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Translating promise into practice: a review of machine learning in suicide research and prevention

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In ever more pressured health-care systems, technological solutions offering scalability of care and better resource targeting are appealing. Research on machine learning as a technique for identifying individuals at risk of suicidal ideation, suicide attempts, and death has grown rapidly. This research often places great emphasis on the promise of machine learning for preventing suicide, but overlooks the practical, clinical implementation issues that might preclude delivering on such a promise. In this Review, we synthesise the broad empirical and review literature on electronic health record-based machine learning in suicide research, and focus on matters of crucial importance for implementation of machine learning in clinical practice. The challenge of preventing statistically rare outcomes is well known; progress requires tackling data quality, transparency, and ethical issues. In the future, machine learning models might be explored as methods to enable targeting of interventions to specific individuals depending upon their level of need—ie, for precision medicine. Primarily, however, the promise of machine learning for suicide prevention is limited by the scarcity of high-quality scalable interventions available to individuals identified by machine learning as being at risk of suicide.

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See **Online** for appendix

Introduction

Machine learning was first described in 1959.[1] However, the widespread emergence of machine learning in the field of health care, and more specifically in suicide prevention, is a relatively recent development. Globally, more than 700 000 individuals die by suicide every year,[2] yet the ability to reliably predict who will attempt or die by suicide is widely acknowledged to be poor.[3] Suicide risk assessment scales cannot determine suicide risk with an acceptable degree of precision or reliability.[4–6] Use of machine learning in suicide research is burgeoning and frequently reported in a manner that emphasises the promise of these techniques for improving the prediction and prevention of suicidal thoughts and behaviours.[3,7,8] Given the additional pressure of the COVID-19 pandemic on already overstretched health-care services, potential gains in scalable quality of care and improvements to resource efficiency are appealing.

Although every suicide is an individual tragedy, the low prevalence of suicidal ideation, attempts, and deaths brings myriad challenges for prediction.[9,10] There are also valid concerns regarding ethical issues of transparency, algorithmic bias, and responsibility for intervening when using machine learning to identify individuals at risk of suicidal ideation or attempts.[11–16] Despite the numerous commentaries and reviews on machine learning and suicide,[8,17] the clinical implications of machine learning and how these techniques might be applied when clinicians encounter patients at risk of suicidal thoughts and behaviours have been largely overlooked. Our Review synthesises the existing empirical literature and reviews on machine learning and suicide prevention, focusing on the practical aspects of how machine learning can be clinically useful, and considering potential caveats. Given the widespread availability of electronic health record (EHR) data, we concentrate specifically on machine learning studies using register-based EHR data, rather than the literature on wearable devices, or content or semantic analysis of suicide notes or social media data using machine learning. As an interdisciplinary author team, comprising research psychologists, clinicians, and computer scientists, we examine the findings through diverse lenses.

We begin our Review with a brief overview of key concepts in machine learning and their implications for suicide prevention, before discussing ethical and clinical implementation issues. Several excellent overviews of how to read machine learning papers have been published, and we direct interested readers to these overviews for general information.[17,18]

Key concepts in machine learning and their implications for suicide research and prevention

For an overview of key terms used in this section, see appendix (pp 1–3). Most clinicians will be familiar with (logistic) regression, which is a statistical technique for both understanding and prediction. When talking about regression analysis in psychiatry, the focus is often on the understanding and interpretation of the relationship between predictors and the outcome variable.[19,20] For example, researchers might investigate whether a past suicide attempt relates more strongly to a recent suicide attempt than gender does. When using logistic regression as a machine learning algorithm however, researchers are concerned with optimising the prediction of suicidal behaviour. To this end, machine learning algorithms, such as regression and random forest, can use any complex combination of variables, in any non-linear relationship with the target outcome. This flexibility can improve the accuracy of the prediction, but can also limit the interpretability, which is a heavily debated topic in health care. To address this problem, a growing field of research aims to open black-box algorithms by improving comprehension, explainability, and trust for end users.[21,22]

The basic concept of machine learning models is that they learn from examples of data. In this instance, examples of suicidal behaviour (cases) and the absence of suicidal behaviour (controls) are used. In supervised learning, which is one approach in machine learning, researchers try to use these examples to build a model that predicts a particular target (in our example, whether it is a case or not) based on other variables. Some models output a prediction about the case classification (eg, attempt *vs* no attempt), whereas others predict the probability that an observation is a case (eg, 42% probability of the case being an attempt). In models that predict the probability that an observation is a case, a threshold value should be determined to classify an observation as a case (eg, >50% probability). Tuning and calibration of this threshold value is beyond the scope of this article.

