

RESEARCH ARTICLE

Machine learning algorithms and their predictive accuracy for suicide and self-harm: Systematic review and meta-analysis

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OPEN ACCESS

Citation: Spittal MJ, Guo XA, Kang L, Kirtley OJ, Clapperton A, Hawton K, et al. (2025) Machine learning algorithms and their predictive accuracy for suicide and self-harm: Systematic review and meta-analysis. PLoS Med 22(9): e1004581. <https://doi.org/10.1371/journal.pmed.1004581>

Academic Editor: Alexander C. Tsai, Massachusetts General Hospital, UNITED STATES OF AMERICA

Received: February 10, 2025

Accepted: August 5, 2025

Published: September 11, 2025

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Data availability statement: The data and code used for the analyses are available to download from the Open Science Foundation. <https://doi.org/10.17605/OSF.IO/KBRZV>

Abstract

Background

There has been rapid expansion in the development of machine learning algorithms to predict suicidal behaviours. To test the accuracy of these algorithms for predicting suicide and hospital-treated self-harm, we undertook a systematic review and meta-analysis. The study was registered (PROSPERO CRD42024523074).

Methods and findings

We searched PubMed, PsycINFO, Scopus, EMBASE, IEEE, Medline, CINALH and Web of Science from database inception until 30 April 2025 to identify studies using machine learning algorithms to predict suicide, self-harm and a combined suicide/self-harm outcome. Studies were included if they examined suicide or hospital-treated self-harm outcomes using a case-control, case-cohort or cohort study design. Studies were excluded if they used self-reported outcomes or examined outcomes using other study designs. Accuracy was assessed using statistical methods appropriate for diagnostic accuracy studies. Fifty-three studies met the inclusion criteria. The area under the receiver operating characteristic curves ranged from 0.69 to 0.93. Sensitivity was 45%–82% and specificity was 91%–95%. Positive likelihood ratios were 6.5–9.9 and negative likelihood values were 0.2–0.6. Using in-sample

Funding: The research was primarily funded by a National Health and Medical Research Council Investigator Grant to MS (grant reference GNT2025205, <https://www.nhmc.gov.au>), which supports his salary and research costs. OK is supported by C+ (grant reference CPLUS/24/009) and C1 (grant reference C16/23/011) grants from KU Leuven (<https://research.kuleuven.be>). AC is supported by a postdoctoral fellowship from Suicide Prevention Australia (<https://www.suicidepreventionaustralia.org>). NK is supported by the National Institute for Health Research Greater Manchester Patient Safety Research Collaboration (grant reference NIHR204295, <https://www.nihr.ac.uk>) and is funded by Mersey Care NHS Foundation Trust. JP holds a National Health and Medical Research Council Investigator Grant (grant reference GNT2026408, <https://www.nhmc.gov.au>) which supports her salary and research costs. The funders had no role in study design, data collection, analysis, decision to publish or preparation of the manuscript.

Competing interests: I have read the journal's policy and the authors of this manuscript have the following competing interests: NK works with NHS England on national quality-improvement initiatives for suicide and self-harm; is on the Department of Health and Social Care (DHSC) National Suicide Prevention Strategy Advisory Group for England; chaired the guideline development group for the 2012 UK National Institute for Health and Clinical Excellence (NICE) guidelines on the longer-term management of self-harm; chaired the guideline development group for the 2022 NICE guideline on depression in adults; and was a topic advisor for the 2022 NICE guideline Self-Harm: Assessment, Management and Preventing Recurrence.

Abbreviations: AUROC, area under the receiver operating characteristic curve; QUADAS 2, Quality Assessment of Diagnostic Accuracy Studies instrument; sROC, summary receiver operating characteristic curves; STARD, Standards for Reporting of Diagnostic Accuracy Studies; TRIPOD, Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis.

prevalence values, the positive predictive values ranged from 6% to 17%. Using out-of-sample prevalence values at an LR+ value of 10, the positive predictive value was 0.1% in low prevalence populations, 17% in medium prevalence populations and 66% in high prevalence populations. The main study limitations were the exclusion of relevant studies where we could not extract sufficient information to calculate accuracy statistics and between-study differences in the follow-up time over which the outcomes were observed.

Conclusions

The accuracy of machine learning algorithms for predicting suicidal behaviour is too low to be useful for screening (case finding) or for prioritising high-risk individuals for interventions (treatment allocation). For hospital-treated self-harm populations, management should instead include three components for all patients: a needs-based assessment and response, identification of modifiable risk factors with treatment intended to reduce those exposures, and implementation of demonstrated effective aftercare interventions.

Author summary

Why was this study done?

- Numerous risk assessment scales have been developed over the past 50 years to identify patients at high risk of suicide or self-harm. These scales classify patients as either at high or low risk, and treatment pathways are frequently based on the results of this assessment.
- In general, these scales have poor predictive accuracy, and this is one of the reasons why many clinical practice guidelines strongly discourage risk assessment for suicide and self-harm.
- The availability of modern machine learning methods and access to electronic health record and registry data has re-focussed attention on developing new algorithms to predict suicide and self-harm.

What did the researchers do and find?

- We undertook a systematic review and meta-analysis to summarise the predictive properties of machine learning algorithms to predict suicide and self-harm.
- The overall quality of the research in this area was poor, with most studies at either high or unclear risk of bias.
- We found that the predictive properties of these machine learning algorithms were poor and no better than traditional risk assessment scales.

What do these findings mean?

- Machine learning algorithms incorrectly classify more than half the people who subsequently present to hospital for self-harm or die by suicide as low risk.
- A classification of high risk poorly forecasts who will engage in suicide or self-harm.
- There is insufficient evidence to warrant changing recommendations in current clinical practice guidelines about risk assessment.
- The findings are limited by the exclusion of studies where we could not extract the information required to undertake a meta-analysis and by the included studies assessing the outcomes over different time periods.

Introduction

Numerous studies have sought to identify patients at high risk of suicide or self-harm so that treatment can be provided specifically to them [1,2]. The risk assessment scales that have been developed stratify patients into high or low risk categories, with treatment pathways based on the classification [3]. The main clinical group that has been the focus of risk stratification is patients treated for self-harm (self-poisoning or self-injury) in the general hospital setting. Patients classified as high risk are typically prioritised for more intensive aftercare interventions than patients classified as low risk. Immediate interventions are classically psychiatric inpatient admission, close nurse observation or more urgent, frequent or intense community-based treatment (supervision). A high-risk classification, however, is not necessary to allocate effective, longer-term therapy-based interventions for suicidal behaviours like cognitive behavioural therapy in unselected self-harm populations [4], dialectical behaviour therapy in selected populations [5] or for suicide prevention in various clinical populations [6].

There is clear evidence that the traditional risk assessment scales used to predict suicide or self-harm have modest sensitivity and low positive predictive values [7–9]. In keeping with these findings, clinical guidelines do not recommend using risk stratification to allocate treatment in hospital-treated self-harm populations, and the US Preventive Services Task Force does not recommend screening for suicide risk in primary care [10–12], although conversely, the US Joint Commission recommends screening for suicide ideation for all patients over 12 years of age in all behavioural health services [13].

