Curr Psychiatry Rep (2018) 20:51
https://doi.org/10.1007/s11920-018-0914-y

PSYCHIATRY IN THE DIGITAL AGE (J SHORE, SECTION EDITOR)

Smartphones, Sensors, and Machine Learning to Advance Real-Time Prediction and Interventions for Suicide Prevention: a Review of Current Progress and Next Steps

John Torous[1] · Mark E. Larsen[2] · Colin Depp[3,4,5] · Theodore D. Cosco[6] · Ian Barnett[7] · Matthew K. Nock[8,9] · Joe Firth[10,11]

Abstract

Purpose of Review As rates of suicide continue to rise, there is urgent need for innovative approaches to better understand, predict, and care for those at high risk of suicide. Numerous mobile and sensor technology solutions have already been proposed, are in development, or are already available today. This review seeks to assess their clinical evidence and help the reader understand the current state of the field.

Recent Findings Advances in smartphone sensing, machine learning methods, and mobile apps directed towards reducing suicide offer promising evidence; however, most of these innovative approaches are still nascent. Further replication and validation of preliminary results is needed.

Summary Whereas numerous promising mobile and sensor technology based solutions for real time understanding, predicting, and caring for those at highest risk of suicide are being studied today, their clinical utility remains largely unproven. However, given both the rapid pace and vast scale of current research efforts, we expect clinicians will soon see useful and impactful digital tools for this space within the next 2 to 5 years.

Keywords Suicide · Apps · Mobile health · Big data · Algorithms · Machine learning · Smartphones · Mental health

Introduction

Despite impressive advances in reducing mortality for cancer and cardiovascular diseases in the last decade, progress in reducing deaths by suicide has been limited. The most recent data from the US Centers for Disease Control and Prevention (CDC) suggest rates of suicide are rising, with a 24% age adjusted increase between 1999 and 2014 (https://www.cdc.

This article is part of the Topical Collection on *Psychiatry in the Digital Age*

✉ John Torous
jtorous@bidmc.harvard.edu

1 Department of Psychiatry and Division of Digital Psychiatry, Beth Israel Deaconess Medical Center, Harvard Medical School, 330 Brookline Ave, Boston, MA 02115, USA

2 Black Dog Institute, University of New South Wales, Sydney, New South Wales, Australia

3 Department of Psychiatry, University of California San Diego, La Jolla, CA, USA

4 Veterans Affairs San Diego Healthcare System, San Diego, CA, USA

5 Sam and Rose Stein Institute for Research on Aging, University of California San Diego, La Jolla, CA, USA

6 Oxford Institute of Population Ageing, University of Oxford, Oxford, UK

7 Department of Biostatistics, University of Pennsylvania, Philadelphia, PA, USA

8 Department of Psychology, Harvard University, Cambridge, MA, USA

9 Department of Psychiatry, Harvard Medical School, Cambridge, MA, USA

10 NICM Health Research Institute, School of Science and Health, University of Western Sydney, Sydney, Australia

11 Division of Psychology and Mental Health, Faculty of Biology, Medicine and Health, University of Manchester, Manchester, UK

Published online: 28 June 2018

gov/nchs/products/databriefs/db241.htm). There are over one millions deaths by suicide per year globally with over 40,000 per year in the USA. This crisis around suicide has spurred national research agendas to fund, study, and create new tools aimed at reducing the morbidity and mortality related to suicide and self-harm. With worldwide shortages of mental health clinicians and services, there is now widespread interest and excitement in using digital technologies and artificial intelligence software to help understand, predict, and prevent suicide. The National Action Alliance for Suicide Prevention Research Prioritization Task Force (http://actionallianceforsuicideprevention.org/research-prioritization-task-force) and its Zero Suicide Initiative (http://zerosuicide.sprc.org/about) supported by the Substance Abuse and Mental Health Services Administration (SAMHSA) calls for research in seven key areas around suicide care including identification of those at risk, delivery of evidence-based treatments, and data driven quality improvement among other items. Digital technologies like smartphones, data science tools like machine learning, and mobile app based delivery platforms each offer new tools and potential real time solutions to help advances these key research areas and reduce suicide. There are also already impressive efforts to use genetics and electronic medical record data and machine learning methods to advance suicide prevention that will not be the focus of this paper covering more mobile and sensor driven systems [1–3]. This article offers an overview of the potential, current state, and next steps for innovative mobile and sensor driven approaches to advance care for those at risk for suicide. While not exhaustive in scope, this article focuses on innovations in smartphone sensing, data science methods, and digital tools as outlined below in Fig. 1.

