Neuropsychopharmacology

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HOT TOPICS

Imaging suicidal thoughts and behavior: the promise of computational models

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Neuropsychopharmacology (2021) 46:219–220; https://doi.org/10.1038/s41386-020-00841-2

Neuroimaging has advanced identification of brain circuitry of suicidal thoughts and behaviors (STBs), highlighting central roles for frontolimbic systems in STBs in adults and their altered trajectories in the development of STBs in adolescence when STBs often first emerge [1]. Critical next steps are to elucidate contributions of biopsychosocial factors and generate individualized prediction. Large-scale multimodal datasets combined with innovative computational approaches are required. Recently forged international consortia (e.g., Help Overcome and Prevent the Emergence of Suicide, HOPES, and Enhancing Neuro Imaging Genetics through Meta-Analysis, ENIGMA) bring new hope; their multimodal imaging and manifold potential risk factor data in large samples provide unprecedented opportunities. However, the numerous and potentially interacting polygenic and exposome factors present complex computational challenges and group level findings may not generalize to the individual [2]. For example, while the ventral prefrontal cortex is a brain region in which STB-related findings have converged, imaging findings have been in gray or white matter structure or function, and have shown varying influences of age, sex, genetic, and immunological factors and exposure to stressors such as child maltreatment [1, 2]. Furthermore, the emergence of large-scale longitudinal data through digital technologies provide unique opportunities for modeling dynamic changes over time, but these present additional computational challenges. Advanced multivariate statistical approaches, such as machine-learning and network-modeling methods, which have shown success in predicting STBs from complex albeit non-imaging data hold promise for addressing these challenges.

Supervised machine-learning techniques are well-suited to analyze multimodal data difficult to theoretically conceptualize and practically model, and can be used to make individualized predictions. Studies using large-scale datasets have started to identify multimodal predictors for future STBs [3]. For example, machine-learning approaches applied to psychological risk data in 3508 young adults (18–34 years) predicted both suicide ideation and suicide attempts at 1-year follow-up with an area under the curve up to 0.83 [4].

Theory-driven multivariate techniques are optimal when there are clear a priori assumptions about the underlying relationships among factors. These include structural equation modeling analyses as they integrate multidomain variables to examine hypothesized causal relations amongst variables based on existing theoretical models. For example, path modeling used to compare four causal models on relationships between social risk factors and self-harm in adolescence supported a cumulative risk model in which adverse social experiences accumulate to increase risk for self-harming behaviors [5]. Another promising technique, network modeling, allows quantification of complex interplays between many interacting variables and can either be theory-driven or data-driven. Recent use of this method, to analyze core risk factors postulated in the interpersonal psychological and integrated motivational–volitional theories of STBs, provided novel views on salient psychological risk factors such as perceived burdensomeness, internal entrapment, mental well-being and interpersonal needs and complex relationships among them [6].

The application of such multivariate computational methods to analyze emerging large-scale imaging and multi-risk factor longitudinal datasets has the potential to identify targets for early and personalized suicide risk detection and prevention strategies [2] to reduce this preventable cause of early mortality.

FUNDING AND DISCLOSURES

The authors' research was supported by the MQ Brighter Futures Award MQBFC/2 (ALvH, LS, and HPB). ALvH was also supported by a Royal Society Dorothy Hodgkin Fellowship (DH15017), and an MRC MRF emerging leaders award; LS by NIMH award R01MH117601 and a NHMRC Career Development Fellowship (1140764); and HPB by awards from the NIMH RC1MH088366, R01MH113230, R61MH111929, and R21MH108940, and American Foundation for Suicide Prevention, International Bipolar Foundation, and For the Love of Travis Foundation. The authors declare no conflicts of interest.

ACKNOWLEDGEMENTS

We thank Rogier Kievit for valuable input on statistical modeling techniques.

AUTHOR CONTRIBUTIONS

All authors have made substantial contributions to the conception or design of the work; drafting the work or revising it critically for important intellectual content; provided final approval of the version to be published; and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Published online: 7 September 2020

ADDITIONAL INFORMATION

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