Prediction is a key goal of clinical medicine in general.[23,24] The core goal of applying machine learning in the context of suicide is to improve our ability to predict and therefore prevent suicide, beyond existing sub-optimal levels,[3–6] by supporting clinicians in their decision making.

Data selection and preparation in machine learning

EHR data are a logical starting point for many applications of machine learning in health care, but they are an underused resource for suicide prevention.[25] The advantages of using EHR data are that they are voluminous, have high external validity, and are routinely collected by health-care services. Moreover, a data-driven approach might provide new theoretical directions and hypotheses,[26] as particular combinations of features might not otherwise be used for investigating suicide risk.[7]

One key difference between analysing EHR data and data from a trial or study is that in a trial, researchers can collect data on variables that have been empirically shown to correlate with suicidal ideation and behaviour. These variables are not commonly represented within structured EHR data,[27–29] although use of natural language processing with unstructured free-text EHR data might broaden the scope of available features.[30–33] When working with EHR data, considerable time is spent on pre-processing.[34] Guided by theory, previous research, and expert knowledge, different attributes in the data must be combined, transformed, or deleted.[31,32,35–37] Alternatively, so-called deep learning approaches can be used. These approaches can learn end to end, eliminating the need to combine or transform the attributes, and giving the advantage of eliminating human bias in the process. However, such approaches often lack insight and cannot always cope well with EHR data. Although machine learning models can handle so-called big data, eliminating insignificant or redundant variables is still crucial, as these variables introduce noise and can lead to overfitting.

Using EHR data comes with important challenges. Noise in EHR data is introduced by the coding of variables, which is often ambiguous or incorrect.[25,28,29,38,39] For example, suicidal behaviour is difficult to classify and is often not precisely registered in EHR systems[28,29,40] or the coding is not used at all because suicidal behaviour is not always a billable diagnosis.[32] Although data from questionnaires[27,41] might capture psychosocial vulnerability and protective factors, these data are not widely available in EHR systems. Greater implementation of psychological measures can benefit both clinical practice and machine learning research. The development of practical brief measures of psychological constructs might facilitate their uptake in clinical practice.[42,43] Few of the studies reviewed commented on data quality,[28,29,44] yet quality of data is crucial for evaluating machine learning models,[16] as such models are only as good as their inputs.

Modelling and evaluation in machine learning

Machine learning aims to make predictions in unseen datasets. Therefore, one dataset is used to train the model, and a different dataset is used to evaluate the model. It is important to use additional unseen data to analyse the generalisability and prevent so-called overfitting. Ideally, the model is evaluated using unseen data from a different site or research study. Researchers often include additional resampling techniques, such as cross-validation and bootstrapping, to assess the generalisability of results.

As there is no golden rule for which machine learning algorithm to use, researchers typically analyse multiple algorithms. Most papers reviewed here used a random forest algorithm;[28–31,44–46] other popular algorithms were support vector machines,[30,32,35,45] regularised regression,[32,33,45,47,48] and naive Bayes,[7,25,45] and only two papers used neural networks[38,49] (appendix p 2). Several studies employed ensemble machine learning methods, in which multiple different algorithms are used.[50–53]

Lack of independent validation is a major limitation of the extant machine learning literature in suicide prevention, as it restricts generalisability of the results. The majority of the studies reviewed here split the data into training sets and testing sets. Two studies used a dataset from seven different health-care systems across nine states,[47,48] and another study used data from five different health-care systems.[7] However, none of the studies used a cross-site design in which a model was trained using data from one site and evaluated using data from another site. Two other studies used bootstrapping with an optimism adjustment for validation,[28,29] although this approach has been criticised.[54] Only one study prospectively validated their models using completely independent data,[44] although training and testing data were also from a single centre. Independent validation of prognostic models is essential and must be a priority for machine learning research going forward.[55]

