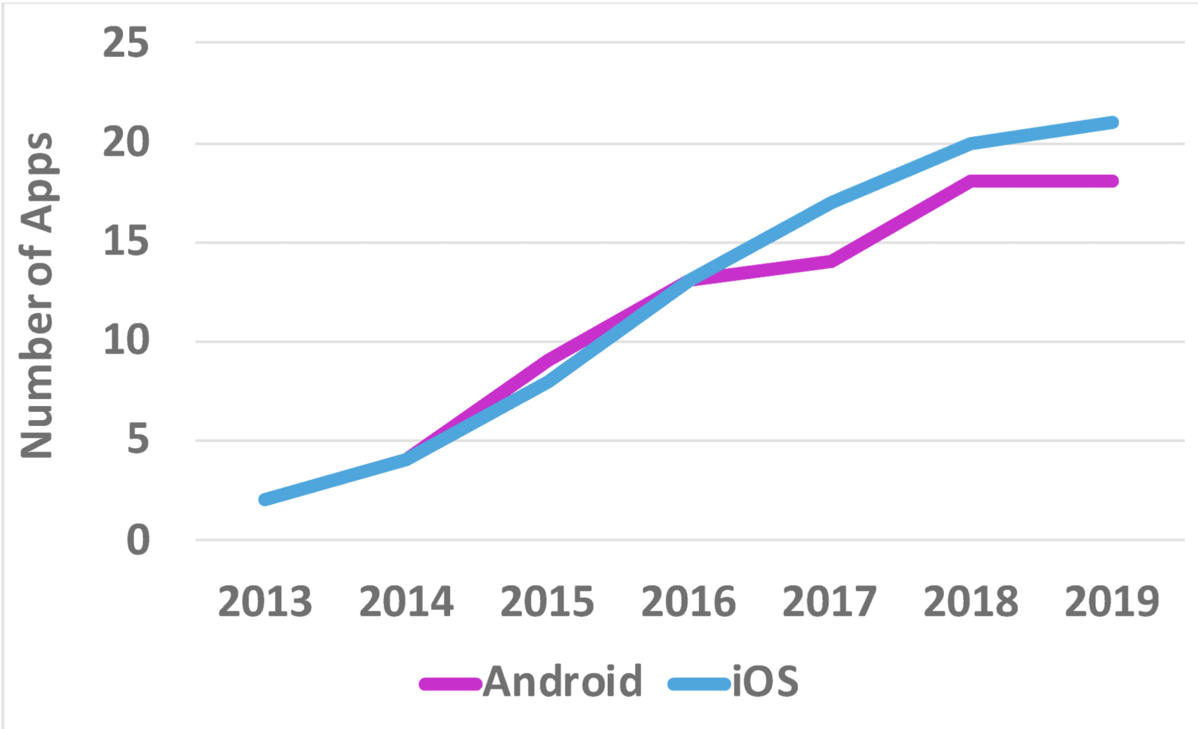

Figure 1. Cumulative number of real-time monitoring apps available, by date of first release

Note: Includes all apps available commercially (i.e., Google Play Store or Apple App Store) and through other public repositories (e.g., GitHub).