Review Article

Artificial Intelligence, Machine Learning Approach and Suicide Prevention: A Qualitative Narrative Review

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Abstract

The initial step in suicide prevention involves identifying individuals who may be at risk of attempting suicide at an early stage. Utilising artificial intelligence (AI) and machine learning (ML) techniques offers innovative avenues for the early detection of such individuals. Nevertheless, there is a lack of clear information regarding the application of AI and ML in suicide prevention. Our objective is to examine the latest research findings on the utilization of AI/ML in forecasting suicidal tendencies. Authors reviewed four databases (PubMed/MEDLINE, Scopus, Web of Science and SCImago) for studies using AI/ML for suicide prevention published in English from 1 January 2000 to 31 December 2021. Search strings and MeSH were employed for searching terms relevant to suicide prevention and AI/ML. Results of the studies were analysed qualitatively, and information was presented as tables and figures. After removing duplicate articles, out of 434 studies, 21 articles, involving a total of 274,876 participants, met the inclusion criteria and were considered for this review. The results suggested that AI/ML-based suicide prediction models might improve healthcare systems by identifying individuals at high risk of suicide by preventing suicidal attempts. However, further researches are needed to perform AI/ML-based evidence-based assessment tools and determine their validity and reliability for suicide prediction models in different contexts.

Keywords: **Artificial Intelligence, big data, depression, machine learning, mental health, suicide**

Introduction

Suicide, a multifaceted and preventable public health issue, presents a significant burden at personal, familial and community levels. It now surpasses both road traffic accidents and homicides, marking an urgent public health crisis with considerable economic implications.[1,2] In India, one of the world's most populous countries, suicide remains a prominent issue, with 153,052 cases reported in 2020 alone.[3] Globally, suicide accounts for 1.4% of premature deaths and is the second leading cause of mortality amongst individuals aged 15–29 years.[4,5] According to the World Health Organisation (WHO), over 700,000 people died by suicide in 2019, equivalent to one in every 100 deaths worldwide. In response, the WHO has developed strategies to help countries address this growing crisis.[6] However, assessing suicide risk remains a challenge due to

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frequent underreporting of symptoms and difficulties in accurately screening for suicidal ideation, intention, and planning at every level of health care.[7,8]

In this context, artificial intelligence (AI) offers several advantages over traditional analytical methods, particularly in predicting suicidal behaviour. AI simulates human cognitive skills such as problem-solving and pattern recognition and uses machine learning (ML) to rapidly process large datasets, enabling the creation of risk algorithms that can assess the impact of protective and risk factors on suicide outcomes.[9] AI and ML techniques have shown promising results in identifying individuals at high risk of suicide, detecting surges in suicidal behaviour and providing tailored interventions.[8,10] Recent advances in the Internet of Things (IoT) and the Internet of Medical Things further enhance AI's ability to gather continuous clinical data through mobile applications and wearable devices, improving healthcare delivery.[11] While AI's role in mental health care, particularly in monitoring, assessment and intervention, shows promise, concerns about data privacy and confidentiality remain crucial.[12-16] The COVID-19 pandemic has exacerbated mental health challenges, with post-COVID-19 syndrome linked to increased suicide risk, emphasising the need for early identification and intervention through digital solutions.[17] This review aims to summarise recent research on AI/ML applications in suicide prevention.

Materials and Methods

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. A comprehensive literature search was conducted across PubMed, Scopus, SCImago and Web of Science databases for articles related to mental health, suicide and AI, published between 1 January 2000, and 31 December 2021. Search terms included 'Artificial Intelligence, 'Machine Learning, 'Big Data', 'Suicide Prevention' and 'Mental Health'. The search focused on quantitative studies that utilised AI/ML for suicide prevention, specifically covering risk assessment, detection, intervention and post-intervention follow-up.

Studies were selected based on their relevance to suicide-related behaviours, such as suicidal ideation and attempts. Qualitative research, case studies, reviews, dissertations, theses and book chapters were excluded. The participation did not limited to specific age groups or population. Only full text available and published in the English language were included. Data extraction was performed by two independent reviewers using standardised tables, and any disagreements were resolved through a predefined arbitration process. Key parameters extracted included publication year, country, participant demographics, the type of AI used and performance metrics. Ethical clearance was not applicable as this study involved a review of previously published research.