Evaluating model performance

An important aspect of the evaluation of suicide classification is a two by two contingency table, also

***Panel 1:* Example of model performance evaluation**

Here we explain the different model performance metrics and try to translate the result into the clinical context, by creating an example based on the published results reported by Barak-Corren and colleagues.[7] The model was developed with data from the University of Texas Health Science Center at Houston (TX, USA) and the prevalence, sensitivity, and specificity are projected to our example. Imagine you are working at a similar medical centre with a total caseload of 2000 patients. Within this caseload there are 12 patients who make a suicide attempt (prevalence=0·006). You want to determine whether a machine learning model can be used as predictive screener, such that these patients can be identified and appropriate care can be given. In the study by Barak-Corren and colleagues,[7] two models are presented, one with greater precision but lower sensitivity, and one with lower sensitivity but greater precision. When applying the first model to our example of 2000 patients, a confusion matrix can be created by making a cross-table of the predicted cases versus the actual cases (table 1). Metrics can then be derived from the confusion matrix (table 2).

The model will identify 21 patients as suicide cases (1 in 100 patients). Of those identified suicide cases, one is an actual case and 20 are wrongly classified as such. In our example, it should be determined whether the identification and possible prevention of one suicide attempt outweighs the incorrect classification of 20 controls as being at risk of attempting suicide. The costs and benefits will depend on the type of follow-up actions and intervention associated with this predictive screener model. This example also shows that even with a very specific model (specificity=0·99), only one in 21 patients is an actual case, a consequence of the low prevalence of suicidal behaviour.

	Suicide case (actual)	Control (actual)	Total
Suicide case (prediction)	1	20	21
Control (prediction)	11	1968	1979
Total	12	1988	2000

A cross-table of predicted cases versus actual cases created after applying the first model outlined in Barak-Corren and colleagues' study[7] (ie, greater precision but lower sensitivity) to our example of 2000 patients (panel 1).

***Table 1:* Example confusion matrix**

	Description	Calculation
Sensitivity	Proportion of cases that are correctly classified	1/12=0·083
Specificity	Proportion of controls that are correctly classified	1968/1988=0·99
Positive predictive value	Proportion of correct cases among the patients classified as case	1/21=0·048
Negative predictive value	Proportion of correct controls among the patients classified as control	1968/1979=0·99

Four metrics often used in the evaluation of a suicide classification model, derived from our example described in panel 1 and table 1.

***Table 2:* Metrics derived from an example confusion matrix**

called the confusion matrix,[20] which presents the predicted cases versus the actual cases. The overall accuracy and the area under the curve (AUC) are the most basic metrics. The most common curve is the receiver operator characteristic (ROC) curve, which combines the sensitivity (the true positive rate) and the specificity (the true negative rate). There is a trade-off between sensitivity and specificity: a model with higher sensitivity will more often classify a control as a case, resulting in a lower specificity. It is therefore important that when there are costs and benefits associated with the results, a model's statistical properties be considered in terms of their implications for clinical practice, and a conscious trade-off must be made. To illustrate this trade-off, we provide a clinical example in panel 1, and tables 1 and 2.

Low prevalence, high complexity

The low base rate of suicidal behaviour is a major challenge for accurate prediction. First, there are fewer case examples from which models can learn, and many studies approach this problem by combining EHR data across years.[29] Second, the low base rate results in imbalanced data, therefore a meaningful interpretation of the accuracy and the ROC curve cannot be made.[9] For example, an algorithm that labels every person as a control (not a case) will frequently be correct (high accuracy), because most people are indeed controls when cases are rare. In such situations, a precision–recall curve can give a more informative picture of algorithmic performance, because it focuses on the trade-off between positive predictive value and sensitivity, and is therefore more tailored for the detection of rare events.[56] Surprisingly, most of the abstracts from the empirical papers we reviewed included information only on accuracy and the AUC of the ROC.[29,37] Third, irrespective of the sophistication of an algorithm, the positive predictive value will always be low.[57] Low positive predictive value is also a criticism of structured clinical judgment,[58] and an important future question is how automated risk detection can improve clinical judgment.