Efforts to improve risk prediction have recently focussed on using machine learning to develop algorithms that can predict suicide and self-harm. Machine learning is a branch of artificial intelligence in which prediction algorithms are developed by automatically and iteratively testing for complex associations between many factors in a dataset. Many studies emphasise the improved accuracy of their algorithms [14], suggesting that the poor accuracy of the traditional instruments has been overcome. But an important limitation of some of these studies, is a reliance on a case-control data to develop and evaluate algorithms. The use of the case-control design in diagnostic accuracy studies has previously been criticised as this design overestimates accuracy [15]. This overestimate occurs because the prevalence of the outcome is determined by the study design, and it is common in case-control studies to use a sample comprising half cases and half controls (meaning the apparent prevalence is 50%). The positive and negative predictive values of any risk score, however, are closely related to the prevalence of the outcome [16]. Suicide and self-harm are rare events, even in populations where the prevalence of these behaviours is high [14]. Thus, the high positive predictive values reported in some studies may be an artefact of the case-control design. This criticism is less likely to apply to cohort studies, although the retrospective nature of many cohort studies, where exposure data are collected when the outcome is already known, may be another potential source of bias.

To test the predictive accuracy of risk prediction algorithms developed using machine learning techniques, we undertook a systematic review and meta-analysis, paying particular attention to study design issues and their implications for prevalence. Our goal was to estimate a range of accuracy statistics of algorithm performance, namely, the area under

the curve, sensitivity, specificity, likelihood ratios and positive and negative predictive values. We focused on studies that predict either hospital-treated self-harm or suicide mortality as these are clinically relevant outcomes used by clinicians to differentially allocate treatment for high-risk patients and which usually rely on the same institutional data sources to identify outcomes for all participants.

Methods

We report our study using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement [17] ([S1 PRISMA Checklist](#)). The study was registered (PROSPERO: CRD42024523074). Screening, full text review, data extraction and quality assessment were undertaken using Covidence.

Search strategy and selection criteria

We searched PubMed, PsycINFO, Scopus, EMBASE, IEEE, Medline, CINALH and Web of Science from database inception until 30 April 2025 with the following search terms (“suicid*” OR “self?harm”) AND (“risk” OR “predict*” OR “class*”) AND (“machine learning”). No language restrictions were applied. We screened reviews, editorials and commentaries for further references. Titles and abstracts were screened independently by two authors. These studies were then assessed for eligibility in full-text review by the same authors. Disagreements were resolved by consensus.

Studies were eligible for inclusion if (a) the outcome was suicide or hospital-treated self-harm or a composite of these two; (b) the study involved primary research using a case-control, case-cohort or cohort design; (c) the study reported on a machine learning algorithm resulting in two or more risk factors measured at the individual level; (d) the study reported outcomes for any population or subgroup within the population (e.g., psychiatric treatment populations, people treated for self-harm); and (e) the study reported sufficient data to extract the number of true positives, false positives, false negatives and true negatives.

We excluded studies if (a) they only used suicidal ideation as the outcome; (b) used self-reported outcomes (e.g., self-reported suicide attempt or self-reported suicide risk); (c) the outcome was a specific suicide method (e.g., suicide by firearm); or (d) they only used aggregate predictors such as the number of firearm stores in an area.

Data extraction

The following data were extracted for each study: the lead author and publication year, title, country where the study was conducted, study population, study design (case-control, case-cohort, cohort), data source, study outcomes (suicide, self-harm, or a combined suicide/self-harm endpoint), machine learning method, time frame over which the outcome was assessed (30 days, 60 days, 90 days, 180 days, 1 year, other), and for each outcome, the number of true positives, false positives, false negatives and true negatives. If multiple thresholds were reported, diagnostic values were extracted at the 95th percentile as this is a commonly used threshold in this literature. If diagnostic values were reported at multiple time points, the longest time point was selected as this will give the most optimistic positive predictive value. Where possible, results from validation samples were extracted. For studies reporting multiple diagnostic values from different algorithms, we prioritised extracting results for the best-fitting model as identified by the authors. If this was unclear, results from the algorithm with the highest sensitivity was instead prioritised. Where results were stratified by sex, these were combined into an overall count. If data from different cohorts were reported, we extracted results from mental health service cohorts. Data were independently extracted by two authors with disagreements resolved by consensus.

Quality and risk of bias

The quality of each study was assessed in two ways. We examined if there was an explicit statement that the study reported against a relevant guideline (e.g., Transparent Reporting of a Multivariable Prediction Model for Individual

Prognosis or Diagnosis (TRIPOD) [18] or Standards for Reporting of Diagnostic Accuracy Studies (STARD) [19]). We then examined adherence to the TRIPOD checklist. Risk of bias was assessed using the second revision of the Quality Assessment of Diagnostic Accuracy Studies instrument (QUADAS 2) [20]. Assessment was done by two authors with disagreements resolved by a third author.

Statistical analyses

We conducted our meta-analyses in four stages. First, we estimated the pooled area under the receiver operating characteristic curve (AUROC) [21]. Next, we estimated the pooled sensitivity and specificity using a bivariate random effects meta-analysis [22]. This method, also known as a Reitsma model, jointly estimates the pooled sensitivity and specificity after a logit transformation by also estimating the negative correlation between these two estimates. We estimated heterogeneity at this stage using the adjusted I^2 statistic [23] and plotted the summary receiver operating characteristic curves (sROC). The adjusted I^2 statistic was developed for the meta-analyses of diagnostic accuracy studies and adjusts for sample size, the largest source of heterogeneity in these types of studies. The sROC is similar to a forest plot except that it plots study-specific estimates on two dimensions, *sensitivity* and the *false positive rate* (i.e., 1 – specificity). Third, we estimated the pooled positive and negative likelihood ratios (LR+ and LR-) using the method proposed by Zwinderman and Bossuyt [24]. They recommend estimating these measures by sampling the sensitivities and specificities derived from the analysis described above using the bivariate normal distribution and then calculating the LR values in each sample. We therefore drew 100,000 samples using a Monte Carlo Markov chain. For each sample, we calculated LR+ and the LR- and then estimated the sample mean and 95% credible intervals (the 2.5 and 97.5 percentiles of the samples). Fourth, we used Bayes' rule to estimate the in-sample positive and negative predictive values. Under Bayes' rule, the positive and negative predictive values are a function of the baseline prevalence of the outcome and the likelihood ratios [25]. We estimated the baseline prevalence from the cohort studies and applied these to both cohort and case-control likelihood ratios. Baseline prevalence was calculated using a random effects meta-analysis, where the proportions were transformed using the standard arcsine transformation prior to analysis. The back-transformed prevalences were therefore used as the pre-test probabilities. We report the median positive and negative predictive values and their 2.5 and 97.5 percentiles. All these analyses were stratified by outcome (suicide, self-harm, suicide/self-harm) and study design (case-control, cohort). Case-cohort and cohort studies were grouped together because case-cohort studies are a subset of cohort studies. We only undertook meta-analysis when data from five or more studies were available for analysis.

To examine how a hypothetical algorithm with indicative accuracy would perform in different clinical populations, we estimated out-of-sample positive predictive values using 1-year baseline prevalences from six different populations for varying LR+ values. These populations (and outcomes) were suicide in general population (0.01%), suicide after discharge from inpatient psychiatric facility (0.5%), self-harm in general population (1.5%), suicide after discharge for self-harm (2.0%), self-harm after discharge from inpatient psychiatric facility (6.5%) and self-harm after discharge for self-harm (16%). These prevalence estimates were drawn from the literature [26–30].