Understanding New Data to Inform Risk Assessment

Digital technologies and artificial intelligence offer new tools and methods to better understand and predict suicide [4]. Risk assessments for suicide involve the evaluation of static and non-static risk factors. Static risk factors are those that cannot be changed, such as age, gender, and history of a suicide attempt. Dynamic risk factors, such as access to firearms, substance use, mental health disorders, post-hospitalization transitions, social support, and limited access to care, are those which can be modified to reduce risk. However, these risk factors are often assessed at a single time point in a single setting of the clinical environment. Mobile and sensor data offers tremendous potential here.

A recent review of the past 50 years' of research on the prediction of suicide and suicide attempts revealed that only one-tenth of 1 % of such studies have examined risk factors of the short-term occurrence of such outcomes—that is, what factors predict whether is going to engage in suicidal behavior over the next 1–30 days [5]. Related research has noted that most known risk factors for suicidal behavior actually predict suicidal ideation, but not the transition from suicidal thoughts to attempts [6]. As such, there is a great need to identify factors that are the strongest predictors in the weeks, days, and hours before a suicide attempt, new objective markers of short-term risk, the need for new methods to combine these risk factors into actionable predictions [7•]. Thus, an important first step for new approaches to suicide prediction is the ability to capture novel dynamic risk data of clinical importance. While data gathered in-person by a licensed clinician remains the current gold standard for both healthcare and legal standards, there is now the ability to augment the clinical exam with new, dynamic, and real time data about potential risk factors for suicidal behavior.

Two evolving sources of this data include social media and smart devices. Focusing here on social media, platforms such as Twitter, Facebook, and Instagram offer important information about mental health and even risk of suicide [8]. Both the patterns of use [9] and nature of content [10] posted on Instagram has been correlated with mood in non-clinical samples—offering real time data that may inform risk. While the causal association between use of social media platforms like Facebook and mental health is still unclear, it is clear that data on both the usage patterns and content experienced provides novel clues to mood and suicide risk [11, 12]. The tragic fact that some individuals may choose to live stream their suicide on social media [13] or search for methods for suicide on Google has promoted responses from these tech platforms, discussed later, that highlight the urgency of understanding social media data to better inform risk for suicide.

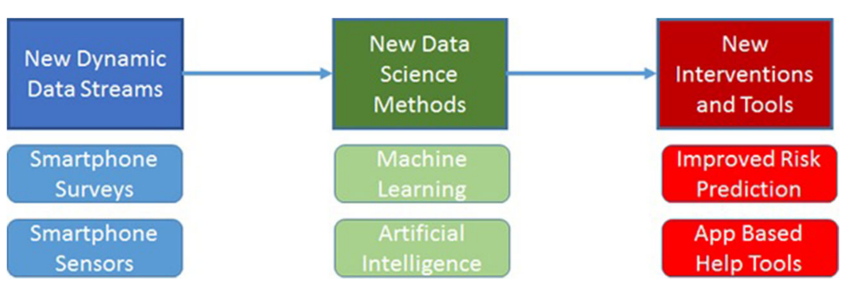

Fig. 1 An overview of how new data and methods can help inform, create new interventions, and develop tools / models for improving risk prediction around suicide

