Elsewhere in *JAMA Network Open*, Willimitis and colleagues set out to resolve a central debate in suicide prevention: do face-to-face risk screenings or electronic health record–based machine learning algorithms provide greater public health benefit? They approach this question by proposing and testing a third option, combining the use of these 2 modes. Their data show clearly that in a large clinical cohort of adults, the combined use of the Columbia Suicide Severity Rating Scale (C-SSRS) and a real-time machine learning model was statistically superior to either method alone in predicting subsequent visits for suicidal ideation or attempts, suggesting that each approach offers benefits that are, at least to some extent, additive and independent. However, a purely statistical interpretation may leave out some other relevant considerations that may lead an institution or service to choose one approach or the other (or both, as proposed in this study).

Direct face-to-face screening has some notable disadvantages compared with machine learning approaches, namely the “commonality of patients denying SI [suicidal ideation] despite being at high risk,” as stated by the study authors, as well as the overall clinical burden of administering and scoring the screening tools. While the combined method (screening plus machine learning) mitigates the issue of underreporting suicidal ideation, it does not counter the issue of clinical load. This clinical burden can be substantial for a relatively complex tool such as the C-SSRS, although it can notably be reduced by opting for a simpler instrument, such as the Ask Suicide-Screening Questions (ASQ), which was developed for adolescents but recently validated for use with adults as well. However, a substantial benefit of the face-to-face approach, which cannot be replicated with machine learning, is that face-to-face screening in itself constitutes a clinical contact and a potential point of entry into a higher level of care. In clinical settings, an individual who has never been asked about suicide may use the screening experience as a time to reach out directly for additional support; this potential benefit has not yet been quantified in the research literature but may yield clinical benefits that otherwise go undetected when examining these screening tools as predictive instruments.

A potential benefit of machine learning, which operates behind the scenes based on existing medical record data, is that it may avoid the stigma of a positive result and particularly the potentially unnecessary stigma of a false-positive result. However, in an era of extensive societal debate about ownership of data and online privacy, an automated scan revealing sensitive and personal conclusions (ie, an individual’s degree of suicide risk) cannot be considered fully benign, particularly if done without explicit consent. In addition to privacy issues, there are concerns (and demonstrated evidence) that machine learning that uses human-generated data as its input source will potentially suffer from the same human biases (eg, racial biases or stigma related to diagnoses) that are present in those human-generated input data, while giving an illusion of objectivity. More ethical and privacy-focused approaches to machine learning are being developed in some medical subfields, yet it remains unclear how to maintain this privacy when applying machine learning findings, such as indicated suicide risk, within clinical settings.

Untangling the risks and benefits of suicide prevention approaches is difficult in cohort studies for several reasons, even when dealing with very large samples. For one, the low base rate of suicidal behavior (particularly over short time periods, when risk detection may be most useful) limits statistical power available to make nuanced comparisons between various methods of suicide prevention and, particularly, between subgroups of the general population. Furthermore, related
studies to date have typically used suicide attempts or suicidal behavior as the primary outcomes, which can serve only as a proxy for the primary outcome of interest, death by suicide. Research focused on death by suicide, however, suffers from an even lower base rate than nonfatal suicidal behaviors and involves the sometimes onerous and logistically difficult process of combining cohort data with official death record data. Finally, a full consideration of which suicide risk prediction approach performs best requires a consideration not only of the predictive performance of the various approaches, but also their clinical risks and benefits. Wilimitis and colleagues have provided us with valuable data on the potential benefits of a combined approach, which can now be weighed against some of these other considerations to determine the best approach for a particular clinical setting.

ARTICLE INFORMATION
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REFERENCES


