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The use of advanced technology and statistical methods to predict and prevent suicide

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Abstract

In the past decade, two themes have emerged across suicide research. First, according to meta-analyses, the ability to predict and prevent suicidal thoughts and behaviours is weaker than would be expected for the size of the field. Second, review and commentary papers propose that technological and statistical methods (such as smartphones, wearables, digital phenotyping and machine learning) might become solutions to this problem. In this Review, we aim to strike a balance between the pessimistic picture presented by these meta-analyses and the optimistic picture presented by review and commentary papers about the promise of advanced technological and statistical methods to improve the ability to understand, predict and prevent suicide. We divide our discussion into two broad categories. First, we discuss the research aimed at assessment, with the goal of better understanding or more accurately predicting suicidal thoughts and behaviours. Second, we discuss the literature that focuses on prevention of suicidal thoughts and behaviours. Ecological momentary assessment, wearables and other technological and statistical advances hold great promise for predicting and preventing suicide, but there is much yet to do.

Introduction

Meta-analyses present a bleak view of the ability to predict[1,2] and prevent[3–6] suicidal thoughts and behaviours. Even the most optimistic interpretation of the literature suggests at best moderate effect sizes across prediction and prevention. In the past five years, there has been a trend towards the view that smartphones[7–10], wearable devices[11–14], machine learning[15,16] and digital phenotyping[17–19] might be leveraged to improve prediction and

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Author contributions

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Competing interests

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prevention of suicidal thoughts and behaviours. This optimism is understandable because these technologies are widely available and easily leveraged to collect data, and although not all papers present an overly ‘rosy’ picture of these technologies and methodologies, the general tendency of these review and commentary papers is to be more positive than is warranted on the basis of empirical evidence.

In this Review, we provide an up-to-date overview of research that has used advanced technology and statistical methodology to understand, predict and prevent suicidal thoughts and behaviours. First, we discuss how various technologies and statistical methodologies (such as smartphones, wearables and digital phenotyping) have been applied to prediction and the potential remaining challenges. Next, we consider the lack of knowledge transfer from prediction studies to intervention studies and discuss how technology (smartphones) can be used to deliver an optimal intervention at the optimal time (by using advanced methodologies like just-in-time adaptive interventions). We conclude by discussing the promise and limitations of these technologies to provide a realistic view of what might be possible in the future.

Using technology to improve prediction

In this section, we discuss two technologies that feature prominently in work on suicide prediction: smartphones, especially in their capacity to collect real-time ecological momentary assessment (EMA) data, and wearable sensors, especially in their capacity for integration with EMA data. We focus primarily on the work using smartphones for ‘active’ data collection, which refers to actively asking questions via smartphone. Smartphones are also capable of ‘passive’ data collection (Box 1), but research on suicidal thoughts and behaviours based on passive data is in its infancy, with grant-funded studies in progress but not yet published. We primarily focus on EMA given its ability to capture real-time, within-day fluctuations in suicidal thoughts and associated risk and protective factors via multiple assessments throughout the day, but we include some daily diary studies (once-per-day assessment of constructs that have occurred over the past day; Fig. 1) where relevant. Several review papers have summarized work using EMA to study suicidal thoughts and behaviours[8,20,21]. Our goal is not to duplicate the in-depth summary provided by these papers, but rather to provide a high-level perspective of the major themes across the literature on suicidal thoughts and behaviours that use EMA.

Smartphone-based ecological momentary assessment

EMA studies (also called experience sampling) initially used ‘low tech’ options such as a physical beeper to signal participants to complete assessments on paper. This method evolved to technology such as personal digital assistants, and now smartphones, which can be used both to signal participants to complete assessments and to record assessment responses. Smartphone-based EMA has been particularly important for suicide research compared to other fields because suicidal thinking and its associated risk factors can fluctuate rapidly[22], and smartphones are ideal to capture these fluctuations as they happen. Indeed, multiple theories include dynamic transitions in risk states or fluctuations in risk[23]. For example, ideation-to-action frameworks[24] such as the three-step theory[25] feature dynamic transitions from having suicidal thoughts to acting on those thoughts. The fluid vulnerability theory[26] places heavy emphasis on the temporal dynamics of rapidly changing risk for suicide. Other work focuses on the 'suicide crisis' – a period of intense distress and agitation that can begin rapidly and might signal acute risk for suicidal thoughts and behaviours[27–29]. Because many people keep their smartphone within arm's reach, there might be a better chance of capturing suicidal thinking and its risk and protective factors as they occur via smartphone-based EMA compared to paper and pencil versions, or other digital versions that require a separate study device, which could be cumbersome for participants to carry with them.

Studies that assess the feasibility and acceptability of studying suicidal thoughts and behaviours using EMA in suicidal adolescents[30,31] and adults[32,33] after discharge from psychiatric care (either inpatient or psychiatric emergency department) as well as in a fully online sample[34] generally find relatively high rates of survey adherence that tends to drop with increased study duration. For example, in one study, daily diary compliance dropped by 20% from the first week (~80% of surveys completed) to the fourth and final week (~60% of surveys completed)[30]. The lower compliance seen later in longer studies is not necessarily problematic, provided that the missed surveys are at random times rather than times of interest. For example, it would be problematic if participants were less likely to complete surveys when feeling distressed in week 4 compared to week 1; it would be less problematic if participants were just less likely to complete surveys as the study goes on, leading to fewer data but not erroneous conclusions based upon the type of data collected later in the study.

Importantly, EMA probably leads to identifying more recall of 'true' experiences of suicidal thinking and does not cause participants to have more suicidal thoughts or encourage iatrogenic reports of suicidal thinking[35,36]. In one study, adolescents discharged from acute psychiatric care for suicide risk tended to report more suicidal thinking via 28-day EMA than aggregated report at the end of the EMA period[36]. It might be that it is difficult to recall every instance of suicidal thinking (especially if the thoughts are fleeting) in a retrospective report, an issue less present with in-the-moment EMA reports. Moreover, asking about suicidal thinking in EMA studies does not cause participants to express more frequent or more severe suicidal thinking[37,38]. For example, one study found no differences on follow-up reports of suicidal thinking or behaviour at the end of the study period between participants who were randomized to complete either two weeks of EMA assessments of negative affect or two weeks of EMA assessments of negative affect and suicidal thinking[37]. This result is in line with non-EMA studies that show that asking about suicidal thoughts and behaviours does not increase risk for suicidal thoughts and behaviours[39].