A total of 492 articles were initially identified. After removing duplicates and irrelevant studies, 21 articles were included in the final analysis [Figure 1].

Results

This review identified 21 studies[18-38] focusing on the application of AI and ML for suicide prevention across various populations and contexts. The studies analysed data from diverse settings, including psychiatric hospitals, social media platforms, military personnel and general population health records. AI models, such as random forest, support vector machines and neural networks, were primarily used to predict suicidal ideation, attempts and risk factors [Table 1].

Overall, the findings indicate that AI/ML models demonstrated a high level of accuracy in predicting suicidal behaviour. For example, prediction models based on clinical records showed that AI could identify suicide attempts with an accuracy of up to 94% [Table 1]. Similarly, AI tools analysing social media content were able to effectively detect depressive and suicidal tendencies among users. In addition, AI models utilising demographic and clinical data from mental health patients successfully classified at-risk individuals, especially those with conditions such as depression, schizophrenia and post-traumatic stress disorder (PTSD).

The studies revealed that AI/ML methods are not only capable of identifying individuals at risk of suicide but also of predicting long-term suicide risk with specificity rates as high as 90%. These technologies, when integrated with clinical decision-making, offer promising potential for improving early intervention strategies in suicide prevention. However, the models require further refinement, especially in naturalistic settings, to ensure broader applicability and consistency across different populations [Figure 2]. AI and ML demonstrate considerable potential in suicide risk prediction, but ethical concerns such as data privacy and the need for more diverse datasets remain significant challenges that need to be addressed.

Discussion

This narrative review encompasses a total of 21 reports, all of which pertain to the utilisation of AI and ML in the context of suicide prevention. Across these studies, most examined the prediction or identification of suicidal behaviour, followed by detecting future suicide risk and predicting treatment outcomes for mental health disorders such as depression. A few studies predicted the risk of suicidal outcomes between different groups.[19,26,33] AI and ML methods are rapidly developing in this area, with nearly half of the reviewed studies being published in the last 3 years, despite the earliest publication being from 1999. This indicates that the field is in its early stages, presenting opportunities to address critical gaps in the literature and lead the future development of AI/ML tools in suicide prevention.

Suicide is a complex phenomenon and remains a pressing public health issue worldwide. Globally, suicide is the second leading cause of death amongst individuals aged 15–29 years.[5] The challenges associated with accurately assessing suicide risk – due to under-reporting of symptoms and the difficulty of predicting suicidal behaviour – highlight the critical role AI can play. AI's ability to simulate human cognitive functions, such as pattern recognition and decision-making, enables more precise prediction and early detection of individuals at heightened risk of suicide.[39]

Epidemiology of suicide

With approximately 26% of the global population and more than 39% of all global suicide cases, the Southeast Asian region exhibits the highest suicide rate at 17.7 per 100,000 individuals.[40,41] Under-reporting and misclassification of suicide cases, particularly in certain Asian countries, may cause

