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Technology Matters: Machine learning approaches to personalised child and adolescent mental health care

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Background

At its core, machine learning, which forms the basis of artificial intelligence (AI), is a technology that learns from data in order to recognise patterns or make predictions from observations. This ability can be harnessed to automate or personalise diagnoses and treatment recommendations. Increasing computational power, sometimes via cloud-based computing, combined with ever-growing amounts of data about individuals, whether that be from electronic health records, free-text in medical records, neuroimaging, genomics, or from the digital footprint of mobile apps and wearable devices, have created the potential for machine learning and AI to increase the efficiency and effectiveness of healthcare delivery, including mental health care (Tiffin & Paton, 2018).

The potential of machine learning in youth mental health services

The possibility of using predictive approaches to enhance the delivery of child and adolescent mental health services (CAMHS) is particularly attractive. Funding and workforce shortages mean many children and young people affected by developmental or mental health issues are unable to access the care they need in a timely manner. For example, in the United Kingdom, CAMHS has struggled to meet demand for services for some time, a situation that has been further exacerbated by the impact of the Covid-19 pandemic (Care Quality Commission, 2021). Workforce shortages are even more pronounced in lower- and middle-income countries (World Health Organization, 2021). Moreover, at least in Western countries, the generation born after the millennium are sometimes referred to as 'digital natives', since technology has always been an integral part of their lives. Thus, their use of digital and mobile technology influences the way that young people now expect to access and use health care. It also creates opportunities to use the data they generate to create interactive assessments and interventions. This lends itself to predictive approaches which can automate or semi-automate certain aspects of care, such as diagnosis, treatment recommendations or psychosocial therapy. This could be used to extend, rather than replace, human clinicians and could help address some of the acute workforce shortages in CAMHS. This may free up staff time to focus on the human aspects of care.

Many of the early, high-profile applications of AI to health care have focused on physical health. However, there are an ever-growing number of examples of how the technology can be used to personalise youth mental health care. Routinely arising data, such as those derived from electronic healthcare records, have been used to predict diagnoses using machine learning; such approaches could be used to automate screening for those with, or at risk of, mental health or developmental conditions. Machine learning has been used to predict medication responses, both in terms of side effects and the impact on symptoms. These predictive technologies could be used to identify the optimal first-line medication for a particular child or young person. Machine learning offers huge promise for the automation of neuroimaging analysis; indeed, when classifying images, AI often provides the accuracy of an experienced clinician. Such tasks could also be developed in conjunction with information available from biomarkers, genetics and the increasing 'data footprint' from wearable or mobile technologies in order to improve the precision of predictions.

Translation into patient benefit: a tetrad of conditions

While there are some examples of AI being implemented in physical healthcare services, within mental health services, such examples, while promising, largely exist in research settings only. There are, however, increasing numbers of private companies developing applications for more widespread use. These include, for example, AI-powered chatbots which aim to deliver cognitive behavioural therapy (Fitzpatrick, Darcy, Darcy, & Vierhile, 2017), and autism screening based partly on home videos (Abbas, Garberson, Garberson, Glover, & Wall, 2018). In some cases, particularly in the United States, such companies have developed links with healthcare providers. Nevertheless, in routine CAMHS services, AI-based applications remain rare. Indeed, there are a number of barriers to realising the actual potential of AI to enhance CAMHS. In order to achieve useful levels of prediction that are likely to translate into patient benefit, a tetrad of conditions should be met: 'right task', 'right data', 'right methods' and 'right context'.