EMA studies that characterize the real-time occurrence of suicidal thinking show that suicidal thinking varies considerably over short periods of time[22,40]. For example, in one EMA study nearly one-third of all reports of suicidal thinking differed by a standard deviation or more from the response given just 4 to 8 hours previously[22]. This work is important because if suicidal thinking can vary within just a few hours, a single response summarizing suicidal thinking over weeks or months would not be able to accurately capture the changes in suicidal thinking that occurred over this time. Yet many widely used measures of suicidal thinking, such as the Beck Scale for Suicide Ideation[41], ask for such a rating. Moreover, the heuristics people rely upon when answering these single-response items are not well understood. It could be that people answer on the basis of their most severe, or most recent, experience of suicidal thinking. Identifying what aspects of suicidal thinking people reference when answering surveys about periods of time during which there were fluctuations in suicidal thinking would help researchers to better understand what exactly these measures assess.

Variability in suicidal thinking not only motivates the use of EMA but is itself an important predictive variable. For example, variability in suicidal thinking (defined by the root mean square of successive differences of EMA reports) across multiple periods over two years did not change over time (that is, those who had highly variable suicidal thinking at the beginning of the study still had highly variable suicidal thinking at the end of the study)[42]. Furthermore, those who had more variable suicidal thinking were more likely to experience suicidal thoughts when exposed to a stressor[42]. Additionally, variability of suicidal thinking during an inpatient stay predicted suicide attempts after discharge from the hospital, above and beyond baseline assessment data[43]. Variability in affect (assessed with EMA) also predicts long-term suicide outcomes[44–47]. For example, more variable negative affect (shame and self-hatred) assessed during the inpatient period was predictive of greater odds of suicide attempt after discharge[45]. Thus, EMA data can improve upon traditional person-level data (for example, baseline assessments) in predicting longitudinal outcomes. It is important to note that consistently high or consistently low mean levels of suicidal ideation would both have low variability. Thus, the mean level of ideation should be examined in conjunction with variability to get a more complete picture of the dynamic nature of suicidal thinking over time[45].

Thus far we have primarily discussed studies that used EMA to better characterize suicidal thinking. There is also a small literature that moves from characterization of suicidal thinking to short-term prediction of suicidal thinking using relatively simple predictive (typically bivariate or multivariate) models[48,49] or more complex network models[50]. Negative affect is arguably the most studied predictor of suicidal thinking in EMA studies[51]. This focus on affect makes logical sense given that affect varies over short periods of time, creating the same assessment issues as those associated with suicidal thinking – assessments over timeframes longer than the amount of time for which an affect state might persist (for example, assessing negative affect over the past week when it changes from hour to hour) can lead to inaccurate assessments. Thus, EMA is ideal for studying affect and its relationship to suicidal thinking. Negative affect has been associated with suicidal thinking both contemporaneously (measured at the same time point) and temporally (negative affect is measured before suicidal thinking)[48,52–55]. Other EMA studies have assessed risk factors for suicidal thoughts and behaviours that fluctuate over time, such as state impulsivity[49] and sleep difficulties[56–58]. A growing number of EMA studies indicate that fluctuations in sleep problems predict suicidal thoughts the next day[56,58,59] – highlighting a short-term association not previously examined.

Only a small number of smartphone-based daily diary studies have assessed factors that are associated with decreased, rather than increased, risk for suicidal thoughts and behaviours. These studies find that higher daily social support[60] and stronger perceptions of coping helpfulness[61] are associated with less severe daily suicidal thinking. Adaptive coping strategies (such as reappraisal) buffer the effect of daily stress on daily suicidal thinking[62]. There is a need for more work in this area, especially work that uses EMA instead of daily diary methods. A better understanding of resilience factors will provide additional modifiable intervention targets as well as a more complete understanding of individuals at risk for suicide.

Much of the EMA work to date has either not been theory-driven, or has focused on just a few (of many) theories of suicide. Arguably, the theory that has been tested the most using EMA is the interpersonal theory of suicide[63], which hypothesizes that the desire to die by suicide is the result of believing that one is a burden to others and does not belong toa social group, and hopelessness that this situation will change. For example, one study found that the interaction between perceived burdensomeness and thwarted belongingness at one time point predicted active suicidal thinking (wanting to kill oneself) at the next time point. Additionally, thwarted belongingness alone (and not its interaction with perceived burdensomeness) at one time point predicted passive suicidal thinking (wishing to be dead) at the next time point[40]. This is an interesting finding given that the interpersonal theory of suicide[64] describes both perceived burdensomeness and thwarted belonging as direct predictors of passive ideation, which is the precursor to active ideation. Work like this suggests that EMA provides an opportunity to test how established theories of suicide perform when assessed in everyday life and the utility of these theories for short-term prediction.

In summary, smartphone-based EMA is a feasible and safe way to assess and characterize suicidal thoughts and behaviours, as well as risk and protective factors that predict short-term changes in suicidal thinking that would be missed with traditional paper-and-pencil self-report measures. Notably, EMA designs move the field beyond between-person risk factors to identify within-person risk and protective processes, which addresses the ecological fallacy (incorrect inference about an individual from data obtained at the group level) and provides useful applications for clinical care (providers can understand risk for an individual based on their own baseline). Smartphone-based EMA studies also have the potential to clarify the relationship between factors of interest on a much finer and proximal temporal scale than was previously possible. This is important because it cannot be assumed in the absence of empirical data that factors traditionally associated with suicidal thoughts and behaviours on a much broader timescale (for example, six months or a year) have similar relevance across much briefer temporal intervals (for example, hours). Moreover, EMA designs can be informative about the strength of the association at this temporal scale, which probably differs from what is observed over longer periods of time. This briefer temporal scale is precisely where the clinical value is greatest insofar as it more closely mirrors the predictive window of concern for clinicians conducting suicide risk assessments.