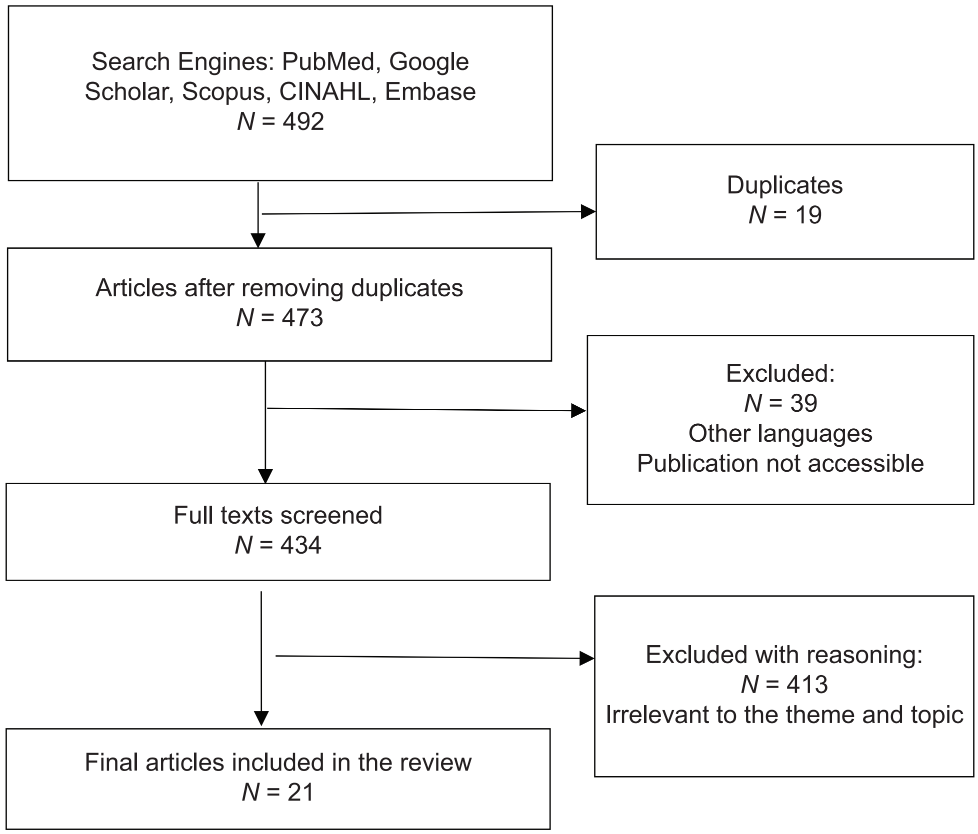

Figure 1: Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram of review

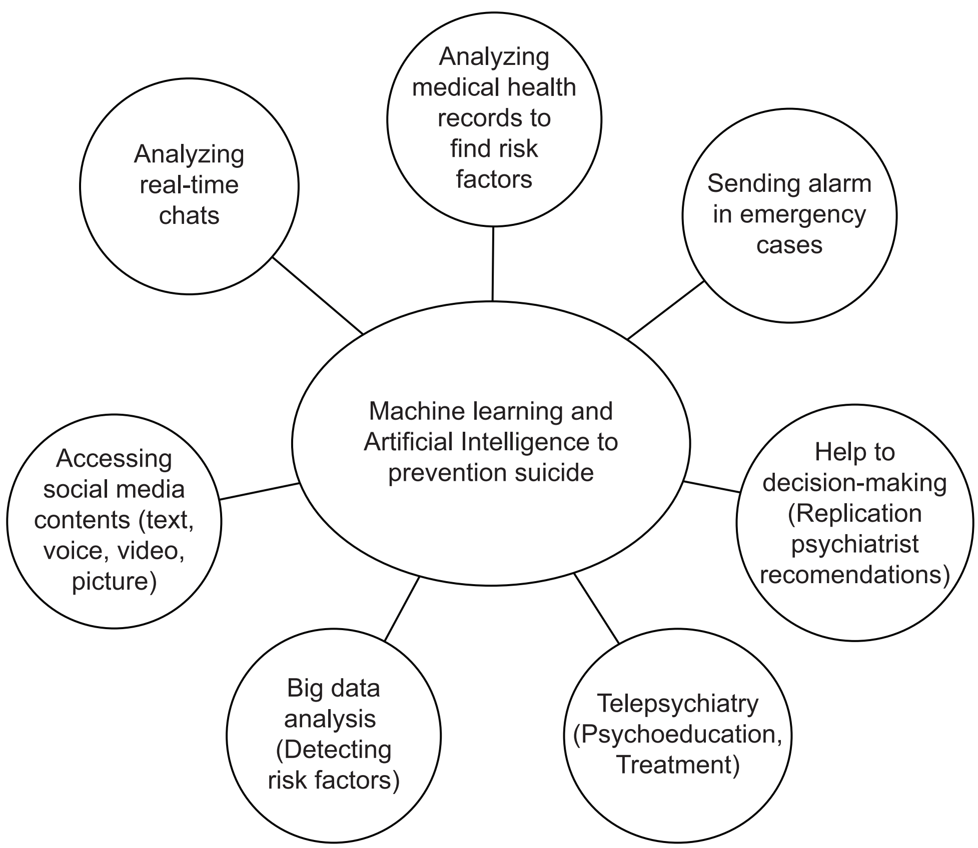

Figure 2: The areas that machine learning and artificial intelligence intervene to prevent suicide