Another novel data stream for understanding suicide risk are smartphones and connected sensors (aka 'wearables') providing real time and context aware monitoring. The ability of smartphones to survey users outside of the clinical visit presents an opportunity to assess suicide risk in a naturalistic setting over a longitudinal time frame. Techniques such as ecological momentary assessment (EMA) can be utilized to capture data on users' current behaviors in real time, increasing the ecological validity of these data [14]. Some evidence suggests that individuals may be more likely to disclose suicidal thoughts to a computer-based or smartphone survey [15]. Sensors on the phone such as GPS which can passively monitor activity patterns, accelerometers which can monitor activity and sedentary behavior, and call and text logs which can monitor social engagement, all already have pilot data supporting clinical correlations in mood, anxiety, bipolar, and schizophrenia disorders [9, 16••, 17, 18•]. EMA research has already helped better characterize risk factors such as suicidal ideation and demonstrated its high variability over the course of days [15, 19••]. Asking about suicide on a smartphone survey or via other EMA tools does not appear itself to be a risk factor for increasing suicidal ideation [20], and early findings suggest that this approach can provide novel information about suicidal thoughts and behaviors. For instance, one recent study identified five potential subtypes of suicidal thinking, a finding replicated across two samples, with one subtype most strongly linked to recent suicidal behavior [19••]. Thus, smartphones can already offer data on real time dynamic risk factors for suicide that are currently near impossible to assess or monitor once the individuals leaves the clinical setting. Despite this potential, there is currently a lack of data regarding which social media or smartphone data streams are the most valuable, and valid, as novel digital risk markers for suicide. Further validation studies will be required to assess the utility of these markers and how these data might be used to inform practice.

Machine Learning and Artificial Intelligence to Analyze Risk Data

The second step in predicting suicide is the ability to analyze these data and generate clinical insights with tools like artificial intelligence, machine learning and statistical modeling. For example, the US Veterans' Administration REACH VET program uses predictive analytics on data derived from veterans' health records to identify those at highest risk for suicide [21]. Such predictive analytical models can be used to identify both long-term and short-term risk, each of which requires different approaches [22].

Focusing first on long-term risk prediction for populations, better forecasting of risk could lead to better allocation of resources, targeted prevention strategies, and improved clinical decision support. New statistical methods are being developed best utilize existing data and make most accurate predictions about risk. These newer statistical methods include machine learning-based tools like support vector machines, deep neural nets, random forests, and many others.

Population level suicide risk prediction studies have reported superior performance for modern statistical methods like elastic-net compared to traditional methods like logistic regression [1]. Many current efforts center around clustering individuals into novel subtypes that may offer a more accurate assessment of risk. For example, instead of using a few variables such as access to weapons, history of prior suicide attempts, etc. that are utilized in today's clinical risk assessments, researchers can now look at hundreds of predictors to generate a more personalized risk profile. Morales et al. examined 345 variables using decision tree techniques [23]. Researchers are also studying if machine learning methods such as neural nets can better classify risk from existing clinical scales and other machine learning methods can be used to identify risk for suicide from publically available Twitter posts [24, 25]. Due to their lack of rigid modeling assumptions, modern machine learning methods have a general advantage over classical statistical methods by being able to adaptively identify complex relationships between large variable sets and suicide risk.

There is also ongoing research on short-term risk prediction that can be used to inform personal risk. Short-term risk prediction is a more difficult problem due to the necessity of inference based on a small amount of data, which means that meaningful signals can more easily be lost due to noise from highly variable behaviors. In order to overcome this hurdle, it is necessary to analyze a wide variety of behavioral data in a multivariate fashion, often collected from a myriad of sources, in order to make successful short-term predictions. Because of this, data integration is particularly essential for the success of short-term risk prediction. Methods like neural networks, which, unlike some classic statistical regression models, are designed to accommodate high-dimensional inputs, can be useful for short-term risk prediction. One study used a neural network to predict suicide risk in the next 72 h for 255 emergency department patients compared to a psychiatrists' risk assessment and reported that the neural network was able to model psychiatrists' decision making [26]. Predicting within person risk is also possible with many other methods. For example, Depp et al. utilized the Least Absolute Shrinkage and Selection Operator (LASSO) statistical method to analyze 20-week self-reported mood-related data in patients with bipolar II to build a model with an 0.91 area under the curve score of 0.91 [27]. The same group also employed functional linear models in a different study to create a model with 88% sensitivity with 95% specificity for elevated suicidal ideation 1 week prior to in-person clinician assessment based on at home self-reported daily measures in a population with bipolar disorder [28]. However, prospective comparisons of machine learning tools to predict short-term suicide risk have not yet been conducted, despite the tremendous potential. In part, this is because the short-term risk factors derived from social media and smartphone as still not well characterized or validated. Crucially, even the best computational methods for risk assessment will only ever be as good as the risk factor data provided to them. Thus improvements in smartphone and sensor data quality are critical for realizing the full potential of new machine learning methods operating with this data.