Wearables

In the past decade there has been an increase in the availability of wearable monitoring devices, typically worn on the wrist like a watch, that can passively collect real-time physiological or behavioural data. These devices range from research-grade wearable devices (for example, the Philips Spectrum Actiwatch and Empatica E4) to commercially available devices that can also provide data to researchers (for example, Fitbit, Polar or Garmin devices). These wearables can assess a variety of constructs such as sleep, movement or autonomic activity, depending on the sensors available (Box 2). Wearables can be used to identify risk for suicidal thoughts and behaviours when self-report is not feasible (for example, because it is probably difficult to self-monitor the highly distressing time leading up to a suicide crisis, or because an individual is unlikely to pause for a survey in the middle of an argument that might precipitate suicidal behaviour) or to improve prediction of suicidal thoughts and behaviours when combined with EMA or other methods. Importantly, these wearable devices are unlikely to identify a ‘signature’ for suicide, given that there is probably not a biological signal of risk for suicidal thoughts and behaviours and that suicidal behaviour is multi-determined and has a low base-rate. Rather, wearable devices can detect correlates of the psychological states surrounding the occurrence of suicidal thoughts and behaviours, which can provide insight into whether someone is having suicidal thoughts at any given moment.

Wearable devices have been primarily used to predict suicidal thoughts and behaviours in the context of two psychobiological risk factors: sleep and dysregulated emotion. The link between subjectively assessed poor sleep and increased risk for suicide[65–67] (including studies that used EMA or daily diary assessments of subjective sleep quality[56,58,59]) provides a strong foundation for work that explores whether objective measures of sleep are associated with suicidal thoughts and behaviours. In one study, greater variability in objective sleep timing assessed using actigraphy (a method of approximating sleep–wake patterns using a wrist-worn sensor) predicted more severe suicidal thinking in undergraduates at seven-day and 21-day follow-ups[68]. Further, in adults with major depression and recent suicidal thoughts or behaviours, shorter sleep duration assessed via EMA and actigraphy predicted greater next-day suicidal thinking[59]. However, in high-risk adolescents, sleep parameters objectively assessed using actigraphy were either unassociated with next-day suicidal thinking, or, in the case of the amount of time awake after initial sleep onset, associated in the opposite direction from hypothesized (more time awake after sleep onset predicted lower suicidal thinking)[56]. These studies do not converge to provide a coherent picture of which objective sleep parameters are associated with suicidal thinking. Moreover, some of the most robust sleep-related factors that are associated with suicidal thoughts and behaviours (such as nightmares[69] and rumination before sleep[56]) are not easily assessed with objective measures.

In terms of dysregulated emotion, self-reported psychological overarousal (agitation[70]) and difficulties regulating this over-arousal[71] are risk factors associated with suicidal thoughts and behaviours. Given that intense emotion and emotion regulation are both difficult to self-report, especially in the moment that they occur, research using wearables has attempted to assess these constructs passively. For example, one study found that assessment of skin conductance responses (a marker of in-the-moment physiological arousal) adds to the ability of EMA to predict the severity of suicidal thinking but not the presence/absence of suicidal thinking[72]. This finding suggests that skin conductance might improve prediction of some, but not all, outcomes related to suicidal thoughts and behaviours.

Greater heart rate variability (variability in the time between heartbeats) is often seen as an index of more adaptive use of emotion regulation[73]. One study found that lower heart rate variability (poorer regulation) measured over a seven-day period was associated with smaller decreases in severity of suicidal thoughts and behaviours (a composite score on the Columbia Suicide Severity Rating Scale) at the end of the seven-day period[74]. This finding mirrors those found using self-report methods of emotion regulation, providing some convergent validity between self-report and psychophysiological methods. Furthermore, this finding demonstrates this association at a finer temporal scale than prior self-report studies, more proximal to an acute suicidal crisis.

In sum, the work using wearable devices to identify correlates of suicide risk factors is in its infancy. This work has found support for factors such as sleep and emotion regulation, providing some corroboration of the self-report assessments of these constructs and some convergent validity for the use of these methods. Because wearables require less effort from participants or patients than active EMA, they have the potential to monitor risk validly in a less burdensome way.

Barriers and potential solutions

Our Review thus far suggests that there is reason to be optimistic that smartphone-based EMA and wearable devices will improve the ability to understand and predict suicidal thoughts and behaviours. However, there are still substantial barriers between what is currently possible with this technology and what might ultimately be possible. These challenges and limitations need to be considered in study design and interpretation of data.

Because smartphone-based EMA research on suicide is still quite new, a basic understanding of how to do this work is lacking. For example, there is only limited validation of EMA assessments of suicidal thinking[54]. Thus, more research is needed to validate the psychometrics of the items currently used to assess suicidal thoughts, to explore other items that might more optimally capture the experience of suicidal thinking (such as a person's wish to live compared to their wish to die[75]), and to clarify the optimal temporal scales for assessing these constructs. Other lingering issues about best practices for studying suicide using EMA include how to improve engagement with surveys and to what extent poor adherence might impede accurate characterization of suicidal thinking (for example, whether people are less likely to complete an EMA survey when they are acutely suicidal). The clearest way to address this barrier is by considering EMA survey length and designing a compensation structure to maximize engagement. Another broader challenge, which is applicable to all suicide research but particularly relevant to suicide research using EMA, is how to respond to imminent suicide risk when it is reported (Box 3).

A final challenge regarding EMA is sample representativeness. Smartphone-based EMA can be used only with individuals who have a smartphone, which covers 85% of all adults in the USA[76] and nearly 80% of all individuals worldwide[77]. Although these numbers are quite high, it is important to consider who is left out when only smartphone owners are included. For example, only 61% of adults over age 65 in the USA and only 76% of those who make less than US$30,000 a year own a smartphone[76]. Thus, older and lower-resourced individuals might be systematically excluded from EMA research, which could magnify mental health disparities in underrepresented and lower-resourced populations that might be at greater risk for suicidal thoughts and behaviours[78–80]. However, it is possible to deliver EMA via text messaging, which is more accessible as it only requires a cellphone (owned by 92% of adults over 65 in the USA and 97% of those making less than US$30,000 a year[76]). Finally, as smartphones continue to become more affordable, researchers can purchase loaner phones for those who do not have a smartphone but are open to using one. Of course, this still excludes those who do not want to use a smartphone or do not want to use their smartphone in a research study.