All analyses were undertaken in R version 4.4.2, with the meta-analyses undertaken using the mada and metafor packages [21,31].

Results

Our search identified 7,319 studies, together with 15 additional studies which were identified from citation searching and other sources (Fig 1). After removing duplicates, we screened the titles and abstracts of 2,853 studies. 2,613 of these were excluded (including three for which we could not obtain a full text version of the article) leaving 240 studies that were assessed for eligibility using full text screening. 187 of these were excluded: 98 because they did not examine suicide or hospital-treated self-harm, 48 because of insufficient data, 21 because they were not primary research, 15 because of the

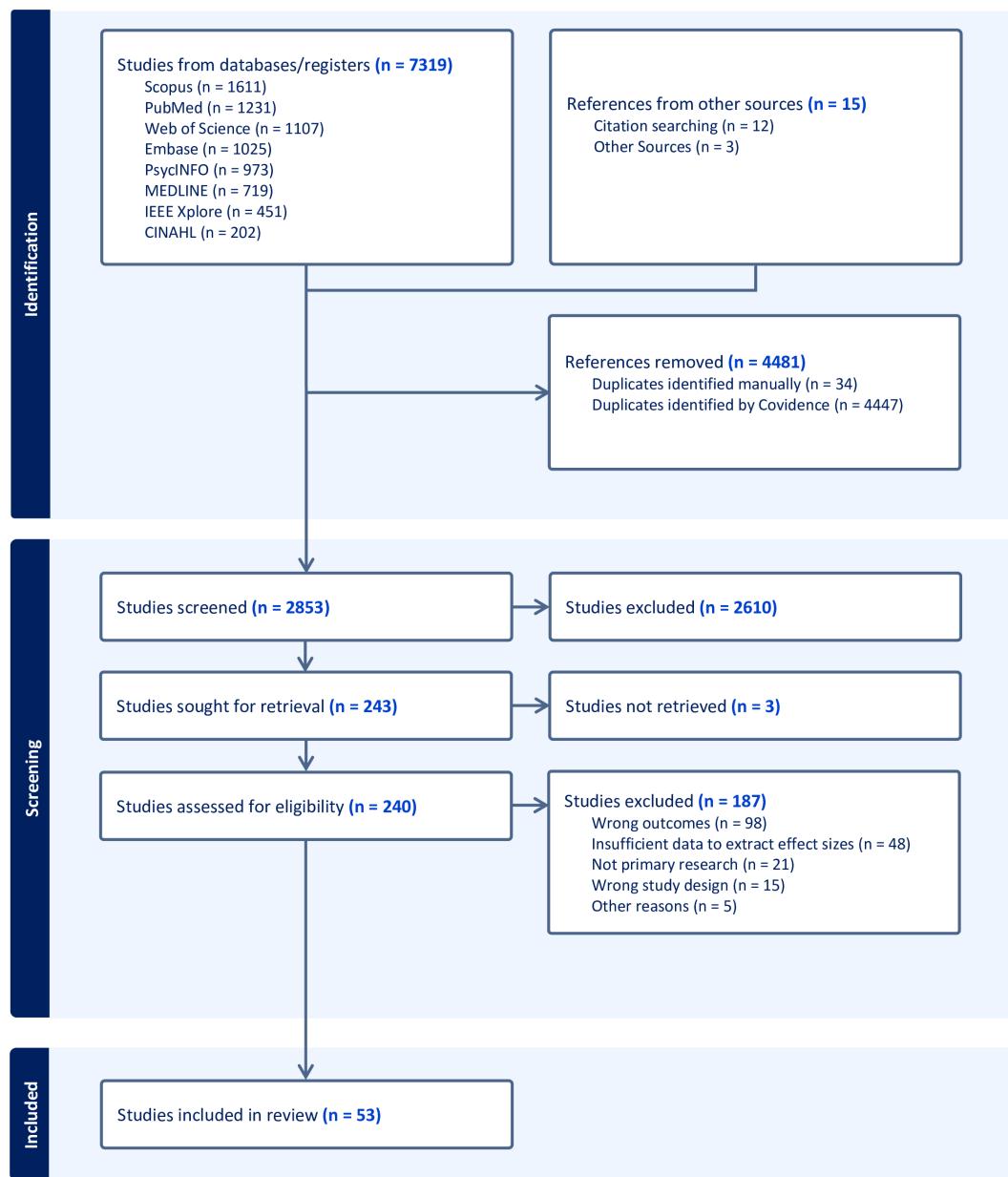


Fig 1. PRISMA flow diagram.

<https://doi.org/10.1371/journal.pmed.1004581.g001>

wrong study design, and five for other reasons. This left 53 studies [32–84]. These studies analysed 35 million records and 249,000 occurrences of suicide and self-harm.

The study characteristics are summarised in [Table 1](#). 30 studies were conducted in the United States, five studies in Denmark, five studies in the United Kingdom, three studies in Canada, two studies in South Korea, two studies in Sweden, and one study each in China, France, Iran, the Netherlands, Spain and Turkey. All studies were published between 2015 and 2025 with 44 of these from 2020 onwards.

Table 1. Characteristics of included studies.

Source	Country	Population	Data source	Study design	Statistical method	Out-come	Outcome ascertain-ment	Sample size	Sensi-tivity	Speci-ficity	LR+	LR-	PPV	NPV	
Amini 2016	Iran	People who had attempted suicide.	Survey linked to mortality records	Cohort	Support vector machines	Suicide	>1 year	3,790	8.4%	53.1%	69.9%	1.8	0.7	14.0%	94.2%
Arora 2023	United Kingdom	People aged 18–30 years who were treated as a mental health inpatient.	National register of mental health inpatient records	Cohort	Random forest and ensemble models	Self-harm	>1 year	6,031	4.6%	73.0%	70.3%	2.5	0.4	10.6%	98.2%
Barak-Corren 2017	United States	General hospital patients with three or more inpatient or outpatient visits.	Electronic health records	Cohort	Naïve Bayes classifier	Suicide or self-harm	Not reported	864,222	1.2%	33.0%	93.9%	5.4	0.7	6.0%	99.2%
Barak-Corren 2020	United States	General hospital inpatients and outpatients aged 10–90 years with 3 or more visits.	Electronic health records from five independent health systems	Cohort	Naïve Bayes classifier	Self-harm	>1 year	1,892,672	1.0%	36.3%	90.0%	3.6	0.7	3.6%	99.3%
Barak-Corren 2023	United States	Patients with multiple sclerosis who are treated in hospital.	Electronic health records	Cohort	Naïve Bayes classifier	Suicide or self-harm	>1 year	7,560	0.7%	23.1%	95.0%	4.6	0.8	3.1%	99.4%
Ben-Ari 2015	United States	US veterans who served in the Persian Gulf War.	Veteran Affairs' electronic health record system.	Cohort	Random forest	Self-harm	>1 year	82,500	2.7%	27.4%	99.5%	55.1	0.7	60.4%	98.0%
Bentley 2025	United States	Patients assessed for suicidal risk in inpatient, outpatient and emergency department settings.	Electronic health records	Cohort	Random forest	Self-harm	180 days	812,114	0.4%	69.7%	86.9%	5.3	0.3	2.2%	99.9%
Bittar 2019	United Kingdom	Cases were patients treated for self-harm in acute physical or specialist mental health services. Controls were age-matched patients from the same health service.	Electronic medical records from a single health service	Case-control	Natural language processing	Self-harm	30 days	4,235	20.0%	63.0%	89.9%	6.3	0.4	61.0%	90.7%
Cansel 2023	Turkey	Patients presenting to the emergency department who had attempted suicide and healthy controls.	Patient health records	Case-control	Extreme Gradient Boosting	Self-harm	>1 year	218	45.0%	77.6%	87.5%	6.2	0.3	83.5%	82.7%
Carson 2024	United States	Youth (12–20 years) hospitalised in a psychiatric inpatient unit.	Electronic health record—structured and unstructured data from the adolescent inpatient psychiatry unit of Cambridge Health Alliance in Massachusetts.	Case-cohort	Random forest classifier and a gradient boosting classifier	Self-harm	90 days	558	1.8%	80.0%	76.3%	3.4	0.3	5.8%	99.5%

