The loss of any life can be devastating, but the loss of a life from suicide is especially tragic.

Around nine Australians take their own lives each day, and it is the leading cause of death for Australians aged 15-44. Suicide attempts are more common, with some estimates stating that they occur up to 30 times as often as deaths.

"Suicide has large effects when it happens. It impacts many people and has far-reaching consequences for family, friends and communities," says Karen Kusuma, a UNSW Sydney Ph.D. candidate in psychiatry at the Black Dog Institute, who investigates suicide prevention in adolescents.

Ms. Kusuma and a team of researchers from the Black Dog Institute and the Center for Big Data Research in Health recently investigated the evidence base of machine learning models and their ability to predict future suicidal behaviors and thoughts. They evaluated the performance of 54 machine learning algorithms previously developed by researchers to predict suicide-related outcomes of ideation, attempt and death.

The meta-analysis, published in the Journal of Psychiatric Research, found that machine learning models outperformed traditional risk prediction models in predicting suicide-related outcomes, which have traditionally performed poorly.

"Overall, the findings show there is a preliminary but compelling evidence base that machine learning can be used to predict future suicide-related outcomes with very good performance," Ms. Kusuma says.

**Traditional suicide risk assessment models**

Identifying individuals at risk of suicide is essential for preventing and managing suicidal behaviors. However, risk prediction is difficult.

In emergency departments (EDs), risk assessment tools such as questionnaires and rating scales are commonly used by clinicians to identify patients at elevated risk of suicide. However, evidence suggests they are ineffective in accurately predicting suicide risk in practice.

"While there are some common factors shown to be associated with suicide attempts, what the risks look like for one person may look very different in another," Ms. Kusuma says. "But suicide is complex, with many dynamic factors that make it difficult to assess a risk profile using this assessment process."

A post-mortem analysis of people who died by suicide in Queensland found that of those who received a formal suicide risk assessment, 75% were classified as low-risk, and none was classified as high-risk. Previous research examining the past 50 years of quantitative suicide risk prediction models also found they were only slightly better than chance in predicting future suicide risk.
"Suicide is a leading cause of years of life lost in many parts of the world, including Australia. But the way suicide risk assessment is done hasn't developed recently, and we haven't seen substantial decreases in suicide deaths. In some years, we've seen increases," Ms. Kusuma says.

Despite the shortage of evidence in favor of traditional suicide risk assessments, their administration remains a standard practice in health care settings to determine a patient's level of care and support. Those identified as having a high risk typically receive the highest level of care, while those identified as low-risk are discharged.

"Using this approach, unfortunately, the high-level interventions aren't being given to the people who really need help. So we must look to reform the process and explore ways we can improve suicide prevention," Ms. Kusuma says.

**Machine learning suicide screening**

Ms. Kusuma says there is a need for more innovation in suicidology and a re-evaluation of standard suicide risk prediction models. Efforts to improve risk prediction have led to her research using artificial intelligence (AI) to develop suicide risk algorithms.

"Having AI that could take in a lot more data than a clinician would be able to better recognize which patterns are associated with suicide risk," Ms. Kusuma says.

In the meta-analysis study, machine learning models outperformed the benchmarks set previously by traditional clinical, theoretical and statistical suicide risk prediction models. They correctly predicted 66% of people who would experience a suicide outcome and correctly predicted 87% of people who would not experience a suicide outcome.

"Machine learning models can predict suicide deaths well relative to traditional prediction models and could become an efficient and effective alternative to conventional risk assessments," Ms. Kusuma says.

The strict assumptions of traditional statistical models do not bind machine learning models. Instead, they can be flexibly applied to large datasets to model complex relationships between many risk factors and suicidal outcomes. They can also incorporate responsive data sources, including social media, to identify peaks of suicide risk and flag times where interventions are most needed.

"Over time, machine learning models could be configured to take in more complex and larger data to better identify patterns associated with suicide risk," Ms. Kusuma says.

The use of machine learning algorithms to predict suicide-related outcomes is still an emerging research area, with 80% of the identified studies published in the past five years. Ms. Kusuma says future research will also help address the risk of aggregation bias found in algorithmic models to date.

"More research is necessary to improve and validate these algorithms, which will then help progress the application of machine learning in suicidology," Ms. Kusuma says. "While we're still a way off implementation in a clinical setting, research suggests this is a promising avenue for improving suicide risk screening accuracy in the future."


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