Although wearables offer an opportunity to collect an unprecedented amount of data, more data are not always better. It is crucial that researchers carefully consider whether the addition of wearables to an EMA study is worth the added cost to researchers and burden to both participants and researchers. This requires a realistic assessment of the extent to which data from wearables can improve understanding and prediction beyond self-report data. It is also important to be realistic about whether wearables will ever be useful without any self-report data collected at the same time (to assess the suicide-related criterion). A potential solution to the necessary coupling of wearable and self-report data is to use the wearable device to collect self-report data by, for example, using an event marker (a button on the device to annotate data, which many watches have) to signal events of interest, such as a period of intense suicidal thought. A more advanced option is ‘micro-EMA’[81], which involves sending surveys via the smartwatch display.

Beyond these issues with wearables – which are somewhat more specific to suicide research than other fields where the interest is in factors that can be assessed without self-report – there are a variety of issues that all areas of psychology must struggle with. For example, more sophisticated algorithms to identify artefacts and to process features from wearables are needed. The common sensors on wearable devices are quite ‘noisy’, especially because they are often placed in less-than-ideal locations[82]. It is therefore important to recognize the limitations inherent to any method and to consider what is and is not realistically possible to detect using any given device. These limitations have implications for study design. For example, statistical power is partly driven by sample size. However, it is also driven by the precision of the measures employed. Therefore, the ‘noisiness’ inherent in some ambulatory measures is an important study design consideration for determining statistical power. A multimethod approach (for example, combining a self-report sleep diary with a wearable) might provide more accurate assessment of constructs of interest. Moreover, technology will continue to improve, probably leading to more accurate wearable devices in the future.

Finally, wearable devices are not equally accurate on all people. Heart rate sensors that use green light to detect blood flow (photoplethysmograph sensors; Box 2) may not work as well on people with darker skin[83,84], which introduces systematic bias into this research. Other studies[85] find differences in accuracy based on activity type (for example, rest and prolonged high heart rate are detected more accurately than are changes in activity). Recognizing systematic bias with some wearable devices can guide device selection for more inclusive psychological science practices. The issue of racial biases in wearables that use photoplethysmograph sensors is closely related to that in pulse oximeters (a related technology), which has received widespread attention in the academic literature[86] and the popular media[87]. Thus, it may be that what is learned in addressing racial bias in pulse oximeters could be applied to photoplethysmograph sensors in the future.

Statistical advances in prediction

EMA and wearable data collection methodologies give researchers an amount of data not frequently seen in psychology. For example, most actigraphy sensors record data at 32 Hz (32 measurements per second), meaning that 28 days of data for a single participant will total 77,414,400 rows of raw data. Even when these raw data are aggregated into features such as activity within a minute, there are still millions of data points per person. Although EMA and wearables offer an unprecedented opportunity to obtain an in-depth picture of experiences among individuals with suicidal thoughts and behaviours, these methods also require researchers to move beyond the data analysis methods used with far smaller datasets. In this section we focus on two advanced statistical methodologies that have been applied in the suicide literature: phenotyping or subgrouping of risk for suicidal thoughts and behaviours, and using machine learning algorithms to predict suicidal thoughts and behaviours. Other analyses are described in Box 4.

Phenotyping or subgrouping

Subtyping involves identifying relatively homogeneous groupings of individuals from a relatively heterogeneous group, typically using mixture models (latent class analysis or latent profile analyses) or clustering analyses (for example, *k*-means clustering) applied to individual-level data (such as baseline data or summary metrics based on EMA data). Subtyping has considerable utility for suicide research because parsing the heterogeneity of presentations of suicidal thoughts and behaviours[88] would allow researchers to identify different strata of suicide risk (low versus medium versus high) or to identify different configurations of suicide risk (for example, different sets of risk factors that put individuals at ‘high’ risk for suicide). The idea that subtypes of different presentations of suicidal thoughts and behaviours could be identified has been around for 60 years[89]. However, there has been a resurgence of interest in subtyping owing to the rise of digital phenotyping[18,90], which involves the use of smartphone (such as GPS, call or text logs, or survey data) and wearable sensing data. Indeed, smartphone-based EMA data are particularly relevant for subtyping because they enable people to be grouped by how their suicidal thinking ebbs and flows over a period of time[91,92]. Importantly, the different sets of terminology for different subgrouping analyses can obscure the underlying notion that these methods all effectively reach the same goal through different mathematical means. Moreover, digital phenotyping is not a mathematical model itself but rather refers to the types of predictor used in any kind of clustering analysis. Therefore, although the mathematical approaches differ in some ways, we focus on their commonalities (identification of subgroups) and discuss the relevant research on subgrouping without distinguishing the specific mathematical model used.

Research using clustering analysis of different expressions of suicidal thinking has found that those with chronically high suicidal thinking (high mean and low variability in suicidal thinking across assessment points) tend to be at the highest risk for suicidal thoughts and behaviours. For example, across four assessments (during hospitalization and at 3, 6 and 12 months after hospitalization) a subgroup of adolescent inpatients who had persistently high levels of suicidal thinking were the most likely to reattempt suicide[93]. A study using more frequent EMA assessments found a similar pattern among samples of adult inpatients and adults who had recently attempted suicide[94]; that is, the subgroup of participants who had persistently high suicidal thinking was most likely to have recently attempted suicide[94].

Other studies have used longitudinal (but not EMA) data to examine subgroups based on different trajectories of suicide risk factors, such as childhood aggression[95], fearlessness about death[96] and capability for suicide more broadly[97]. For example, one study[97] showed that the capability for suicide (for example, fearlessness of death and high pain tolerance) is relatively stable over time. This work suggests that suicide capability does not necessarily need to be assessed frequently. Although one study found that suicide capability might fluctuate from hour to hour[98], that study's assessment of suicide capability includes an item ("Today I could have killed myself if I wanted to") that probably reflects both capability and opportunity. The opportunity to attempt suicide is likely to fluctuate over time (for example, depending on whether others are present during the day). There are clear signs that more work using clustering methods on longitudinal data are forthcoming, given that there are several published study protocols describing such work[99–101]. Together, this work suggests that it is possible to identify meaningful subgroups of individuals that can both inform research on risk for suicidal thoughts and behaviours and provide a signal for which factors merit more (versus less) frequent assessment.