(Continued)

Table 1. (Continued)

Source	Country	Population	Data source	Study design	Statistical method	Outcome	Outcome ascertainment	Sample size	Sensitivity	Specificity	LR+	LR-	PPV	NPV
Chen 2020	Sweden	People aged 18–39 treated as inpatients and outpatients of psychiatric specialty care services.	National registry data	Cohort	Random forest classifier and a gradient boosting classifier	Suicide or self-harm	90 days	108,276	3.7%	47.2%	96.6%	14.0	0.5	34.9%
Chen 2024	United States	Cases were patients treated for self-harm in inpatient, outpatient or emergency department settings (aged 18–64 years). Controls were age-sex matched patients from the same settings.	Electronic health records	Case-control	Tree guided feature selection and logic aggregation	Self-harm	>1 year	13,398	9.1%	22.7%	96.8%	7.0	0.8	41.3%
Cho 2020	South Korea	General population.	National health insurance data	Cohort	Random forest and bootstrap aggregating	Suicide	1 year	111,843	0.1%	65.7%	78.8%	3.1	0.4	0.3%
Cho 2021	South Korea	General population aged 65 and over	Health screening cohort database	Cohort	Random forest	Suicide	Not reported	48,047	0.2%	60.0%	82.2%	3.4	0.5	0.7%
Coley 2021	United States	Patients aged 13 years or older who had at least one outpatient mental health specialty visit.	Electronic health records	Cohort	Random forest	Self-harm	90 days	530,639	0.7%	49.1%	92.0%	6.2	0.6	4.0%
Coley 2023	United States	Patients aged 13 years or older who had at least one outpatient mental health specialty visit.	Electronic health records and insurance claims data linked with state mortality records	Cohort	Random forest	Suicide	90 days	3,754,137	0.0%	39.2%	100.0%	853.5	0.6	13.9%
DelPozo-Banos 2018	United Kingdom	Cases were people who died by suicide. Controls were matched by gender and age from the general population.	Data linkage of mortality, demographic, primary care, hospital and emergency department data.	Case-control	Artificial neural networks	Suicide	>1 year	60,684	4.3%	64.6%	81.9%	3.6	0.4	13.8%
Edgcomb 2021a	United States	General hospital patients with serious mental illness (major affective and chronic psychotic disorders).	Electronic health records	Cohort	Classification and regression trees	Self-harm	1 year	780,884	5.2%	73.3%	82.2%	4.1	0.3	18.3%
Edgcomb 2021b	United States	Women treated in hospital for mental health.	Electronic health records	Cohort	Classification and regression trees	Self-harm	1 year	15,644	1.4%	83.0%	81.1%	4.4	0.2	5.8%

(Continued)

Table 1. (Continued)

Source	Country	Population	Data source	Study design	Statistical method	Outcome	Outcome ascertainment	Sample size	Sensitivity	Specificity	LR+	LR-	PPV	NPV
Edgcomb 2023	United States	Children (aged 10–17) treated in emergency departments.	Electronic health records	Case-control	Random forest	Self-harm	Not reported	600	47.3%	85.6%	91.8%	10.4	0.2	90.3% 87.6%
Fernandes 2018	United Kingdom	Psychiatric patients treated in secondary and tertiary care.	Electronic health records	Case-control	Natural language processing	Self-harm	Not reported	500	77.6%	98.2%	29.5%	1.4	0.1	82.8% 82.5%
Gholi Zadeh Kharrat 2024	Canada	Cases were people aged 15 years and older who died by suicide. Controls were a 1% random sample of the Quebec population.	Linked data from five sources: health insurance registry, physician billing database, hospitalisation database, prescription claims database and a vital statistics database.	Case-control	Extreme gradient boosting and multilayer perception	Suicide	>1 year	654,489	1.4%	8.3%	99.9%	99.5	0.9	57.8% 98.8%
Gradus 2020	Denmark	Cases were people who died by suicide. Controls were drawn from the general population.	National registry data	Case-cohort	Classification and regression trees and random forest	Suicide	>1 year	279,286	5.0%	38.0%	96.7%	11.7	0.6	38.3% 96.7%
Gradus 2021	Denmark	Cases were all people who had made suicide attempt. Controls were drawn from the general population.	Nationwide registry data	Case-cohort	Classification and regression trees and random forest	Self-harm	Not reported	288,157	8.0%	43.8%	98.4%	26.7	0.6	69.8% 95.3%
Haroz 2024	United States	Patients treated in an American Indian health service.	Electronic health records from a single Indian Health Service in the Southwestern United States	Cohort	Penalised LASSO	Self-harm	90 days	16,835	1.9%	36.7%	71.9%	1.3	0.9	2.5% 98.3%
Jiang 2021	Denmark	Cases were people discharged from a psychiatric hospital. Controls were drawn from the general population.	National registry data	Case-cohort	Classification and regression trees and random forest	Suicide	30 days	25,764	4.7%	28.5%	96.0%	7.1	0.7	25.9% 96.5%
Jiang 2024	Denmark	People with depression.	National medical and administrative registries in Denmark	Case-cohort	LASSO	Self-harm	>1 year	17,995	33.5%	14.0%	99.6%	38.0	0.9	95.0% 69.7%
Kessler 2020	United States	Veterans who had psychiatric hospital admission	Veteran Health Administration health records linked with mortality data	Case-control	Super learner ensemble machine learning	Suicide	1 year	117,278	0.3%	22.4%	94.9%	4.4	0.8	1.2% 99.8%

(Continued)

Table 1. (Continued)