Digital Technology for Suicide Prevention

While predicting risk of suicide is important, ensuring that information is acted upon is critical in preventing deaths. Common reasons that those at high risk for suicide do not seek professional help include lack of time, preference for self-help, and stigma [29]. Smartphone and technology-based suicide resources thus appear as promising tools that may be able to soon identify those at highest risk and one day offer just in time interventions without the stigma of conventional treatment. However, the evidence today suggests that current smartphone apps targeting suicide on the commercial marketplaces including the Apple App Store and Google Play store are largely not evidence based and few have been clinically validated [30, 31]. Larsen et al. noted in 2016 that not a single app they examined on the Apple or Android operating system offered comprehensive evidence-based support for suicide [31]. Given that there are already over 10,000 mental health-related smartphone apps available on the iTunes and Android marketplaces [32] and few of these apps, especially for suicide prevention, have ever been assessed—selecting an app can be challenging.

Current research studies are evaluating various online and mobile interventions for reducing suicidal thoughts and behaviors. One such technique uses automated text messages sent following a hospital-treated suicide attempt, where participants have been shown to re-engage with healthcare services after receive a message [33]. This intervention, sharing elements of the successful Caring Letter suicide prevention intervention [34] which was shown to prevent suicide deaths, may offer even more potential if in the future able to send on demand and customized messages based off environmental and personal triggers.

A web-based intervention has been shown to be effective [35] and cost-effective [36] at reducing suicidal ideation in a randomized controlled trial with open community recruitment in the Netherlands. A similar study in Australia, however, found no significant difference in a study including participants with more severe suicidal ideation and when compared to a control group receive an attention-matched (rather than waitlist) control [37]. Recently, research from the Nock Lab at Harvard University has explored the potential of smartphone apps designed increase aversion to self-injurious thoughts and behaviors [38]. Sadly, there are also dangerous apps and online programs available to anyone today, including even apps that encourage self-harm and suicide (https://www.forbes.com/sites/andrewrossow/2018/02/28/cyberbullying-taken-to-a-whole-new-level-enter-the-blue-whale-challenge/#4336725d2673). Thus, it may be important to ask patients about app use and help steer them towards better online and apps tools while avoiding harmful ones.

There is little data on the use of these smartphone apps for child and adolescent populations [39] with concerns remaining about the privacy, legal, and efficacy considerations given the current limited research and evidence base. This is concerning as rates of suicide are increasing most rapidly in younger demographics. Likewise, there is also a dearth of research on digital tools for suicide prevention in older adults. Considering that older adults are at highest risk for death by suicide, there is an even greater need to offer new effective tools for this population.

In part, the current limitations of these tools reflects that the algorithms and clinical decision support behind them remains limited, as alluded to in the above sections. While the need for these tools is obvious, they can only be as effective as the data science and data driving them.

Other Limitations

The potential of a closed-loop system using mobile technology to collect real-time data on dynamic risk factors is impressive, and the prospect of using artificial intelligence to predict imminent risk from this sea of data to prevent suicide 'just in time' is exciting. However, there are several key barriers which must also be considered. The ethics, real-world implementation, and legal liability are complex issues which cannot be overlooked. Briefly addressing ethical issues—the amount of personal data that today's smartphone sensors are able to gather and implications of algorithms predicting suicide risk when it is not present, and conversely a false negative of missing risk, raise questions related to informed consent, basic privacy protections, and autonomy—some of which were relevant following the 2014 launch of the Samaritans' Radar app for Twitter [40] and again raised with the 2018 Cambridge Analytica Facebook data misuse. Further consideration for real-world implementation raises issues of suicide prevention algorithms and apps outside of the research environment raises unknown issues of cost, data stewardships and control, and clinical systems integration. Finally, the medical legal issues around technology driven suicide prevention also must be clarified. Parallel to issues raised self-driving cars harming humans, who will be liable for harm caused by errors in these suicide prevention systems? The answers to each of these problems remain complex ethical-social-legal questions that require broad collaborations beyond psychiatry and data science.