However, there are several open questions regarding phenotyping methods. For example, it is not known whether class membership changes over time and whether changes in class membership indicate changes in risk or a critical period in which suicidal thoughts or behaviours are likely to occur. Moreover, there are unique challenges to the digital phenotyping aspect of clustering. First, even the most expansive digital phenotyping approaches cannot capture all possible data. Suicidal thoughts and behaviours are complex, multi-determined constructs that might not easily be captured via indirect metrics of psychosocial functioning such as text-messaging logs and GPS. Second, despite the opportunities presented by digital phenotyping, the hype has outpaced the empirical evidence. Indeed, there have been far more papers discussing the promise of digital phenotyping for suicide than have used digital phenotyping to study suicide. At the beginning of the second quarter of 2022, PubMed had 14 papers under the search terms 'digital phenotyping' and suicide. Six of those papers were commentaries[17,102–106], four were feasibility studies[107–110] and two were study protocols[99,100]. This leaves only two papers that mention digital phenotyping and include empirical data. This is not to say that these papers are not useful – indeed, commentaries and feasibility studies are often the foundation of new areas of research. However, there is a clear need for more research that would enable proper evaluation of the utility of digital phenotyping and similar approaches.

Machine learning

Machine learning is a broad term that refers to methods that can be used to develop algorithms. 'Supervised' machine learning models, in which an outcome is known and models are created to predict that outcome, are those most often used in suicide research.

Several studies have used machine learning to identify who will attempt suicide in the future by creating a 'risk score' using all available data in the medical record (for example, past and current diagnoses, prior suicide attempt history and reasons for admission)[111–115]. Meta-analyses of these studies show generally strong accuracy in detection of suicidal thoughts and behaviours[116]. However, many prior studies examined model performance with retrospective data (that is, suicidal thought and behaviour status was already known). There is less research on how well these models perform prospectively when assessing new instances of suicidal thoughts and behaviours, which is a particular concern in the case of identifying state-sensitive risk factors for these outcomes. If these risk scores can predict future suicidal behaviours with a sufficient degree of accuracy, they can be added to medical record software and used to inform clinical care, as is currently done in other areas of medicine (for example, stroke risk scores[12]). Indeed, one study shows that providers are open to the use of such models in clinical practice[117].

Risk scores calculated from medical record data can also be used to improve the accuracy of traditional methods of assessing risk for suicide in clinical care (such as asking the patient or clinician to estimate risk for suicidal behaviours in the future)[118]. Because much of the machine learning work thus far has used medical record data, many of the strongest longitudinal predictors of suicidal thoughts and behaviours according to meta-analyses[119] – including unbearable psychological pain and perceived burdensomeness[120] – have not been applied to a machine learning framework. Future work might find that including these predictors improves the accuracy of risk scores.

Although machine learning is not often applied to the types of intensive longitudinal data we have discussed thus far (EMA and wearable data), there are clear applications for doing so. For example, machine learning might be useful to identify which factors, among a large set of factors assessed over time, are most relevant to imminent suicide risk. Identifying these factors could lead to a better understanding of risk for suicidal thoughts and behaviours and reduce the number of items presented to participants (which reduces burden) without losing the information gained from the assessments. Work that uses statistical modelling to identify patterns of risk in computerized suicide risk assessment measures, such as the computerized adaptive screen for suicidal youth (CASSY)[121], is already under way.

However, there is evidence that machine learning greatly inflates suicide prediction estimates[122] and leads to models that fit well only to the initial dataset used to create the algorithms[123]. This bias is especially notable when these models are used to predict outcomes in groups with minoritized identities (which are not well represented in algorithm development). One study found that the accuracy of prediction models using medical record data to predict suicide attempts was considerably less accurate for Indigenous and Black patients, as well as those who did not report their racial identity, relative to other groups[124]. This finding underscores the need for caution in applying these models in practice because of the biases that might exist in data included in machine learning models[125].

Suicide prevention

The ultimate focus of suicide research is to prevent suicide. A meta-analysis of the past 50 years and more of research has reported over 1,000 randomized controlled trials evaluating suicidal thoughts and behaviours as outcomes[3]. Despite this large literature, there has been little translational research that takes what has been learned in studies that use advanced technology and statistics to better understand suicidal thoughts and behaviours and apply it to suicide prevention. In some ways, this is understandable given the preliminary nature of some of these findings. However, there are some findings that are likely to be imminently applicable. At the same time, it is important to realistically contextualize how well the research on prediction can inform the research on prevention. Specifically, if technology does improve the prediction of suicidal thoughts and behaviours, it does not necessarily mean that improvements in prevention will follow[126]. Indeed, knowing that someone is currently suicidal in the moment (for example, via EMA or a signal of distress from a wearable) does not implicitly translate into knowing how to help someone become less suicidal. However, studies that aim to understand suicidal thoughts and behaviours, especially if done through a broader theoretical model, might improve both prediction (by identifying factors that signal risk) and prevention (by elucidating mechanisms that can reduce risk)[127].

In this section we describe how technology and advanced statistics have been used to improve suicide prevention, what might be possible using technology and advanced statistics in the future, and the limitations that must be addressed.

Mobile apps and ecological momentary intervention

Ecological momentary intervention involves delivering therapeutic content (usually via smartphone app) to patients during their daily life in a way that enables them to learn and practice psychotherapy skills[128]. Ecological momentary intervention can be integrated with EMA to deliver assessments (for example, of intervention effectiveness) along with therapeutic content. Ecological momentary intervention is becoming an increasingly important technology for therapeutic interventions[129], with some work in suicide prevention over the past five years[130,131].

Imminent suicide risk is difficult to treat and requires a higher level of care than a mobile app alone can provide. Accordingly, ecological momentary intervention might be useful in two broad cases. The first is when used as a standalone intervention, which might be most useful for those at lower suicide risk, those not yet suicidal (for example, as a prevention approach in school or community settings[132,133]) or those who cannot or will not access therapy through other more appropriate or effective means for their level of clinical severity. The second is when ecological momentary intervention is used to supplement or augment existing treatment for high-risk individuals, for example by providing opportunities to practice psychotherapy skills learned with a therapist[134]. The idea of practicing therapy skills outside sessions is not a new one. Indeed, phone coaching (reviewing skills outside a session with the goal of helping the patient to generalize the skills) is a key aspect of dialectical behaviour therapy. Smartphone technology can automate processes like this and apply them to other therapy modalities.