Source	Country	Population	Data source	Study design	Statistical method	Outcome	Outcome ascertainment	Sample size	Sensitivity	Specificity	LR+	LR-	PPV	NPV
Martinez-Romo 2025	Spain	Cases were patients treated for self harm in a psychiatry department of a hospital. Controls were all other psychiatric patients.	Electronic health records including free text notes	Case-control	Guardian-BERT	Self-harm	>1 year	778	18.0%	90.7%	97.0%	30.5	0.1	87.0%
Metzger 2017	France	Patients attending the emergency department for any reason.	Electronic health records of structured and unstructured data	Case-control	Naïve Bayes	Self-harm	Not reported	390	25.1%	94.9%	99.0%	92.4	0.1	96.9%
Nielsen 2023	Denmark	Patients discharged after a psychiatric inpatient stay.	National registry data	Cohort	Gradient boosting and categorical boosting model	Suicide	30 days	180,795	0.1%	52.3%	81.7%	2.9	0.6	0.3%
O'Reilly 2024	Sweden	Mental health outpatients aged 9–18 years.	Population-based registries	Cohort	Random forest	Suicide or self-harm	1 year	12,933	0.6%	83.7%	48.0%	1.6	0.3	1.0%
Obeid 2020	United States	Cases were patients treated for self-harm in hospital. Controls were patients with no history of self-harm.	Electronic health records	Case-control	Deep neural networks	Self-harm	>1 year	342	50.9%	69.5%	88.7%	6.1	0.3	86.4%
Penfold 2021	United States	Patients aged 13 years and <18 years had outpatient visits at mental health clinics.	Electronic health record and administrative claims data	Cohort	LASSO	Suicide or self-harm	90 days	361,176	1.4%	26.5%	95.3%	5.6	0.8	7.2%
Sanderson 2020a	Canada	People presenting to the emergency department for self-harm.	Registry data from statewide health system	Case-control	Gradient boosted trees	Suicide	Not reported	39,028	9.1%	69.8%	82.9%	4.1	0.4	29.0%
Sanderson 2020b	Canada	Cases were people who died by suicide. Controls were drawn from the general population.	Electronic health records linked with mortality records	Cohort	Gradient boosted trees	Suicide	90 days	33,694	0.8%	68.7%	89.1%	6.3	0.4	4.8%
Sheu 2023	United States	Psychiatric emergency department patients	Electronic health records	Cohort	Random survival forests	Self-harm	1 year	13,098	2.3%	29.2%	95.0%	5.9	0.7	12.3%
Sheu 2024	United States	All patients treated within a hospital system (consisting of eight hospitals)	Electronic health records	Cohort	Neural ordinary differential equations	Self-harm	>1 year	170,238	0.1%	68.6%	95.0%	13.7	0.3	1.6%
Shortreed 2023	United States	Patients with mental health specialty visits.	Electronic health records linked to state mortality data	Cohort	Ensemble models	Suicide	90 days	4,574,921	0.0%	13.6%	99.0%	13.1	0.9	0.3%

(Continued)

Table 1. (Continued)

Source	Country	Population	Data source	Study design	Statistical method	Outcome	Outcome ascertainment	Sample size	Sensitivity	Specificity	LR+	LR-	PPV	NPV	
Simon 2018	United States	Patients aged 13 or older with mental health specialty visits.	Electronic health records linked to state mortality data	Cohort	LASSO	Suicide	90 days	3,596,725	0.0%	48.1%	95.6%	11.0	0.5	0.3%	100.0%
Simon 2024a	United States	Patients aged 11 or older who visited specialty mental health clinicians.	Insurance claim data and electronic health records	Cohort	LASSO and random forest models	Suicide or self-harm	90 days	4,753,514	0.6%	42.2%	95.3%	8.9	0.6	5.3%	99.6%
Simon 2024b	United States	Patients attended emergency department for mental healthcare.	Electronic health records with suicide death recorded and insurance claims	Cohort	Random forest	Suicide	90 days	2,069,170	0.0%	34.8%	95.0%	7.0	0.7	0.3%	100.0%
Su 2020	United States	Patients aged 10–18 attending emergency department for any reason.	Electronic health records	Cohort	Logistic regression classifier with a sequential forward selection procedure	Self-harm	1 year	8,366	0.7%	38.3%	94.7%	7.3	0.7	5.0%	99.5%
Tsui 2021	United States	Cases were patients attending emergency departments or inpatient units for suicide attempts for the first time. Controls were patients without a history of suicide attempts.	Electronic health records	Case-control	Natural language processing and ensemble of extreme gradient boosting	Self-harm	90 days	11,079	8.8%	95.0%	69.9%	3.2	0.1	23.2%	99.3%
van Mens 2020	Netherlands	Cases were patients attending general practice appointments for attempted suicide. Controls were patients attending general practice appointments for psychological treatment.	Electronic health records	Case-control	Random forest	Self-harm	Not reported	53,822	0.3%	39.1%	97.6%	16.2	0.6	4.6%	99.8%
Walsh 2017	United States	Cases were patients who had made a suicide attempt. Controls were patients with self-injury ICD codes but who had not made an attempt (e.g., unintentional drug overdose, accidental injury, non-suicidal self-injury, injury with unclear intent).	Electronic health records	Case-control	Random forest	Self-harm	1 year	5,167	62.9%	98.3%	58.2%	2.3	0.0	79.9%	95.2%

(Continued)

Table 1. (Continued)

Source	Country	Population	Data source	Study design	Statistical method	Outcome	Outcome ascertainment	Sample size	Sensitivity	Specificity	LR+	LR-	PPV	NPV
Wang 2023	United Kingdom	Cases were UK Biobank participants who had attempted or died by suicide. Controls were randomly selected living participants from the biobank with no recent suicidal behaviour.	UK Biobank data	Case-cohort	Light gradient-boosting machine	Suicide or self-harm	1 year	4,683	4.8%	57.8%	95.1%	11.8	0.4	37.2%
Wilimitis 2022	United States	General hospital patients aged ≥18 years.	Electronic health records	Cohort	Ensemble models	Self-harm	180 days	120,398	0.4%	58.6%	95.0%	11.8	0.4	4.8%
Xu 2020	China	Cases were patients aged >10 years with at least one self-harm diagnosis. Controls were patients aged >10 years without a self-harm diagnosis.	Electronic health records	Case-control	Diagnosis to vector (Dx2vec) and deep neural network	Self-harm	1 year	8,149	5.7%	72.0%	96.3%	19.4	0.3	54.0%
Xu 2022	United States	Children, adolescents and young adults (10–24 years) with at least one non-suicide related hospitalisation.	Insurance claims database linked with inpatient data	Case-control	Targeted fusion learning framework	Self-harm	Not reported	3,930	1.2%	65.3%	94.7%	12.2	0.4	13.4%
Yang 2025	United States	Veterans treated as psychiatric inpatients.	Electronic health records linked with the National Death Index	Cohort	TransformEHR	Suicide	180 days	126,800	0.1%	45.2%	96.3%	12.3	0.6	1.6%
Zang 2024	United States	Patients aged 10–24 years in three hospital systems.	Electronic health records	Cohort	Regularised logistic regression	Self-harm	>1 year	57,055	1.2%	59.1%	90.0%	5.9	0.5	6.8%
Zheng 2020	United States	General hospital patients.	Electronic health records	Cohort	Deep neural networks	Self-harm	1 year	112,095	0.2%	6.9%	99.9%	62.2	0.9	10.1%

Note: Sample sizes represent the sample in which diagnostic accuracy statistics were calculated. If a study separated the data into training and validation samples, the sample size will be from the validation sample.

<https://doi.org/10.1371/journal.pmed.1004581.t001>

Thirty-six studies used a retrospective cohort design and 17 used a case-control design. Thirteen studies predicted suicide, 30 predicted hospital-treated self-harm, 7 predicted suicide/self-harm and three studies developed algorithms separately for suicide and self-harm. The time frame over which these predictions were made were 30 days (3 studies), 90 days (12 studies), 180 days (3 studies), 1 year (11 studies) and >1 year (15 studies). In nine studies, the prediction window was not reported. There was considerable variation in the study populations. Twenty-four studies developed their algorithms in general population or general patient populations. Twenty-two studies developed algorithms in patients treated for psychiatric problems. Six studies developed algorithms in patients presenting to hospital for self-harm or with a history of self-harm. One study used data from another population (patients with multiple sclerosis). The data were predominately drawn from electronic health records, insurer claims data and registry data. The studies used a variety of machine learning methods, including random forests (10 studies), gradient boosted trees (8 studies), classification and regression trees (5 studies), LASSO models (5 studies) naive Bayes classifiers (3 studies) and ensemble learning (3 studies).