Several studies attempted to solve the problem of low positive predictive value by focusing on a subgroup of high-risk individuals. For example, Kessler and colleagues studied recently discharged patients;[53] however, the average suicide mortality in such groups is approximately 10 per 100 000 individuals—ie, a prevalence of 0·01%.[59] Even using a subpopulation with a prevalence of 1% (indicating a risk 100 times higher), with a good model (sensitivity=90%; specificity=90%), the chance of being positively classified as a case (suicide death), would still only be 8%.[9]

Notably, low positive predictive value does not automatically imply that a model lacks practical value. As Kessler argued, even with a low positive predictive value, the net benefits related to a true positive largely outweigh the costs of a false positive.[60] The practical utility of a model depends on the costs and benefits associated with the outcomes in the confusion matrix (see the evaluating model performance section). In the case of suicide and many other clinical contexts, the benefits of preventing one suicide could outweigh the small cost of administering an assessment or intervention to individuals incorrectly identified by a model as at risk. In a simulation study,[61] the economic benefits (reduced health care costs) and society benefits (reduced patient time and lost productivity) of intervening for suicide risk with active follow-up or with cognitive behavioural therapy were found to outweigh the costs at model positive predictive values of 1% (active follow-up) and 2% (cognitive behavioural therapy). However, positive predictive value varied on the basis of whether the outcome was suicidal ideation or attempts. Therefore, the authors contended that the relatively low positive predictive values observed in published machine learning models should not preclude their implementation in health care; intervention is routinely offered in other health care settings in which positive predictive values are similarly low—eg, primary prevention of breast cancer and stroke, and the relative benefits to reducing suicide rates are still favourable even when positive predictive value is low.[61]

Ethical issues

Although there is widespread consensus that machine learning in suicide research and prevention is accompanied by ethical challenges,[11–16] there appears to be a dearth of literature that substantively discusses how these ethical issues might be addressed in the context of EHR data. None of the empirical articles that we reviewed discussed ethical aspects of machine learning, therefore in this section, we draw upon discussion from other reviews and commentaries published in the past 4 years.[12,14,15] Here we focus on two issues, bias and transparency, that have received comparatively little attention within previous reviews.

Bias in machine learning

Fairness and bias are growing concerns within the artificial intelligence field, not only in health care,[62] but also in fields such as the criminal justice system.[63] Despite bias in data being an issue in all medical research, discussions around bias are especially prominent in artificial intelligence research. A high-profile case of algorithmic racial bias emerged in which an algorithm was systematically discriminating against Black individuals when flagging patients for entry into a programme of enhanced health-care resource provision in the USA, on the basis of their previous health-care costs.[64] Researchers then collaborated with the health-care provider to develop and implement a less biased algorithm, which was subsequently implemented within the health-care system. This example highlights a number of important points. First, the necessity for independent and continuous evaluation of machine learning algorithms, even after implementation within a health-care system.[16] Second, that bias in models and training datasets can exacerbate existing health inequalities.[62] Algorithms for predicting suicide that rely upon EHR data might be especially vulnerable to racial and socioeconomic bias, as these data reflect systemic bias in accessibility of health-care services.[12,13,65,66] Third, and more positively, collaboration between researchers and health-care providers offers opportunities for reducing bias.