Recommendations for Clinicians Regarding Apps

Understanding both the potential and easy availability of mental health apps from commercial marketplaces like the Apple Itunes and Android Google Play stores, clinicians should expect patients to begin asking about use of these apps. Using the American Psychiatric Association's App Evaluation framework [41], we offer some general guidance towards informed decision making and discussions about apps. Given how quickly apps update and how diverse patient presentations are, this framework does not recommend any particular app but rather guides collaborative and informed decision making around apps. A first step is to evaluate the privacy and security of the app. Any app monitoring self-harm or thoughts of suicide should offer strong digital security protections and privacy with a commitment not to sell user data like many health apps. Checking the privacy policy will often be informative. As a second step, clinicians should educate patients on the current evidence—much of which is summarized above—and explain that the evidence is still nascent. This does not mean that an app will not be effective for a given individual, but rather that that individual needs to be informed that any app use is likely "off label" when recommended by a clinician. Third, assessing for usability is critical as the majority of mental health apps are never opened more than once. Checking that an app is easy to use and appropriate for the individual in question is always necessary. Finally, and fourth, there must be a plan for the app data to be shared with the clinician and used as part of the treatment plan. The goal of app use is never to fragment care, but rather augment care through strengthening the clinician-patient relationship. More details on evaluating apps are available on the American Psychiatric Association's website at https://www.psychiatry.org/psychiatrists/practice/mental-health-apps/app-evaluation-model

Conclusion

Whereas the potential of a new generation of real time suicide risk prediction data, algorithms, and tools is real—challenges remains before they are ready for widespread clinical use. Appropriate data collection mechanisms will be need to developed, machine learning models trained, and suicide markers tested in validation studies before this potential can be fully realized. This will need to be conducted with the complex ethical landscape of technological innovation in mind, in order to encourage users to engage with and trust these novel applications.

Compliance with Ethical Standards

Conflict of Interest John Torous, Colin Depp, Theodore D. Cosco, Ian Barnett, Matthew K. Nock, and Joe Firth declare that they have no conflict of interest.

Mark E. Larsen reports a grant from the National Health and Medical Research Council.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

1. Kessler RC, Hwang I, Hoffmire CA, McCarthy JF, Petukhova MV, Rosellini AJ, Sampson NA, Schneider AL, Bradley PA, Katz IR, Thompson C. Developing a practical suicide risk prediction model for targeting high-risk patients in the Veterans health Administration. Int J Methods Psychiatr Res. 2017;26(3). https://doi.org/10.1002/mpr.1575.
2. Bernecker SL, Rosellini AJ, Nock MK, Chiu WT, Gutierrez PM, Hwang I, et al. Improving risk prediction accuracy for new soldiers in the US Army by adding self-report survey data to administrative data. BMC Psychiatry. 2018;18(1):87.
3. Stein MB, Ware EB, Mitchell C, Chen CY, Borja S, Cai T, et al. Genomewide association studies of suicide attempts in US soldiers. Am J Med Genet B Neuropsychiatr Genet. 2017;174(8):786–97.
4. Larsen ME, Cummins N, Boonstra TW, O'Dea B, Tighe J, Nicholas J, Shand F, Epps J, Christensen H. The use of technology in suicide prevention. Proceedings of the 37th Annual Conference of the Engineering in Medicine and Biology Conference (EMBC). 2015. 7316–7319.
5. Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, et al. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. Psychol Bull. 2017;143(2):187.
6. Nock MK, Kessler RC, Franklin JC. Risk factors for suicide ideation differ from those for the transition to suicide attempt: the importance of creativity, rigor, and urgency in suicide research. Clin Psychol Sci Pract. 2016;23(1):31–4.
7.• Glenn CR, Nock MK. Improving the short-term prediction of suicidal behavior. Am J Prev Med. 2014;47(3):S176–80. **This paper outlines the need for short-term prediction and clearly outlines future strategies and methods that remain of relevance today.**
8. Robinson J, Cox G, Bailey E, Hetrick S, Rodrigues M, Fisher S, Herrman H. Social media and suicide prevention: a systematic review. Early Interv Psychiatry. 2016;10(2):103-21.
9. Frison E, Eggermont S. Browsing, posting, and liking on Instagram: the reciprocal relationships between different types of instagram use and adolescents' depressed mood. Cyberpsychol Behav Soc Netw. 2017;20(10):603–9.
10. Reece AG, Danforth CM. Instagram photos reveal predictive markers of depression. EPJ Data Sci. 2017;6(1):15.