The findings of nine studies were reported using TRIPOD or STARD guidelines. Of the 31 items in the TRIPOD checklist, three items were judged to be not relevant for most studies and were removed from the quality assessment. Of the remaining 28 items, the mean number of checklist items that were adhered to across the studies was 20. Checklist items with low adherence were explaining how the sample size had been arrived at (11 studies), describing how missing data was handled (19 studies), reporting unadjusted associations between candidate predictors and the outcome (10 studies) and providing details about how the risk groups were created (11 studies) ([S1 Table](#)).

For patient selection, 18 studies were judged as having low risk of bias, 24 were at high risk of bias with the remaining 11 studies at unclear risk of bias ([Fig 2](#) and [S2 Table](#)). For choice of index test, 6 studies were at low risk of bias, three

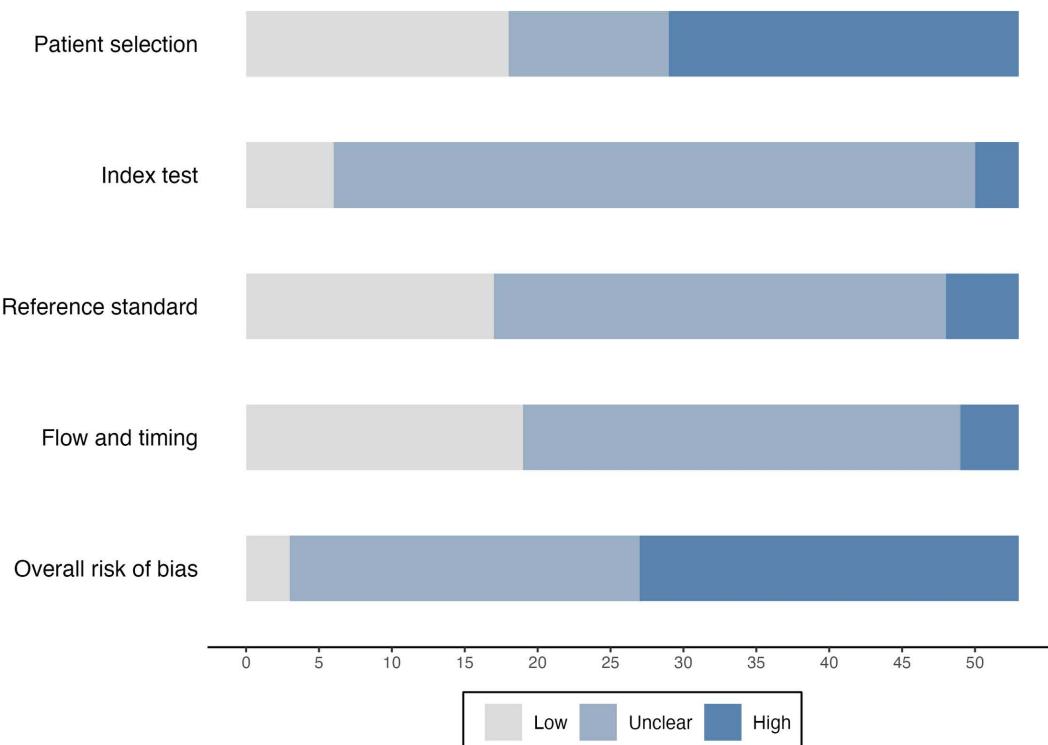


Fig 2. Risk of bias assessments.

<https://doi.org/10.1371/journal.pmed.1004581.g002>

were at high risk of bias and 44 studies were at unclear risk of bias. For the reference standard, 17 studies were at low risk of bias, 5 studies were at high risk of bias and 31 studies were at unclear risk of bias. For flow and timing of patients, 19 studies were at low risk of bias, 4 were at high risk of bias and 30 studies were at unclear risk of bias. Overall, three studies were judged to be at low risk of bias, 26 studies at high risk of bias, and 24 studies at unclear risk of bias.

The pooled AUROCs ranged from 0.69 to 0.93 with the lowest value for the prediction of suicide from cohort studies and the highest for predicting self-harm from case-control studies (Table 2). The pooled sensitivities ranged from 45% to 82% and the specificities from 91% to 95%. The LR+ values ranged from 6.5 to 9.9 and the LR- from 0.2 to 0.6. Using baseline 1-year prevalence values of 0.7% for suicide, 2.1% for self-harm and 1.6% for suicide/self-harm, the positive predictive values were 6% for suicide (in cohort studies), 16% and 17% for self-harm (in case-control and cohort studies, respectively) and 9% for suicide/self-harm (in cohort studies). The corresponding negative predictive values were 99% for suicide, 90% and 96% for self-harm and 97% for suicide/self-harm.

Table 3 shows the positive predictive values for a hypothetical algorithm with LR+ values ranging from 1 to 50 alongside indicative 1-year probabilities of suicidal behaviours in different populations. In a low prevalence population, for example, predicting suicide in the general population (baseline prevalence 0.01% per year [30]), in the LR+ values we observed (LR+=6–10), the positive predictive values ranged from 0.06% to 0.10%. In a medium prevalence population, for example, predicting suicide after discharge from hospital for the treatment of self-harm (baseline prevalence 2% per year [29]), positive predictive values ranged from 11% to 17%. In a high prevalence population, for example, predicting self-harm after discharge from hospital for self-harm (baseline prevalence 16% per year [29]), the positive predictive values ranged from 53% to 66%. Positive predictive values improved at higher LR+ values than we observed in our pooled analysis. At LR+=20, the positive predictive value was 29% in a medium prevalence population (79% in a high prevalence population), and at LR+=50, it was 51% (91% in a high prevalence population).

The sROCs are contained in S1 Fig. The figure shows that the estimates are generally clustered close together on the two dimensions (sensitivity and the false positive rate). I^2 estimates ranged from 1.6% to 11.4%.

Table 2. Pooled diagnostic accuracy statistics of machine learning instruments to predict suicide, self-harm and suicide/self-harm.

Outcome	Study design	Number of estimates	AUROC	Sensitivity, % (95% CI)	Specificity, % (95% CI)	LR+, (95% CrI)	LR-, (95% CrI)	Positive predictive value, % (95% CrI)	Negative predictive value, % (95% CrI)
Suicide									
	Case-control	4	--	--	--	--	--	--	--
	Cohort	12	0.69	45 (35, 55)	95 (87, 98)	9.9 (3.8, 21.9)	0.6 (0.5, 0.7)	6 (3, 14)	99 (99, 99)
Self-harm									
	Case-control	13	0.93	82 (66, 92)	91 (82, 96)	9.2 (4.8, 16.2)	0.2 (0.1, 0.4)	16 (9, 26)	90 (81, 94)
	Cohort	20	0.80	46 (35, 58)	95 (90, 97)	9.4 (5.6, 14.8)	0.6 (0.5, 0.7)	17 (11, 24)	96 (95, 97)
Suicide/self-harm									
	Case-control	0	--	--	--	--	--	--	--
	Cohort	7	0.80	46 (29, 63)	93 (84, 97)	6.5 (3.6, 11.0)	0.6 (0.4, 0.7)	9 (5, 15)	97 (96, 98)

Notes: Analyses only undertaken when there are at least five studies available for meta-analysis. All pooled sensitivity and specificity estimates calculated using the binomial-normal model that jointly estimates both (logit transformed) pooled values and adjusts for the negative correlation between them. Pooled LR values calculated by sampling sensitivity and specificity values from the bivariate normal distribution using a Monte Carlo Markov chain with 100,000 samples. Positive and negative predictive values calculated using Bayes rule with the following baseline prevalence estimates (suicide 0.7%, self-harm 2.1%, suicide/self-harm 1.6%). CI, confidence intervals. CrI, credible intervals.