A study of racial and ethnic bias in machine learning models for predicting suicide death in the USA found that AUC and sensitivity were lower for Black individuals, American Indian and Alaskan Native individuals, and patients with no race or ethnicity recorded in EHR data, relative to White individuals.[66] Implementing such an algorithm would therefore probably result in a high rate of false positives and unnecessary interventions. As discussed earlier in our Review, when cost of intervention is low, false positives are not necessarily problematic. However, as Coley and colleagues highlight,[66] unnecessary interventions might come at a high cost for individuals from specific racial or ethnic groups in particular countries; for example, because of the disproportionately high risk of harm they face from law enforcement contact (eg, African American men and women, American Indian and Alaskan Native men and women, and Latino men in the USA)[67] and involuntary hospital admission (eg, Black Caribbean, Black African, and south Asian individuals from high-income countries).[68] Minimising bias requires insight into how predictions are made and critical discussions with domain experts about the meaning of an algorithm's output, as well as transparency regarding training datasets and algorithms that are often proprietary or protected due to privacy considerations.

Transparency

Transparency is an important issue in the use of machine learning for suicide prevention. The suicide research field as a whole could benefit from increased transparency,[69,70] but some features of machine learning in suicide research present specific challenges in this regard. If machine learning studies do not report or inconsistently report information across studies,[41,71] then adequate evaluation by the clinical and research community is hampered. In 2020, the first standardised reporting guidelines for clinical trials involving artificial intelligence (CONSORT-AI[72]) and standardised protocol items for intervention trials involving artificial intelligence technologies (SPIRIT-AI[73]) were released. Reporting guidelines for clinical prediction and diagnostic models using machine learning (TRIPOD-ML[74] and STARD-AI[75]) are in development. It is crucial that other types of research are also held to high standards that promote consistency and transparency of reporting. Journal editors and reviewers are instrumental in ensuring high-quality machine learning literature—eg, by requiring authors to use reporting guidelines.[73]

However, sharing algorithms without data will not yield better transparency.[76] To enable independent evaluation of machine learning algorithms, data and underlying code must be shared. Some researchers have made their code and full feature lists available,[7,32,33,35–37,44,47,48] but this is the exception rather than the rule. Given the nature of EHR data they are unlikely to be shared,[33] consequently limiting transparency and reproducibility of EHR-based machine learning models. Independent regulatory oversight of machine learning algorithms and their use in practice is essential to ensure adherence to ethical principles.[12,14,15] Encouragingly, worldwide initiatives to develop regulatory and ethical models for machine learning and artificial intelligence as applied to psychiatry are emerging (see Nebeker and colleagues for an overview[15]).

Clinical utility

Although the term machine learning often appears to conjure ideas of automated artificial intelligence replacing clinicians,[16] extant reviews and commentaries are unequivocal—machine learning should be considered complementary to clinician judgement and not as a replacement.[10,16,57,58,77,78] Several of the empirical studies within this Review stated explicitly that the algorithms they report are not yet ready for implementation within clinical settings,[30,36–38] and have neither the goal nor the potential to replace clinicians.[7,25] Implementation of machine learning-based decision support systems is dependent on not only their acceptability to clinicians, but also approval from governments and regulatory bodies for use of these systems as medical devices.[80] Developers of algorithms must not overpromise. The management of expectations from clinicians, patients, policy makers, and health-care providers regarding machine learning for suicide prevention is essential, to ensure that expectations are realistic.

Machine learning as a clinical decision-support tool

A realistic promise of machine learning for the advancement of suicide prevention is as a clinical decision-support tool. Such a tool might be embedded within EHR systems, for example, where an on-screen notification during a consultation informs the clinician about their patient's suicide risk.[25] These notifications might be particularly beneficial in health-care settings in which a patient does not always see the same clinician, and the clinician might not be aware of a patient's full history.[44] In this regard, machine learning decision-support tools can give new insights that clinicians might miss. A key consideration overlooked by most existing studies and reviews is who the target users are for machine learning decision-support tools. One study stated that their algorithm was aimed at a wide range of professionals who might encounter individuals at risk of making a suicide attempt—eg, police, prison workers, and emergency department staff.[38] Machine learning algorithms might have particular value as training aids for junior clinicians and health-care students, by enabling the creation of virtual patients, to teach awareness of key vulnerabilities and protective factors for suicidal ideation and behaviour.[57] There are many suicide prevention algorithms; therefore, different algorithms are likely to be used in different settings and for different purposes,[44] and the intended audience should be explicitly discussed in empirical research. The setting and intended users should also inform the choice of algorithm implemented within a health-care system.