11. Shakya HB, Christakis NA. Association of Facebook use with compromised well-being: a longitudinal study. Am J Epidemiol. 2017;185(3):203–11.
12. Inkster B, Stillwell D, Kosinski M, Jones P. A decade into Facebook: where is psychiatry in the digital age? Lancet Psychiatry. 2016;3(11):1087–90.
13. Li A, Huang X, Zhu T. A systematic analysis of online broadcasts of suicidality in China. Asia-Pacific Psychiatry. In press. Accepted 12 September 2017. https://doi.org/10.1111/appy.12302
14. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. Annu Rev Clin Psychol. 2008;4:1–32.
15. Torous J, Staples P, Shanahan M, Lin C, Peck P, Keshavan M, et al. Utilizing a personal smartphone custom app to assess the patient health questionnaire-9 (PHQ-9) depressive symptoms in patients with major depressive disorder. JMIR Mental Health. 2015;2(1):e8.
16.•• Saeb S, Lattie EG, Schueller SM, Kording KP, Mohr DC. The relationship between mobile phone location sensor data and depressive symptom severity. PeerJ. 2016;4:e2537. **This paper features novel smartphone geolocation and mood data that offers a clear example of the feasibility and potential of using smartphone sensors to capture novel real-time data about depression.**
17. Dogan E, Sander C, Wagner X, Hegerl U, Kohls E. Smartphone-based monitoring of objective and subjective data in affective disorders: where are we and where are we going? Systematic review. J Med Internet Res. 2017;19(7):e262.
18.• Barnett I, Torous J, Staples P, Sandoval L, Keshavan M, Onnela JP. Relapse prediction in schizophrenia through digital phenotyping: a pilot study. Neuropsychopharmacology. 2018;22:1. **This paper features multimodal smartphone sensor and survey collection and offers links to both the algorithms used to process the data as well as links to the source code for the app used to collect the data**
19.•• Kleiman EM, Turner BJ, Fedor S, Beale EE, Huffman JC, Nock MK. Examination of real-time fluctuations in suicidal ideation and its risk factors: results from two ecological momentary assessment studies. J Abnorm Psychol. 2017;126(6):726. **This paper presents two studies which represent the most fine-grained examination of suicidal ideation to date.**
20. Husky M, Olié E, Guillaume S, Genty C, Swendsen J, Courtet P. Feasibility and validity of ecological momentary assessment in the investigation of suicide risk. Psychiatry Res. 2014;220(1):564–70.
21. Lyon J. New data on suicide risk among military veterans. JAMA. 2017;318(16):1531.
22. Walsh CG, Ribeiro JD, Franklin JC. Predicting risk of suicide attempts over time through machine learning. Clin Psychol Sci. 2017;5(3):457–69.
23. Morales S, Barros J, Echávarri O, García F, Osses A, Moya C, et al. Acute mental discomfort associated with suicide behavior in a clinical sample of patients with affective disorders: ascertaining critical variables using artificial intelligence tools. Front Psych. 2017;8:7.
24. Burnap P, Colombo G, Amery R, Hodorog A, Scourfield J. Multi-class machine classification of suicide-related communication on Twitter. Online Soc Netw Media. 2017;2:32–44.
25. O'dea B, Larsen ME, Batterham PJ, Calear AL, Christensen H. A linguistic analysis of suiciderelated Twitter posts. Crisis. 2017;38(5):319-329. https://doi.org/10.1027/0227-5910/a000443.