The existing landscape of ecological momentary interventions for suicide risk reduction consists of several categories of intervention, the most popular being apps that facilitate access to crisis services such as the national suicide prevention lifeline[131,135,136]. Other interventions attempt to digitize elements of traditional therapy. For example, one ecological momentary intervention enacts the Stanley–Brown Safety Planning Intervention[137], which provides participant-centred methods of coping for use in times of distress[138]. Another ecological momentary intervention enacts the Hope Box intervention. The Hope Box is traditionally a physical box with items that remind the patient of reasons for living, positive experiences, and other things that give hope that can be positive reminders in times of suicide crisis. There is support for digital versions of this intervention where users can include personalized pictures or audio messages to help them cope in a time of distress[139,140]. A final set of ecological momentary interventions involves combining skills taught by a therapist with an app that allows individuals to practice those skills as needed in daily life[130].

There are several benefits to interventions delivered via ecological momentary intervention. First, they can be easily accessed in a discreet manner, allowing suicidal individuals to access therapeutic content when it is needed in a less stigmatizing way than other options, such as presenting in a treatment setting. Second, ecological momentary intervention can make treatment more accessible to the large number of individuals with substantial barriers to traditional mental healthcare options. Third, ecological momentary interventions, especially if used in a prevention or risk-reduction context, might divert people from a higher level of care that they do not need, freeing up resources for those who need them. Together, studies of ecological momentary interventions might address possible ethical issues surrounding a lack of inclusion and representativeness seen in other studies[141]. For example, participants who are unwilling or unable to go to the psychiatric emergency department are not included in studies that recruit individuals from the emergency department. Ecological momentary interventions, which can be deployed remotely, might be more likely to include individuals who are typically underrepresented in traditional intervention research (for example, those in rural areas with less access to mental healthcare).

Although there are many benefits to treatment with ecological momentary interventions, there are also several drawbacks. Like any mobile app, it is difficult to maintain engagement, especially if app users have difficulty in using it. Moreover, it is still difficult to program ecological momentary interventions to deliver interactive and timely therapeutic content, which limits their use as a research tool.

The goal of ecological momentary interventions is to deliver interventions in daily life when they are needed most. However, this is probably also a time when someone is in considerable distress and might not recall that they should use the ecological momentary intervention. Technology that assesses suicide risk could conceivably be used to address this issue. Specifically, wearables could be used to provide information about when someone needs an intervention (for example, after a night of poor sleep when intense agitation is detected). This technology would be particularly useful if it could detect periods of elevated risk that is not yet so severe or distressing that intervention is less likely to be effective. However, there is no ‘signature’ for suicide and any assessment will capture proximal but transdiagnostic risk (for example, distress). Thus, in some cases, a wearable device might signal a false positive in suicide risk, triggering an intervention when it is not needed. If this happens often enough, users might lose trust in the intervention. Additionally, wearables add considerable burden to care (devices must be purchased, used and supported). So, much like other aspects involving technology, it is crucial to evaluate the cost–benefit ratio of using these devices in treatment.

Just-in-time adaptive interventions

As noted above, it might be difficult to remember to use a smartphone intervention during a time of intense distress (for example, in a suicide crisis state). Just-in-time adaptive interventions (JITAIs)[142] involve algorithms that deliver the correct amount of treatment at the time it is needed. JITAIs have been developed for depression[143], which suggests that similar JITAIs could be developed for other related behavioural health outcomes such as suicidal thoughts and behaviours[144]. However, there is no empirical work in this area. Ideally, JITAIs would deliver an intervention during the highly distressing time leading up to suicidal thoughts and behaviours ('suicide crises'), during which an individual might have difficulty accessing the skills learned in therapy without some sort of external aid.

JITAIs must establish tailoring variables that indicate when someone needs an intervention. For suicide prevention, the factors signalling imminent suicide risk must be known. This requirement creates a set of challenges that must be addressed before JITAIs can be a workable solution for suicide prevention. First, suicidal thinking changes rapidly[22], leaving a small window in which to identify when an intervention is needed if suicidal thinking is used as the tailoring variable. This challenge suggests a need to shift from targeting suicidal thinking directly to targeting upstream outcomes such as intense distress, which is less specific to suicide but is probably a more addressable outcome. Second, suicide risk is heterogeneous and multi-determined[120], meaning that different factors predict risk for different people. This challenge is not necessarily problematic because JITAIs can flexibly account for between-person differences. However, it complicates the process because more advanced statistical modelling and greater computational power would be needed to do so. Third, JITAIs to date have primarily focused on outcomes such as insufficient physical activity[145]. These outcomes are easier to define and monitor (because they are more objective) than suicide risk. Thus, it might be that JITAIs for suicide risk – or any mental health outcome[143] – will potentially be less effective than prior JITAIs owing to the challenges associated with measuring subjective outcomes. A more optimistic view of these challenges is also possible: the challenges with JITAIs and suicide risk, as laid out here, are well defined and potentially addressable with sufficient research. Indeed, research on suicide risk prediction might directly translate to improvements in JITAIs. For example, work using wearable devices to detect distress associated with suicidal thinking[72] might help to identify when someone is in need of an intervention; a JITAI could then send an intervention to a patient's smartphone when distress is high.

Personalized treatment with idiographic models

Idiographic models involve the intensive study of an individual. Idiographic models of human behaviour have been discussed generally for nearly 60 years[146] and specifically with respect to suicide more than two decades ago in studies of suicide notes[147] and single-case designs[148]. Both studies of suicide notes and single-case designs focus on extracting information about a single individual (or a group of individuals) to better understand that person. Such models have become increasingly popular because methods such as EMA allow researchers to collect in-depth data that maximize what can be learned about a person. Therapists could use idiographic models to create a personalized treatment based on problem prioritization or specific problematic links between factors[149]. Personalized treatment could be very useful for suicide risk, which is a multi-determined outcome that makes it difficult for any single treatment strategy to work for most people[120]. Idiographic models could be used to determine which contexts lead to suicidal thinking for a given individual, providing treatment targets that might be most effective for that individual. For example, some individuals might be more likely to experience suicidal thinking in the presence of interpersonal stressors (versus achievement-related stressors). These individuals might benefit from treatments geared towards interpersonal effectiveness. Someone who experiences suicidal thinking in response to achievement-related stressors might benefit from an intervention that targets perfectionism.