Table 1: Some suicide prevention implications of artificial intelligence

Authors-year	Country	Population	Implication	Type of AI	Findings
Leung *et al*., 2021[33]	Canada	Patients with cancer	Analysing online support group text data to track emotional distress	Beta test	An AI-based co-facilitator is developed to recognise and track stress in participant's thoughts. AI will analyse online support group text data and will alarm therapists about distress contents (ongoing study)
Kim *et al*., 2021[32]	Republic of Korea	Child and adolescent psychiatric patients (124 cases, 12–17 years)	Classification of patients according to the risk of suicide and analysing using the PAI	LR, RF, ANN, SVM, and XGB	Using ML techniques in analysing PAI profiles of child and adolescent patients who received outpatient psychiatric care showed superior performance. The RF model exhibited the best performance (sensitivity of 0.92, a specificity of 0.88, a PPV of 0.8, an accuracy of 0.89%)
Coley *et al*., 2021[18]	USA	Depressed patients (5554 cases)	Predicting outcomes of psychotherapy for depression	RF method	Based on clinical records, the prediction model performance was poor for depression symptom severity and treatment outcome (AUC=0.57)
Bone *et al*., 2021[28]	United Kingdom	People who have access to psychotherapy	Predicting outcomes of psychotherapy	Bayesian updating algorithm, elastic net regularisation, XGB, SVM, and neural networks based on a multilayer perceptron algorithm	Dynamic prediction models using sparse and readily available symptom measures have high accuracy in predicting psychological treatment outcomes. (AUC=0.81 [0.77–0.86], PPV=0.79, NPV=0.69)
Cusick *et al*., 2021[19]	USA	18,815 clinical notes of psychiatric encounters	Using weak supervision and deep learning to identify SI in clinical notes of EHR systems	The NLP approach labels the training and validation notes (*n*=17,978). Using this large corpus of clinical notes, they trained several statistical ML models, logistic classifier, SVM, Naive Bayes classifier and one deep learning model, namely a text classification CNN	Among statistical ML models, the CNN model showed an accuracy of 94% in detecting documented SI
van Vuuren *et al*., 2021[37]	Netherlands	Students in the second and 4th year of secondary education (4693 cases – 13–16 years)	Using ML for predicting suicidal behaviour in adolescents	RF and Lasso Regression methods	ML models performed slightly better than a simple decision rule predicting adolescent suicidality. The models need further improvement to be effective in natural settings
García de la Garza *et al*., 2021[20]	USA	The National Epidemiologic Survey on Alcohol and Related Conditions records (34,653 cases older than 18 years)	Identifying future suicide risk factors in the general population	RF, out-of-fold model prediction	ML models helped to identify suicide risk factors by searching survey questions. The receiver operator characteristic curve of 0.857 with a sensitivity=85.3% (95% CI, 79.8–89.7), specificity=73.3% (95% CI 72.8–73.8)
Zhu *et al*., 2020[34]	China	43 BD-II with a history of suicide, 62 BD-II without a history of suicide, 62 healthy control group (18–55 years)	Predicting suicide risk using altered fronto-limbic resting-state functional connectivity	SVMs	The study showed that decreased rsFCs in the fronto-limbic system might be critical objective features of suicidality in BD-II patients (classification accuracy of 84%)

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Table 1: Contd...