It is vital we start by identifying the 'right task'. That is, a task that is well suited to AI-approaches and where the output will be perceived as useful in influencing the care of young people. This is crucial to ensure 'clinician buy-in'. If mental healthcare professionals do not think a system is practically useful they will not use it. Regarding this, we have previously performed a Delphi exercise to elicit consensus on what predictive tasks would be useful to automate in CAMHS. An expert panel of 15 psychiatrists was asked to rate the usefulness of a variety of tasks that a machine could perform. Consensus (defined in this case as >75% agreement) was reached that 'predicting medication side effects' would be very useful, whereas 'supporting specific diagnoses' of conditions would only be moderately useful. The reasons for the relative lack of support for AI-based diagnoses were explored in free-text responses. Reasons included doubts over the utility of diagnosing specific conditions, many of which exist on a continuum, and also the added value an AI-based tool could provide over human clinicians. This finding stands in contrast to the published literature in the field, where many papers focus on diagnoses, while relatively few focus on medication side-effects. Another area highlighted by the Delphi as potentially highly useful was the use of machines to automate feedback for psychological therapy. Indeed, the prediction of treatment response and automated feedback of the patient response to psychological therapies have been identified as two of the most promising areas for machine learning applications in adult mental health (Chekroud et al., 2021). However, the subject remains under-researched in a CAMHS setting, despite its potential effectiveness and acceptability to clinicians.

Certainly, the 'right data', in terms of both quality and quantity, need to be fed to machines in order to achieve useful predictions that can generalise to a demographically diverse set of patients. Currently, routinely arising data in CAMHS can be of variable quality, often relying on busy clinicians to input symptom ratings and other useful data. Moreover, the quantity of both routine and research related data in CAMHS can be much less than those available for working-age adults. Also, many of the outcomes which we may wish to predict in a CAMHS setting, such as completed suicide, are (thankfully) rare events. Such uncommon events are hard to predict, even by machines. This risks swamping hard pressed services with 'false positives', which require further assessment, rendering such approaches impractical.

In terms of 'right methods', a plethora of machine learning approaches exist. No one algorithm can be assumed, a priori, to have superiority over another (the so called 'no free lunch' theorem). Nevertheless, 'deep learning' which uses layers of 'artificial neurones' to mimic the functioning of the brain cortex is often best suited to modelling 'unstructured' data such as neuroimages and free-text. In contrast, tree-based models, which sequentially partition data, often work well with structured (i.e. numeric) data sets like electronic healthcare data.

Finally, the 'right context' is crucial, ensuring healthcare workers and patients respond to automated systems in a positive way. Having an AI system that performs the 'right task' is one element of this, but there needs to be consideration of the 'human computer interaction' too. Relatively few clinicians are currently being taught the skills they need to understand the advantages, limitations and risks of AI-based systems. Such knowledge and abilities are required so that clinicians feel confident in being able to use automated systems and communicate the results effectively with patients and carers. Automated decision-support tools are not new, but they are often overridden by clinicians. Addressing this knowledge gap may help ensure that AI-based systems succeed where other automated systems have not. Moreover, there are unresolved ethical dilemmas. Machine learning methods are often complex and uninterpretable to humans (so called 'black box' algorithms). However, patients and carers often have a 'right to explanation'. Such issues need resolving.

Conclusions

Overall, machine learning has the potential to help alleviate the current crisis in access and provision of CAMHS, and could exploit the ever increasing quantities of healthcare data generated in a way that allows mental health care to be personalised. However, if AI is a powerful 'hammer', it is vital that the right nails are identified if this predictive technology is to translate into tangible benefits for services, young people and their families.

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Ethical information

No ethical approval was required for this article.

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References

Abbas, H., Garberson, F., Glover, E., & Wall, D.P. (2018). Machine learning approach for early detection of autism by combining questionnaire and home video screening. *Journal of the American Medical Informatics Association*, *25*, 1000–1007.

Care Quality Commission (2021). *The state of health care and adult social care in England 2020/2021*. www.cqc.org.uk/sites/default/files/20211021_stateofcare2021_print.pdf

Chekroud, A.M., Bondar, J., Delgadillo, J., Doherty, G., Wasil, A., Fokkema, M., … & Iniesta, R. (2021). The promise of machine learning in predicting treatment outcomes in psychiatry. *World Psychiatry*, *20*, 154–170.

Fitzpatrick, K.K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial. *JMIR Mental Health*, *4*, e19.

Tiffin, P.A., & Paton, L.W. (2018). Rise of the machines? Machine learning approaches and mental health: Opportunities and challenges. *British Journal of Psychiatry*, *213*, 509–510.

World Health Organization (2021). *Mental Health Atlas 2020*. https://www.who.int/publications/i/item/9789240036703

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