However, a truly idiographic model requires the collection of a large amount of data from an individual before a treatment can be personalized for them. Because it takes so long to 'get to know someone', a critical window for intervention could pass before an intervention is sufficiently tailored to be helpful. This might be especially true for idiographic models of suicidal behaviour, which would, in theory, require someone to engage in suicidal behaviour before the model can be established. This challenge can be overcome with methods such as group iterative multiple model estimation[150] that build models for individuals while also incorporating common features across individuals. One study[151] that used EMA data to construct idiographic models via group iterative multiple model estimation found that there was considerable heterogeneity in which risk factors predicted suicidal thinking over a few hours. Indeed, there was no risk factor that significantly predicted suicidal thinking for more than a tenth of the sample. This result suggests that there is considerable heterogeneity in the pathways that lead to suicidal thoughts.

In summary, there is promise in personalized predictive models and just-in-time treatment approaches. However, this promise will be realized only in the long term, given the current state of the science.

Summary and future directions

In the past decade, an impressive amount of research using advanced technology and statistical methods has reached several broad conclusions about the nature of suicide risk and how to prevent it. In terms of prediction, the body of research on EMA and suicide shows that it is feasible to repeatedly assess suicidal thoughts and related risk and protective factors, that some risk factors (such as negative affect) are associated with momentary ratings of suicidal thinking, and that EMA is useful for capturing person-level factors not easily assessed retrospectively (such as variability in affect). There is also great promise in combining EMA with wearable physiological and behavioural monitors that can provide objective information on behavioural indicators such as sleep. However, the benefit of integrating objective and subjective data is still unclear.

In terms of treatment, technology has the promise to supplement treatment, make treatment accessible for those who are not willing or able to access it otherwise, or act as a first-line treatment for those with less severe risk. However, there are technological and scientific hurdles that must be cleared first. In our opinion it is highly unlikely that technology will completely replace the human connection needed in therapy for those at high risk for suicide. Indeed, past studies have shown that rapport and therapeutic alliance are important factors determining treatment outcome[152–154]. Certainly, there is a role for technology to augment therapeutic skills, track symptom progress over time, and flag when someone might be at heightened risk. However, at a certain point, the human role will still be needed.

Going forward, research should test existing theories of suicide using EMA. For example, according to the hopelessness theory of suicide[155], suicide risk is the result of the combination of the occurrence of negative events and negative cognitive style (negative attributions about the cause of the event and negative inferences about the implications for the self and the future as a result of the event). Typically, theoretical components are assessed using a trait measure of attributions and inferences about hypothetical events. These measures capture the tendency to make certain attributions and inferences. By contrast, EMA can capture attributions and inferences about specific actual events, as they occur. EMA could also be used to test theories that focus on ‘suicide crisis states’ (the highly distressing period when one is imminently suicidal)[27,156] or ideation-to-action theories that capture the transition between having thoughts of suicide and acting on those thoughts[25]. Moreover, EMA is especially well positioned to examine theories that focus on the dynamic components of short-term changes in suicidal thinking. One example of such a theory is the fluid vulnerability theory[26,157], which conceptualizes risk for suicide as a non-linear process, consisting of baseline and higher-risk states that can be transitioned to as a result of external factors (such as negative life events).

At the same time, most of the theories in the suicide literature were created before EMA was a readily available tool. Therefore, existing theories need to be refined, or new theories created, to better capture short-term dynamic changes in suicide risk[127]. For example, existing theories say very little about the time-course of suicidal thoughts and behaviours (for example, what happens in the moments before suicidal thoughts or behaviours)[158,159].

There are several clear future research directions. First, researchers must determine how to leverage prediction and prevention work to improve clinical practice. This is a topic of discussion across psychology broadly, especially with respect to new approaches such as phenotyping and idiographic treatment[160]. For example, therapists report some hesitancy in using idiographic treatment approaches[161], and clinicians are more willing to act on information from a risk algorithm if the underlying risk data are provided to them[162]. These issues could be addressed by providing training to therapists in how to use the data provided to them and soliciting their input in the use of such approaches.

Second, more work is needed to develop validated measures that are sensitive to short-term change and to assess the factor structure of these measures. In other words, EMA is a method for studying constructs related to suicide risk, but the utility of this measure relies heavily on construct quality. Continuing to measure the same constructs with EMA in essentially the same manner that they have been studied for years is unlikely to advance understanding of the real-time occurrence of suicide risk. Additionally, more advanced modelling needs to be applied to these data. At the same time, it is important that these methods are used only when the research questions necessitate their use (rather than using the newest analytic approaches for the sake of novelty) and when basic understanding of the science and theory supports their use[163].

Third, advances at the interface of computer science, statistics and psychology are needed. For example, to use wearables to trigger an intervention when someone is very distressed, computer scientists must be able to reliably analyse wearable data in real time (for example, on the wearable itself or via a reliable Bluetooth-like connection to a smartphone), biostatisticians must develop models that can flexibly adapt to new information arriving in real time, and psychologists must develop a better understanding of how best to assess the factors that characterize a period of high distress.

Ultimately, there is no guarantee that technology will live up to all the possibilities expressed here and in other papers, and a technological solution will never directly replace (but will hopefully supplement and aid) human involvement in suicide prevention. However, it is likely that there will continue to be advances that overcome the challenges laid out here, leading to a set of tools that can become part of standard assessment and prevention of suicidal thoughts and behaviours. The field has good reason to be cautiously optimistic.

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Passive smartphone sensing

Passive data collection involves harvesting data being collected on a smartphone's existing sensors (such as GPS, accelerometer and call record) or from the phone's apps (for example, screen captures of social media activity). Several commentary papers discuss the promise of passive sensing[7,13], but few studies have actually adopted this method. One study showed that it was feasible to use a smartphone app to collect passive data[107]. Another paper presented a set of single-case designs showing that suicidal thinking might be associated with call and text frequency, although the direction of this association is unclear[164].

There are several potential reasons for the relatively limited research using passive sensing despite the interest in such work. First, it is probably easier to collect these data than it is to analyse them. Passive sensing (much like wearable sensors) creates a lot of complicated and noisy data from which it might be challenging to extract meaning (for example, it would be difficult to create features that capture different types of communication on social media). Second, there is a need to continually adapt to new messaging and social media platforms. For example, in 2012, 42% of adolescents said that Facebook was their most used social media platform. By 2021, this number had dropped to just 2%[165]. Meanwhile, other social media platforms (TikTok and Snapchat) emerged and became the dominant social media channels (35% of adolescents say that Snapchat is their preferred platform and 30% say that TikTok is their preferred platform[165]). It is difficult to continually develop methods to capture and make sense of data from these platforms. Yet doing so is crucial because missing one popular app means potentially missing critical information. Third, there are likely to be biases resulting from missing data. For example, those who carry their phone less provide less data[166].