Scalability of capacity for detection, but not intervention

A profound strength of prediction-based modelling approaches to suicide prevention is that algorithms that predict individuals' increased risk for suicidal ideation, attempts, and death can be scaled in ways that human-provided health care cannot.[13] However, who will intervene and provide support when an algorithm identifies a person at risk of suicide? The scalability of machine learning and the scalability of support provision or resources are inextricably linked. Suicide prevention efforts will not improve if vulnerable individuals are identified but left unsupported. Identification of individuals at risk without provision of support might even make things worse; some researchers have suggested that the development of effective, evidence-based interventions for suicidal thoughts and behaviours must precede the large-scale implementation of machine learning models of suicide risk.[9] Using digital interventions might provide opportunities to meet some demand for support services, but the vast majority of digital interventions are not evidence based.[81] Furthermore, the use of digital interventions raises questions about who will be responsible for assuring the quality and safety of such interventions that are enlisted to meet the support needs of individuals identified by machine learning algorithms as being at risk of suicide.[57]

Another crucial consideration is time horizon—when is the predicted risk going to occur? Time horizons in machine-learning-based models for suicide prevention should differ on the basis of the specific setting in which the model will be used. A model implemented in the emergency department might aim to predict the risk of a suicide attempt within the next few hours, whereas a model used in a public health setting might be focused on predicting risk within upcoming months. Predicting short-term risk is crucial to suicide prevention.[82] However, as is the case for suicide research more generally,[83] the focus of machine learning research is on longer term prediction of suicide-related outcomes—ie, months and years in the future. For machine learning models to be able to support clinical decision making, future research should focus on short-term prediction.

Interpreting and communicating machine learning outcomes to patients and clinicians

A crucial question within EHR-based machine learning and suicide research is how to most effectively communicate outcomes to patients and clinicians[78]—ie, how to inform patients they have been identified by an algorithm as being at elevated risk of suicide. This question has received surprisingly little attention within the empirical machine learning and suicide research literature. As is the case for any type of medical test, the results must be sufficiently understandable and explainable to act as a basis for shared clinical decision making. What should model output look like to be understandable to clinicians and, in turn, to enable clinicians to explain outcomes to their patients? For machine learning to be implemented effectively in suicide prevention, the communication needs of clinicians and patients must be fully understood, which requires strategies for communicating machine learning-based outcomes for suicide prevention to be co-designed with patients, family members, and clinicians.[57,84] For example, system-generated notifications can be co-developed with clinicians to confirm notifications are understandable and explainable.[25]

Recommendations and future directions

Our Review has focused on the practical and clinical considerations relevant to the implementation of machine learning in the prediction and prevention of suicidal thoughts and behaviours. Building upon the identified gaps in the literature, in this section we describe four key directions for future research and practice.

Improving data quality and interoperability of machine learning technology

To move EHR-based machine learning from experimentation to implementation, there must be greater standardisation within EHR data.[84] Policy and regulatory mechanisms are required to improve semantic standardisation and interoperability across EHR systems. An example is detailed clinical models, which provide common data elements and terminology (data blocks) to collect data across different locations, independent of time and technology.[85] With these data blocks, several databases can be linked and the common definitions mean information quality is improved. For example, in the Netherlands, definition codes currently used in EHR data for suicide do not clearly differentiate between an actual attempt and a consultation regarding an attempt.[40] A clear definition that distinguishes these two events would substantially improve information quality. These common data blocks can also be used in an application programming interface. As most machine learning models are not developed within the EHR systems themselves, an application programming interface is required for a machine learning model to communicate with an EHR. Moreover, a standardised application programming interface will improve the scalability of machine learning implementation across different EHR systems.[84]

Given that 77% of the world's suicides occur in LMICs,[2] it is imperative that interoperability in global health-care settings is considered a future priority. At present, predictive models specific to each setting need to be developed.[44] Some examples of data standards for interoperability of EHR data already exist.[86–89] However, the majority of EHR machine learning studies in suicide research have been conducted in high-income countries (usually the USA). Consequently, the extent to which predictive models developed in these settings can inform the development of predictive models in low-income and middle-income countries (LMICs) is uncertain. Research from LMICs is needed to inform feature selection, because risk factors for suicide differ between high-income settings and low-income and middle-income settings.[90]