Authors-year	Country	Population	Implication	Type of AI	Findings
Weng *et al*., 2020[35]	China	58 healthy controls, 41 depressive patients with SI, 54 depressive patients without suicidal thoughts (NS)	Discriminate SI subjects from NS	CNN-based autoencoder model, the supervised ML algorithm XGB, and LR	The study found that among ML models, the best structure pattern across multiple brain locations can classify suicidal ideates with a prediction accuracy of 85%, a specificity of 100% and a sensitivity of 75%
Burke *et al*., 2020[21]	USA	Paediatric primary care patients (13,325 cases- mean age=17) from a children's hospital ED (12,001 mean age=15.7)	To classify suicide attempt history among adolescents	Decision trees and RFs methods	The decision trees and RFs methods were used to develop algorithms to classify suicide attempt history and validate it. The ridge regression was employed to evaluate the performance of the ML approaches. This study showed that ML models did not accurately classify lifetime or recent suicide attempt history among youth across medical care settings
Huang *et al*., 2020[22]	USA	3869 cases	To address differences between suicide ideators and attempters	RF and $_p$ROC packages	ML algorithms with all variables showed good accuracy; the differences between suicide ideators and attempters were complex and may be better understood on a psychological primitive level than a biopsychosocial factor level
Su *et al*., 2020[23]	USA	Clinical records of 41,725 cases, in 10–18 years range	Suicide risk prediction in children and adolescents	LR, out-of-sample performance metrics	AI has 90% specificity in predicting short and long-term suicide risk. Furthermore, the LR was able to predict suicide risk after 365 days with the accuracy of 0.81% (0.77–0.85)
Tasmim *et al*., 2020[30]	Canada	Schizophrenia (189 cases - mean age=43.5)	To find early-life stressful events as a risk factor for suicide	LR, RF, and classification tree	Three types of ML models showed that childhood sexual molestation and mental illness are suicide risk factors for schizophrenia. (accuracy range: 62–69%)
Lin *et al*., 2020[36]	Taiwan	Military personnel, 3546 cases, between 18 and 55 years	Predicting the presence of suicide ideation	LR, decision tree, RF, gradient boosting regression tree, SVM and multilayer perceptron	Six types of ML techniques were used to predict the presence of suicide ideation in military staff. The accuracies of the multilayer perceptron and SVM provided were about 100%, others were about 100%, and others were over 98%
van Mens *et al*., 2020[38]	Scotland	Young adults, 3508 cases between 18 and 34 years	Predicting future suicidal behaviour	Tree, RFs, gradient boosting and SVM	Participants completed several measures to predict SI and suicide attempts at a one-year follow-up. The RF algorithm was the best to predict suicide ideation (sensitivity of 0.63, a specificity of 0.87, a PPV of 0.4, an accuracy of 0.75%, and an AUC of 0.85), and the gradient boosting predicted suicide attempts (sensitivity of 0.48, a specificity of 0.87, a PPV of 0.07, an accuracy of 0.68, and an AUC of 0.74)
Chen *et al*., 2020[29]	Sweden	Psychiatric patients, 126,205 cases between 18 and 39 years	Prediction of suicidal behaviour by using Swedish national registry data	Elastic net penalised LR, RF, gradient boosting, and a neural network	Four hundred twenty-five predictor factors were extracted from national registry data. ML predicted suicide attempt/death in 30- and 90-days following visits. Results showed that the performance of this model is highly accurate. (AUCs on the test set were 0.88 (95% confidence interval=0.87–0.89) within 90 days, and 0.89 (95% CI=0.88–0.90) within 30 days)

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Table 1: Contd...

Authors-year	Country	Population	Implication	Type of AI	Findings
Carson *et al*., 2019[24]	USA	Psychiatrically hospitalised adolescents (73 cases)	Identifying suicidal behaviour in EHRs	Natural language processing, RF	Natural language processing was done to identify phrases related to suicide from medical notes of patients with suicide attempts. The RF ML algorithm was applied to develop a classification model. The final model was successful, and had a sensitivity of 0.83, a specificity of 0.22, a PPV of 0.42, an accuracy of 0.47%, and an AUC of 0.68
Ryu *et al*., 2019[31]	Republic of Korea	Participation in the Korea National Health and Nutrition Examination Survey with 5773 cases above 19 years	Detection of Suicide Attempters among Suicide Ideators	RF models	The ML method compared two groups of suicidal people who attempted suicide and those who did not. This method can predict individuals at elevated risk of suicide (AUC=0.947 with an accuracy of 88.9%)
Fulmer *et al*., 2018[25]	USA	College students, 74 cases with 70% females, mean age was 22.9 years	To decrease self-identified depression and anxiety	Integrative psychological AI, Tess	Psychological AI (Tess) effectively reduces self-reported measures of depression and anxiety among university students compared to the control group. (P=0.045)
Reece *et al*., 2017[26]	USA	Twitter users, 204 cases: 105 depressed and 99 healthy	To detect depression and PTSD in Twitter users	State-space time series model	After assessing participants' tweets, computational models were developed. This model is capable of detecting depression and PTSD in healthy individuals. It supported a data-driven model for the early screening of mental disorders. (accuracy of 0.76%)
Desjardins *et al*., 2016[27]	USA	ED participants, 255 cases	Preventing suicides in medical/surgical units and the ED	Expert-based neural network model	A tablet - suicide risk assessment tool was developed, and it was trustable for three purposes: 1. Prediction of psychiatrist's assessments of risk of suicide in the hospital within 72 h (AUCs were above 0.938). 2. Replication of psychiatrist-recommended interventions (AUCs were above 0.914) 3. Participant's satisfaction