It is also important to understand the ethics of collecting passive smartphone sensing data[167]. Participants must be fully informed about how their data will be stored (for example, whether GPS data will identify the specific address) and used (for example, whether GPS data will be used to find the location of a participant during a period of high suicide risk for an active rescue).

Frequently used sensors in wearable devices

Accelerometer

An accelerometer, which measures motion, is the most common sensor available in wearables. Accelerometers, especially when combined with a gyroscope (which measures direction), can assess factors such as number of steps or sleep–wake information. Actigraphy (which refers to using movement data to determine sleep) is often combined with a sleep diary that has self-reported sleep and wake times[168].

Heart rate sensor

The second-most-common sensor is a photoplethysmograph, which assesses changes in blood volume and can be used as an indirect measure of heart rate. Blood volume can be a useful measure of physical activity or autonomic responding (for example, as a potential measure of heart rate variability[169]).

Light sensor

Light sensors can be used to capture time spent outdoors or the amount of light in a room when sleeping (for example, the presence of blue light prior to, or during, the sleep period).

Skin conductance

Some devices contain a set of electrodes that can capture electrical resistance on the skin[170], which corresponds to autonomic activity (that is, perspiration associated with autonomic activity). There are a variety of issues associated with assessing skin conductance with wearables. For example, the wrist is a less-than-ideal recording site and skin conductance cannot provide information about the context of the physiological arousal.

Responding to imminent suicide risk in EMA studies

Unlike other studies of suicidal thoughts and behaviours that collect information about suicide risk over long periods of time (for example, the desire to die by suicide, reported retrospectively as a single answer averaging over the past month), EMA studies can collect information on the present moment (for example, how likely someone is to desire to die by suicide right now). This creates a more urgent need to take action in some cases to protect participants who report high risk for suicide.

A review of current practices for suicide risk monitoring and intervention in EMA studies[171] finds several common approaches. These include collecting data anonymously and providing all participants with a list of resources (for example, suicide hotlines) for how to get help if they are at imminent risk for suicide, setting a threshold for ‘high risk’ and sending automated resources to help, and setting a threshold for ‘high risk’ and reaching out to the participant to do a follow-up risk assessment (the time frame of this follow-up varies from immediate to set time intervals specified in advance). These options are not mutually exclusive.

When intervention is needed, participant safety is a higher priority than data validity. First, researchers should consider whether the participant is in treatment already, and whether the intervention plan for the research study would interfere with their treatment. For example, a call from the study team could interrupt the participant, preventing them from using skills learned in therapy to reduce risk on their own. Second, researchers should consider the ethical implications of their risk response plan. For example, suggesting a participant go to the emergency room when it is not necessary for them to do so could lead to burdensome expenses and aversive contact with the mental healthcare system, potentially reducing participant willingness to communicate risk and/or to engage with acute care resources in the future (when risk might be more severe and the need to intervene greater). In addition, protocols that could lead to an active rescue should be clearly communicated to the participant, particularly given the potential risk for some communities when interacting with responding members of law enforcement. Third, researchers should also consider what the implications are for their data if the response to suicide risk is leading to less frequent or severe ratings of suicidal thinking, either in reaction to the risk response (for example, participants may report lower scores to avoid being called by the research team) or owing to a reduction in risk as a result of the research team’s intervention.

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Other analyses

There is currently early-stage work on a variety of modelling techniques that have been applied either to EMA data or to suicide using non-EMA data.

Network analysis

Network analysis is useful for examining relationships among a large set of variables and therefore might be useful for examining the large set of predictors that might be associated with suicidal thoughts and behaviours[172]. One study that used network analysis to examine the relationships between affect variables and suicidal thinking using EMA found that hopelessness was one of the strongest predictors of suicidal thinking at the next EMA timepoint[50].

Natural language processing

Natural language processing is useful for uncovering patterns and discerning meaning in free-response data. Natural language processing has been applied to free-text fields in medical records to identify information about suicidal thoughts and behaviours[173,174], because such information is not often entered in a ‘searchable’ field (for example, a yes/no question about attempting suicide). These studies find that natural language processing can accurately detect suicidal behaviours noted in a medical record.

Automated natural language processing might be particularly useful for EMA assessments with free-response questions because it would not be possible to manually code the high volume of data such questions would produce when assessed repeatedly. However, like machine learning, there is emerging evidence that natural language processing does not accurately classify risk for suicidal thoughts and behaviours at a similar rate across racial or ethnic groups[175]. Moreover, researchers should weigh up the pros and cons of the burden of having repeated free-response items in an EMA study.

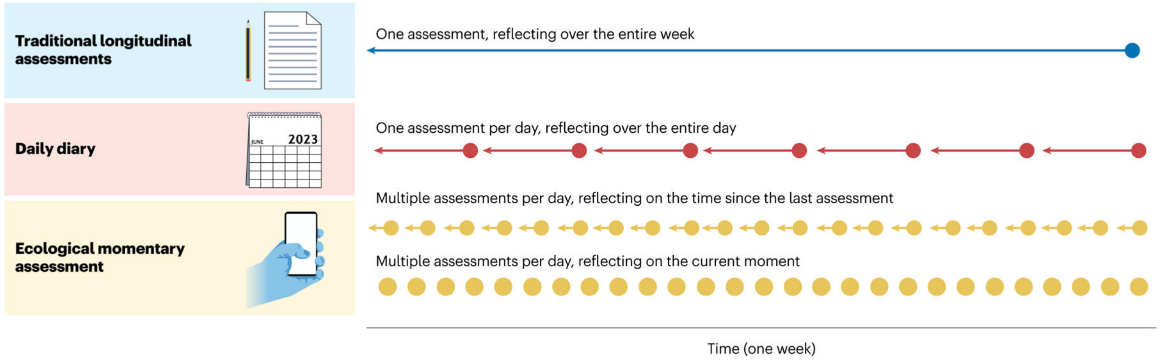

Fig. 1 |. Overview of different sampling frequencies.

Traditional longitudinal assessments ask for retrospective assessments once over a long time period (for example, once per month). Daily diary studies ask for one retrospective assessment over a day. Ecological momentary assessment includes multiple assessments per day that are either retrospective or reflect current context.