26. Desjardins I, Cats-Baril W, Maruti S, Freeman K, Althoff R. Suicide risk assessment in hospitals: an expert system-based triage tool. J Clin Psychiatry. 2016;77(7):e874–82.
27. Depp CA, Thompson WK, Frank E, Swartz HA. Prediction of near-term increases in suicidal ideation in recently depressed patients with bipolar II disorder using intensive longitudinal data. J Affect Disord. 2017;208:363–8.
28. Thompson WK, Gershon A, O'hara R, Bernert RA, Depp CA. The prediction of study-emergent suicidal ideation in bipolar disorder: a pilot study using ecological momentary assessment data. Bipolar Disord. 2014;16(7):669–77.
29. Czyz EK, Horwitz AG, Eisenberg D, Kramer A, King CA. Self-reported barriers to professional help seeking among college students at elevated risk for suicide. J Am Coll Heal. 2013;61(7):398–406.
30. de la Torre I, Castillo G, Arambarri J, López-Coronado M, Franco MA. Mobile apps for suicide prevention: review of virtual stores and literature. JMIR Mhealth Uhealth. 2017;5(10):e130.
31. Larsen ME, Nicholas J, Christensen H. A systematic assessment of smartphone tools for suicide prevention. PLoS One. 2016;11(4):e0152285.
32. Torous J, Roberts LW. Needed innovation in digital health and smartphone applications for mental health: transparency and trust. JAMA Psychiatry. 2017;74(5):437–8.
33. Berrouiguet S, Larsen ME, Mesmeur C, Gravey M, Billot R, Walter M, et al. Toward mHealth brief contact interventions in suicide prevention: case series from the Suicide Intervention Assisted by Messages (SIAM) randomized controlled trial. JMIR mHealth uHealth. 2018;6(1):e8.
34. Luxton DD, Thomas EK, Chipps J, Relova RM, Brown D, McLay R, et al. Caring letters for suicide prevention: implementation of a multi-site randomized clinical trial in the US military and veteran affairs healthcare systems. Contemp Clin Trials. 2014;37(2):252–60.
35. van Spijker BAJ, van Straten A, Kerkhof AJFM. Effectiveness of online self-help for suicidal thoughts: results of a randomised controlled trial. PLoS One. 2014;9(2):e90118.
36. van Spijker BAJ, Majo C, Smit F, van Straten A, Kerkhof AJFM. Reducing suicidal ideation: cost-effectiveness analysis of a randomized controlled trial of unguided web-based self-help. J Med Internet Res. 2012;14(5):e141.
37. van Spijker BAJ, Werner-Seidler A, Batterham PJ, Mackinnon A, Calear AL, Gosling JA, et al. Effectiveness of a web-based self-help program for suicidal thinking in an Australian community sample: randomized controlled trial. J Med Internet Res. 2018;20(2):e15.
38. Franklin JC, Fox KR, Franklin CR, Kleiman EM, Ribeiro JD, Jaroszewski AC, et al. A brief mobile app reduces nonsuicidal and suicidal self-injury: evidence from three randomized controlled trials. J Consult Clin Psychol. 2016;84(6):544.
39. McManama O'Brien KH, LeCloux M, Ross A, Gironda C, Wharff EA. A pilot study of the acceptability and usability of a smartphone application intervention for suicidal adolescents and their parents. Arch Suicide Res. 2017;21(2):254–64.
40. Lee N. Trouble on the radar. Lancet. 2014;384(9958):1917.
41. Torous JB, Chan SR, Gipson SY, Kim JW, Nguyen TQ, Luo J, et al. A hierarchical framework for evaluation and informed decision making regarding smartphone apps for clinical care. Psychiatr Serv. 2018;69(5):498–500.
42. Faurholt-Jepsen M, Bauer M, Kessing LV. Smartphone-based objective monitoring in bipolar disorder: status and considerations. Int J Bipolar Disord. 2018;6(1):6.