AUC: Area under the curve, PPV: Positive predictive value, PAI: Personality assessment inventory, ED: Emergency department, LR: Logistic regression, RF: Random forest, ANN: Artificial neural network, SVM: Support vector machine, XGB: Extreme gradient boosting, CNN: Convolutional neural network, rsFCs: Resting-state functional connectivity, PTSD: Post-traumatic stress disorder, HER: Electronic health record, BD: Bipolar disorder, SI: Suicidal ideation, AI: Artificial intelligence, ML: Machine learning, NPV: Negative predict value, NLP: Natural language processing, CI: confidence interval, NS: with No Suicidal

these rates to be underestimated.[42] The region has a higher average suicide rate, lower male-to-female suicide ratio and higher suicide rates amongst the elderly compared to Western nations.[43] In low- and middle-income countries (LMICs), women are often more vulnerable to suicide, with a gender ratio of 1.6 in LMICs compared to 3.5 in high-income countries.[43] For instance, younger women in countries like India exhibit higher suicide rates compared to men.[44,45] The implications of this disparity suggest that targeted AI interventions could help address these vulnerabilities by better identifying at-risk groups.

The role of artificial intelligence in the prevention of suicide risk

AI and ML techniques have demonstrated significant improvements in predicting suicide risk compared to traditional statistical approaches.[46] Random forest models and other AI algorithms have been found to be highly accurate in predicting suicide attempts, ideation and short- and long-term risks.[22-24,30,35,38] The ability to process large datasets, including clinical history, psychiatric diagnoses and ongoing mental health conditions, allows AI tools to assess individual risk with specificity as high as 90%.[23] AI has also shown efficacy in reducing self-reported symptoms of depression and anxiety[25] and detecting conditions like PTSD in otherwise healthy individuals.[26] This ability to predict suicide risk is complemented by AI's capacity to analyse social media activity, where early signs of distress can be identified and interventions can be made accordingly.[47,48]

Big Data, Internet of Medical Things and social media

The expansion of electronic medical records (EMRs) and big data has further enhanced AI's potential in suicide prevention. AI/ML tools can analyse vast datasets, facilitating continuous risk assessment and optimising treatment for individuals at risk of suicide.[23] In addition, AI models, such as the expert-based neural network developed by

Desjardins *et al*., have shown high levels of satisfaction amongst healthcare providers in predicting suicide risk.[27] Moreover, social media platforms are increasingly being used as valuable tools for analysing behavioral data and predicting suicidal tendencies. Platforms such as Facebook and Twitter use AI algorithms to detect patterns indicative of suicidal thoughts and intervene by connecting users to mental health services.[33,49-52] This highlights the broader utility of AI in both clinical and non-clinical settings.

Controversies and challenges of using artificial intelligence in mental health care

Despite its potential, the application of AI in mental health care raises concerns about data privacy, security and ethical usage.[53] Patient confidentiality must be maintained at all stages of data collection and processing. Social media platforms, in particular, pose risks where data may be shared with third parties unintentionally or intentionally, undermining patient trust.[54] The accuracy of AI algorithms in predicting suicide also varies based on the data available and can lead to false positives or unnecessary interventions.[55] Furthermore, AI systems have demonstrated biases related to religion, race, gender and other social factors, necessitating improvements in algorithmic design to prevent unintended consequences.[56,57]

There are several gaps in current AI and ML applications for suicide prevention:

1. Data insufficiency: The recorded data on suicide attempts and suicidal ideation are often less than the actual occurrences, leading to insufficient data for training accurate models
2. Generalisability issues: Models trained on specific populations or datasets may not perform well when applied to different populations
3. Ethical and privacy concerns: The use of personal data, such as electronic health records and social media activity, raises significant ethical and privacy issues
4. Integration into clinical practice: There is insufficient evidence supporting the integration of AI/ML tools into everyday clinical practice.

Policy and programmatic interventions

The integration of AI into mental healthcare presents both policy and programmatic opportunities, especially in LMICs, where resources are often limited. AI tools can be implemented in primary care settings, such as Health and Wellness Centres in India, to enhance mental health services under the National Health Mission. These centers are designed to address various public health issues, and AI tools could support clinicians in screening and diagnosing mental health conditions, particularly in detecting early signs of suicidal tendencies.[4] AI could enable earlier interventions, better resource allocation and personalised treatment plans, improving outcomes for individuals at risk of suicide.