Moving beyond existing EHR data

EHR data provide only a small array of features for machine learning, and commonly, these features are not typical psychosocial factors from the suicide research literature.[27,37,41] Although applying machine learning to self-reported questionnaire data has been posited as a potential solution,[27] this method does not always yield the desired improvements.[41] In addition to structured data (eg, appointments and demographics), EHR data includes unstructured data from clinical notes (eg, when the clinician has recorded the presence of an active plan). Applying natural language processing to these unstructured data might improve prediction models by incorporating data on psychosocial risk and protective factors that are otherwise neglected when relying on structured EHR data alone.[30–33]

Researchers have begun to explore different types of data for use in machine learning. The experience sampling method (ESM[91,92]), also known as ecological momentary assessment (EMA[93]), offers many possibilities for providing data on individuals' behaviours and experiences in real time, in the context of their everyday lives. One study found that supplementing EHR data with ESM data improved its algorithm's recall for predicting suicidal ideation from 48·13% to 67·78%.[94] To our knowledge, this is the only study to apply machine learning to combined ESM and EHR data, and this approach warrants replication. A pilot study found that EMA data collected during hospitalisation for suicidal ideation or behaviour might be useful for predicting suicide attempt following discharge.[95] Other reviews have discussed the potential for applying machine learning to data from the so-called Internet of Things, the network of internet-connected devices (eg, smartphones, wearable devices, and smart-home devices), to detect individuals at risk of suicidal behaviour.[57,96] Real-time data that individuals are already generating (eg, from activity trackers), is collected passively, minimising issues of recall bias and selective reporting. These data might also enable shorter-term prediction of suicidal thoughts and behaviours and pave the way for ecological momentary interventions. Such interventions, including just-in-time adaptive interventions, could be highly personalised, maximising the fit between individual and intervention.[97] Several studies have applied machine learning to social media data with the goal of predicting suicidal thoughts and behaviours.[98,99] The use of ESM, wearable devices, and social media data creates myriad possibilities, but also adds to the ethical problems raised by machine learning research in the context of suicide prevention.[96] Responsibility for intervening and the nature of intervention when an algorithm identifies an individual as being at risk of suicide in real-time must be addressed in future studies.[12] Initial work on the implementation and acceptability of ESM in clinical practice has already begun.[100]

Care of a person identified as being at risk of suicide

Helping clinicians to identify people at risk will not reduce suicide attempts or deaths unless the treatment needs of people identified as being at risk are met. Identification alone is insufficient to prevent suicide.[9]

Treatment and intervention provision within the health-care system is already under enormous strain, especially in LMICs, where the majority of suicide deaths occur.[2] Around 35% of individuals who die by suicide have contact with services in the week before their death.[101] Of the patients who present to hospital for self-harm, many do not receive a psychosocial assessment.[102,103] These clinical encounters are opportunities for identifying individuals at risk of suicide, and this identification might be supported by machine learning-based decision support systems. How the additional demand for treatment and intervention for suicidal ideation and behaviour will be met and who will meet it are crucial questions that should receive substantive focus in future research. Greater precision in being able to identify individuals who are not at risk of suicide might conserve resources for those who are at risk, but we also need to ensure that people are not denied access to treatments that might benefit them.[4] Machine learning might be able to help by allowing more nuanced decisions regarding which treatments are optimal for an individual, based on their level of predicted risk. What machine learning cannot do is increase the number of treatments and interventions within clinicians' suicide prevention toolkits, or increase the effectiveness of those currently available. Most interventions produce only small aggregate effects on suicide prevention,[104] yet, particular treatments and interventions might work better for some patients than others.[60] Determining which treatments are suited to which patients is at the core of precision medicine, and machine learning models can play a central role in this process. However, it is imperative that advances in capacity for identification are not seen as replacements for intervention; developing better identification of individuals at risk of suicide should be coupled with prioritising intervention development. Consequently, implementation factors should be included as standard in machine learning studies, specifically to address how these systems would function in relation to treatment and intervention.