<https://doi.org/10.1371/journal.pmed.1004581.t002>

Table 3. Positive predictive values by 1-year base prevalences and positive likelihood ratios.

Base prevalence	0.01%	0.5%	1.5%	2.0%	6.5%	16%
Example outcome and population	Suicide in general population	Suicide after discharge from inpatient psychiatric facility	Self-harm in general population	Suicide after discharge for self-harm	Self-harm after discharge from psychiatric facility	Self-harm after discharge for self-harm
LR+	Positive predictive values					
1	0.01%	0.5%	1.5%	2.0%	6.5%	16.0%
2	0.02%	1.0%	3.0%	3.9%	12.2%	27.6%
3	0.03%	1.5%	4.4%	5.8%	17.3%	36.4%
4	0.04%	2.0%	5.7%	7.5%	21.8%	43.2%
5	0.05%	2.5%	7.1%	9.3%	25.8%	48.8%
6	0.06%	2.9%	8.4%	10.9%	29.4%	53.3%
7	0.07%	3.4%	9.6%	12.5%	32.7%	57.1%
8	0.08%	3.9%	10.9%	14.0%	35.7%	60.4%
9	0.09%	4.3%	12.1%	15.5%	38.5%	63.2%
10	0.10%	4.8%	13.2%	16.9%	41.0%	65.6%
15	0.15%	7.0%	18.6%	23.4%	51.0%	74.1%
20	0.20%	9.1%	23.3%	29.0%	58.2%	79.2%
50	0.50%	20.1%	43.2%	50.5%	77.7%	90.5%

Note: LR+ is defined as sensitivity/(1 – specificity). Shaded region refers to the range of pooled LR+ values observed in the meta-analysis.

<https://doi.org/10.1371/journal.pmed.1004581.t003>

Discussion

In this systematic review and meta-analysis of algorithms developed using machine learning tools to predict suicidal behaviour, we found these algorithms had good accuracy when assessed using a global measure, the area under the curve, but poor accuracy when assessed against more clinically relevant individual measures. We found that the algorithms had modest sensitivity and high specificity. This combination of sensitivity and specificity meant that while the algorithms are good at identifying people who will *not* re-present for self-harm or die by suicide, they are generally poor at identifying those who will. The modest sensitivity observed in the cohort studies indicates that more than half of those who repeat self-harm or die by suicide are misclassified as low risk.

The sensitivity and specificity values we observed translate into LR+ values that are just under the clinically meaningful minimal threshold of $LR+ \geq 10$ [85]. However, the low baseline prevalence of suicidal behaviour, taken either from the cohort studies included in our review or from externally derived prevalence estimates [26–30], meant that the positive predict values of these algorithms were also very low. To illustrate, the in-sample positive predictive values were 6% for suicide, 16%–17% for self-harm and 9% for suicide/self-harm. When an LR+ value of 10 was applied to low, medium and high prevalence populations, the positive predictive values were 0.10%, 17% and 66%. The only theoretical scenarios where the positive predictive values were high enough to be clinically useful would be when the LR+ was ≥ 50 and the base prevalence was $\geq 6.5\%$ per year (equivalent to an event rate of 6,500 per 100,000 person years) or when LR+ was ≥ 20 and the base prevalence was $\geq 16\%$ per year (16,000 per 100,000 person years). These high positive predictive values are unlikely to be realised in real-world clinical settings for two reasons. First, predictions in high prevalence populations, such as in patients who have been discharged from a psychiatric facility or received treatment in hospital for self-harm, will be most clinically useful over a shorter window than the 1-year prevalence estimates used here (for example, 24 or 48 h after discharge through to 30 days). Prevalence will therefore be much lower than the values we used, and consequently, the positive predictive values will also be lower. To illustrate, while the 1-year baseline probability of

self-harm after discharge from a psychiatric facility is 6.5%, the 4-week estimate is only 2.1% [28]. At this value, the positive predictive value is only 30% for an LR+ value of 20. Second, it is difficult to develop an algorithm with high LR+ values as it requires identifying a threshold with both high sensitivity and high specificity. In practice, there is a trade-off between sensitivity and specificity. Finding a threshold that increases the value of one of these measures will result in decreasing the value of the other. Most ways of getting a high LR+ value require very high specificity values ($\geq 97\%$) which means sensitivity is likely to be correspondingly low, leading to most cases being misclassified as low risk.

There appear to be two reasons for the recent focus on the development of new algorithms to predict suicide and self-harm. One reason is to screen for risk of suicide and self-harm [34,36,41,44,45,48,50,56,71,72,76,79,81,82,84]. In this model, the algorithm flags high-risk patients in the electronic medical record and these patients then undergo a further risk assessment. Most studies have focussed on this two-stage process being applied to psychiatric inpatients and outpatients, but it has also been suggested that this be applied to general practice patients [76]. If these algorithms are to be used for automatically screening medical records then they should meet the criteria set down for a viable, effective and appropriate screening programme [86]. Yet against the 12 consolidated screening principles [87] the algorithms for suicide and self-harm appear to meet one criterion: the epidemiology of the disease or condition is adequately understood; and another partially: that there is an agreed-upon course of action for screening participants with a positive test result. The algorithms do not appear to meet the other criteria, namely: the natural history of the disease or condition is clearly understood; the target population for screening is clearly defined; the screening test has sufficient performance characteristics; the screening test results are clearly interpretable; there is adequate infrastructure to allow for timely access to all components of the screening programme; the screening programme is coordinated with the broader healthcare system; the screening programme is acceptable and ethical; the overall benefits of the screening programme outweigh the harms; the full costs of the screening programme have been assessed in an economic evaluation; and the screening programme has clear goals and it is evaluated against these goals. On this basis, none of the algorithms we studied appear to be suitable as a screening tool for suicide or self-harm in unselected clinical populations.

The second reason machine learning algorithms have been developed is to prioritise the highest risk individuals for expensive or high-intensity interventions (for example, psychiatric hospitalisation or intensive case management by psychiatric services after discharge) [59,64,66,78,88]. One illustrative study found that among those with mental health speciality visits, those in the top 5% of risk accounted for 43% of suicide attempts and 48% of suicides over a 90-day prediction window [71]. The problem with this approach is that it results in algorithms with modest sensitivity and poor positive predictive values [3,89]. As the threshold that defines a positive test result is raised, the number of cases of suicide or self-harm detected by the algorithm (the true positives) decreases and the number of undetected cases increases (the false negatives). At a very high threshold (for example, the top 5% of risk continuum), it is likely that the number of undetected cases outnumber the detected cases (i.e., sensitivity will be $< 50\%$). Regarding the specificity, increasing the threshold will benefit the specificity of the algorithms because the number of non-cases that fall below the threshold (the true negatives) will increase. This is the pattern of results we see in our meta-analysis. The pooled sensitivities were generally below 50% and the specificities above 90%, and when combined with the low case prevalence, meant the positive predictive values were very low (because of the large proportion of false positives). The implication of using a high threshold to allocate treatment is that most cases of suicide and self-harm will be misclassified as low risk, and most people who test positive will receive an intervention they may not need. In other words, these intensive and expensive services will largely be delivered to the wrong people.