Policy implications

The integration of AI into national mental health strategies requires robust policy frameworks that ensure ethical use, data protection and equitable access to AI technologies. Policymakers must ensure that AI systems complement, rather than replace, clinical judgement and that healthcare providers are equipped with the tools and training needed to use these technologies effectively. In addition, increasing access to AI-driven mental health services in LMICs should be a priority, particularly in addressing suicide risk amongst vulnerable populations. The implementation of AI-based suicide prevention tools in Health and Wellness Centers across India, as proposed by Lahariya, can significantly strengthen primary healthcare services and address the mental health crisis more effectively.[58-65]

Limitations and future research

Strengths

This review highlights the considerable potential of AI and ML in suicide prevention. AI's capacity to analyse vast datasets rapidly allows for early detection of individuals at risk, offering more accurate risk assessments than traditional methods. AI models are also adaptable and can be integrated into various clinical settings, social media platforms and even non-clinical environments. The inclusion of big data and EMRs enables a more comprehensive understanding of a patient's biological, psychological and social state, supporting more personalised and timely interventions.

Limitations

The generalisability of the findings is limited due to the specific datasets and geographical contexts from which the studies were drawn. Most research included in this review may not directly translate to different populations or regions, as the factors influencing suicidal behaviour vary widely across contexts. In addition, the use of diverse AI techniques and statistical methods across studies hinders direct comparison and synthesis of results. The varying methodologies, sample sizes and data sources used in the studies reviewed further contribute to this limitation. Future studies would benefit from using larger, more diverse datasets and standardising AI models to enhance the reliability and applicability of the findings.

Future research scope

Future research should focus on enhancing the applicability of AI and ML in diverse populations by using larger, more representative datasets that span different geographical regions and cultural contexts. This would improve the generalisability of AI models in suicide prevention. In addition, there is a need for standardised methodologies across studies to allow for better comparison and synthesis of results. Research should also explore the integration of AI with clinical decision-making, ensuring that AI complements, rather than replaces, human judgement. Furthermore, the ethical implications of AI, including data privacy, algorithmic bias and the potential for over-dependence on technology, should be a critical area of study. Developing AI systems that are transparent, explainable and accountable will be crucial for their safe and effective implementation. Finally, exploring the potential of AI in non-clinical settings, such as social media platforms and mobile health applications, could expand the reach of suicide prevention strategies and improve access to mental health care, particularly in underserved communities.

Conclusion

AI and ML present exciting opportunities for improving suicide prevention efforts. The ability of AI to process large datasets and recognise complex patterns can significantly improve early detection of suicide risk and lead to more targeted interventions. However, while the technology holds promise, its integration into clinical practice should be approached with caution, particularly in addressing ethical concerns such as data privacy and algorithmic bias. There is also a need for ongoing development to ensure that AI models are refined and tested across diverse populations.

Combining AI with clinical expertise can enhance the precision of suicide risk assessments, especially when AI tools are embedded within healthcare workflows. The integration of AI with emerging technologies, such as the IoT and social media analytics, can further transform mental health care and suicide prevention strategies. However, this process should be iterative and ethically managed to avoid over-reliance on AI models, ensuring that human oversight remains central to suicide prevention efforts.

Relevance to preventive medicine:
AI and ML contribute significantly to preventive medicine by enabling early detection of individuals at risk for suicide, thereby allowing timely interventions and reducing preventable deaths.[9]

Implications for clinical practice:
The integration of AI/ML models in clinical practice can enhance decision-making for suicide risk assessment, making it possible for healthcare professionals to identify high-risk patients more accurately and provide individualized care.[10]

Author contributions

Sheikh Shoib conceptualized, planned methodology and drafted the article; Ilham Zaidi supervised in preparing the article. All authors contributed reviewed and edited, approved the final version, and agreed to be accountable for all aspects of the work.

Data availability

Statement: Data sharing is not applicable to this article as no original datasets were generated or analyzed for this study.

Use of AI in drafting of manuscript

Artificial Intelligence (AI) tools were not used in drafting, editing, or finalizing any part of this manuscript.

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Conflicts of interest

There are no conflicts of interest.

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