Patients' and clinicians' experiences of machine learning decision support

Consideration of patients' and clinicians' experiences, ideally through patient and participant involvement and co-design, is essential for developing all interventions. Are machine learning decision-support tools acceptable to clinicians, and are they user-friendly? Interpretability of machine-learning-derived predictions of suicide risk by clinicians can be challenging,[30,77] and low interpretability might reduce clinicians' trust in the results.[78] Improving digital technology literacy among both clinicians and patients[11,14,15] will be crucial. Training on machine learning should be included in the professional training curriculum for psychiatrists, general practitioners, psychologists, and other mental health professionals.[14,105] Little is known regarding acceptability of machine-learning-based decisions from the patients' perspective, which should be explored in qualitative research.

Conclusion

In this Review of a broad selection of the literature on machine learning in the context of suicide research and prevention, we showed that machine learning as a clinical decision support tool has a potential role in suicide prevention, but is a long way from being implemented in routine daily practice. With health-care services around the world under unprecedented strain due to COVID-19, the idea of machine learning as a shortcut to decreasing suicides might seem promising; however, evidence does not support the idea that machine learning algorithms are currently able to prospectively predict suicide. Substantial challenges to overcome include improving data quality and interoperability (locally and globally), incorporating new data sources, and determining the acceptability of machine learning for clinicians and patients. Machine learning research in suicide must also diversify to include LMICs, where the need for suicide prevention is greatest. With further research and refinement, machine learning might develop into a tool that can complement and

Search strategy and selection criteria

We searched Web of Science, PsycINFO, Embase (including MEDLINE), IEEE Xplore, and ACM Digital Library) from Jan 1, 2000 to Feb 25, 2020, using the search terms ((“machine learning” OR “predictive modelling” OR “big data” OR “data mining” OR “Pattern recognition” OR “Artificial Intelligence” OR “prognostic model” OR “decision support systems”) AND suicid*). The initial search returned 1006 hits. Following duplicate removal, 801 article and review abstracts were screened by OJK, with 33 included within the final review. These results were supplemented with other emerging and landmark papers that we identified through authors’ knowledge and an automated Web of Science search for (“machine learning” AND suicid*) that repeated weekly until the Review was submitted for publication. Additional articles were also identified during revision of the Review and some were suggested by peer reviewers. A systematic review was published in 2019,[8] and a practical review was published in 2020,[17] of machine learning in the context of suicide, therefore we decided to focus on machine learning studies using register-based and electronic health record data, rather than literature on content or semantic analysis of suicide notes or social media data using machine learning, which are less available to clinicians. As an invited, topical review with a limit of about 100 references, inclusion of articles was necessarily selective, but covered the full breadth of the literature. The full list of search results is publicly available on the Open Science Framework. Studies and reviews were included irrespective of sample age group. Given that methodological issues were a key area of focus within our review, study quality and methodology were not exclusion criteria.

For a **full list of our search terms and hits** see https://osf.io/yph3g/

improve existing suicide prevention efforts by supporting clinicians and facilitating precision medicine. However, machine learning will improve suicide prevention only if the resulting increased demand for treatments and interventions can be met.

Contributors
All authors contributed to conceptualisation and methodology; OJK contributed to data curation; OJK, KvM, and DdB contributed to investigation and writing the original draft; all authors contributed to reviewing and editing.

Declaration of interests
OJK reports grants from UCB Community Health Fund, outside the submitted work. NK reports grants and personal fees from the UK Department of Health and Social Care, the UK National Institute of Health Research, the UK National Institute of Health and Care Excellence (NICE), and Healthcare Quality and Improvement Partnership, outside the submitted work; and has worked with the National Health Service England on national quality improvement initiatives for suicide and self-harm. NK sits on the Department of Health and Social Care’s (England) National Suicide Prevention Strategy Advisory Group. NK has chaired and been the Topic Advisor for NICE guideline committees for self-harm and depression.

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