One argument in favour of using risk prediction algorithms is that it may be a cost-effective way of allocating expensive interventions. This strategy could be appealing to third-party payers and public health providers in an environment where healthcare resources are scarce. Some research has examined the circumstances under which a suicide risk prediction test might be cost-effective [88]. In a simulation study, the authors found an active contact and follow-up intervention could be cost-effective when people were allocated to this intervention using a test with sensitivity of 17% or greater when

specificity was 95%. Similarly, the same study showed cognitive behavioural therapy could be cost-effective when the test used for allocation had sensitivity of 36% or greater when specificity was 95%. However, there are important caveats to these findings. First, the low sensitivity implies that a high threshold was being used to allocate treatment in these simulations, but a high threshold means that only a small number of people are allocated to these interventions. Second, and as discussed above, when sensitivity is less than 50%, there are more undetected cases at that threshold than detected cases. Many of these people could have benefited from the intervention, but would not have received it as they scored below the threshold on the risk assessment.

The diagnostic accuracy of machine learning algorithms for suicide and self-harm is similar to that of traditional risk assessment instruments [7,9]. The poor accuracy of these traditional instruments was one of the factors that led to clinical guidelines in several countries recommending that risk stratification not be undertaken in order to allocate aftercare services and that alternatives, such as needs-based psychosocial assessment be offered to patients instead in order to foster and focus aftercare interventions [10,12]. The National Institute of Clinical and Health Care Excellence guidelines [12] recommend that after an episode of self-harm, a mental health professional should carry out a psychosocial assessment to develop a therapeutic relationship with the patient and a shared understanding of why they have self-harmed, undertake needs assessment, ensure the patient is offered the care they need, and give family and carers information about the patient's condition and diagnosis. Ideally, mental health clinicians should develop a therapeutic alliance with the patient that is organised around four components: predisposing factors (their history of self-harm, mental health and other relevant events), modifiable factors (things that are changeable, such as relationship issues, substance use, mood and mental health and access to means), future factors (anticipated events such as anniversaries, discharge from hospital or criminal proceedings) and protective factors (problem-solving skills, social and family support, engagement with services, insight and hope) [90]. Given that machine learning algorithms, including those that use dynamic risk formulation [68,70,77], appear to be no better at predicting suicide or self-harm than traditional risk assessment instruments, we see no compelling new evidence to warrant a change to these guidelines.

More generally, there are a number of effective aftercare interventions suitable for people presenting to hospital for self-harm that can be applied without first undertaking risk stratification to determine the allocation of treatment. Examples of interventions that have been shown to be effective for reducing the repetition of self-harm include psychological and psychosocial interventions (e.g., cognitive behavioural therapy or interventions with an interpersonal focus [4,91], brief contact interventions [92], multilevel interventions for the reduction of suicide and suicide attempts in clinical populations [6], and safety planning interventions [93]). All these interventions have financial and non-financial costs associated with them, and decisions about whether to deploy them in a hospital setting should be made with due consideration of whether the intrusiveness, burdensomeness and ethicality are proportionate to the benefits. Finally, we are concerned that the focus on risk assessment can be falsely reassuring and a distraction from the delivery of basic clinical services like ensuring all patients who present to the emergency department for self-harm are seen in a timely manner, are properly assessed and receive appropriate follow-up care [94]. In the UK and Australian context, this is apparent in the concerns of patients and service users about impersonal tick boxes rather than holistic assessments [95] and clinicians or health services being preoccupied with potential blame rather than delivering high-quality care [96,97].

Instead of predicting suicide and self-harm, there may be other ways in which artificial intelligence could be used to contribute to better outcomes for suicidal patients. Future research could consider how machine learning methods could be used to augment existing collaborative psychosocial assessments. Specifically, can machine learning methods be used to identify modifiable risk factors for suicide and self-harm for individual patients? This may be a more tractable problem as the prevalence of many risk factors is likely to be higher than the prevalence of suicide or self-harm. If such modelling can be done, then there are interesting follow-on questions about the acceptability of this approach for patients and clinical staff, and whether such an approach is superior to gathering information directly from patients and caregivers. Another interesting question for future research is to consider how artificial intelligence could be used to inform clinical decision

support tools. This is distinct from using a risk classification to allocate treatment; rather, it is a question about whether artificial intelligence, when combined with information about an individual patient, can make suggestions for treatment pathways. Some work on this has been undertaken in other areas of medicine (e.g., in oncology to optimise drug dosage for individual patients [98]), and it is an open question as to whether this approach can be applied to the treatment of individuals with psychiatric symptoms and disorders.

Our study has a number of strengths. We used a broad set of search terms to capture studies that have used machine learning to predict suicidal behaviour. We searched eight databases that comprised a wide range of disciplines (e.g., medicine, psychology, health sciences, engineering and computer sciences). We focussed only on suicide and hospital-treated self-harm as the outcomes, not self-reported behaviour or scores on an instrument. The included studies use a variety of different machine learning methods. We were able to assess the quality of the literature, and we showed that at least half the studies on this topic are at high risk of bias and a substantial number are at unclear risk of bias. We were able to examine a range of diagnostic accuracy statistics, and we were able to recalibrate case-control studies to estimate positive and negative predictive values using the prevalence from cohort studies. Finally, we were able to estimate the positive predictive values for different outcomes (suicide or self-harm) in different populations (the general population, psychiatric patients, patients treated for self-harm).

Against this, our study had limitations. We had to exclude 48 studies because they did not present sufficient information for data extraction. The period over which follow-up outcome data were gathered varied between studies, from 30 days to 2 years for the majority of studies. Most of the included studies were judged to be at high or unclear risk of bias. We were unable to estimate pooled values for two groups of studies: case-control studies of suicide and case-control studies of suicide/self-harm. We were unable to assess publication bias as tools have not been developed to assess publication bias of diagnostic and accuracy studies. We were unable to assess the potential biases in individual algorithms. Finally, a number of studies used data collected from the same health system or data-linkage system. We were unable to adjust for this in our analyses.

In conclusion, our systematic review and meta-analysis has shown that algorithms developed using machine learning tools to predict suicide and self-harm suffer from the same problems as the traditional risk scales used to predict suicidal behaviour. The algorithms have modest sensitivity and low positive predictive values, resulting in most cases of suicide or self-harm occurring amongst those classified as low risk, and a large proportion of false positives in those classified as high risk.

Supporting information

S1 PRISMA Checklist. PRISMA 2020 Checklist. This checklist is licensed under the Creative Commons Attribution 4.0 International License (CC BY 4.0; <https://creativecommons.org/licenses/by/4.0/>).

(S1_PRISMA_Checklist.DOCX)

S1 Table. TRIPOD checklist adherence for 53 included studies.

(S1_Table.DOCX)

S2 Table. Risk of bias ratings for each study.

(S2_Table.DOCX)

S1 Fig. sROC curves of machine learning instruments to predict suicide, self-harm, suicide/self-harm.

(DOCX)

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