**“What new ideas would you like to bring to the field of eating disorders, which can help our patients and their carers?”**

**Dr George Reid,**

**CT1 in psychiatry**

**Avon and Wiltshire NHS trust**

**Word count: 1827**

## The scope for innovation in eating disorders

Eating disorders (ED) are recognised as one of the most highly morbid and challenging conditions to treat in the field of psychiatry. They are often characterised by significant delays in diagnosis and intervention, with the length of time between initial symptoms and first treatment in the range of 2.5 to 6 years, depending on eating disorder type.[1] Additionally, whilst treatments can be effective in a proportion of eating disorder patients, 20-30% of patients fail to exhibit considerable improvement in symptoms or achieve remission, despite recognised treatments.[2] These only modestly effective treatments are further compounded by complex disease dynamics; some individuals become increasingly attached to their symptoms and a proportion of patients come to identify with these, leading to an ambivalence to change.[3] This can lead to poor motivation to engage with services, a reduction in treatment adherence and ultimately worse outcomes. The consequence of these features mean that patients with eating disorders have significant mortality rates, which are close to 6 times that of the standard population.[2] This illustrates the great scope for improvement and innovation in eating disorders diagnosis, early intervention and treatment strategy itself.

## Artificial intelligence in healthcare

Given the obvious need for innovation and new ideas in eating disorders, perhaps a 21st century solution could be found in artificial intelligence (AI). AI was first conceived in the 1940s by Mculloch and Pitts, who drew on inspiration from the neurons of the human brain. They suggested a network of interconnected 'artificial neurons', with different neurons firing in response to differing stimuli. They proposed that with the correct parameters these neural networks could 'learn' and responses could improve over time.[4] Fast forward to modern day and AI has become a fashionable topic, widely used in many different sectors and areas of everyday life, from the finance sector to supermarket 'self-check-outs'. An example of AI is Machine learning (ML) which is an innovative approach to data analysis and has dominated the field of AI in recent decades. It uses advanced statistics and probability to predict outcomes from vast sets of data. Importantly, it generates models from these data sets that it can apply to gradually increase accuracy and results over time.[5] ML is split into two main areas; supervised and unsupervised. The one most applicable to the analysis of healthcare data, is supervised learning. This method uses 'labelled' data as both the input variables (e.g. traits such as age and gender) and outcome variables (e.g. diagnosis). It uses this data to create models which can generate the probability of the outcome occurring because of the input variables, with improving accuracy.[6] Simply, an example would be predicting the probability of getting a specific disease based on different variables such as patient demographics and other healthcare data.

ML in healthcare is becoming more and more prevalent, specifically, it has been used in the modelling and risk stratification of disease. Cardiology, neurology and oncology are particular areas where it has already been extensively used.[7] Examples include identification of novel or important risk factors in cardiac disease and early prediction of diabetic risk from patient specific healthcare data.[8,9] Likewise, Machine learnings use in mental health has also been investigated with it being utilised in a number of ways.[7] In suicide for example, ML has been useful in detecting patients who have had a previous suicide attempt from healthcare records. It has also assisted in risk stratifying at risk patients and the identification of important risk factors in certian patient groups, such as those discharged post suicide attempt.[10-12] Similarly, ML has been used to predict disease severity in patients with major depressive disorder based on self-reported data and in individuals with schizophrenia, researchers were able to predict patients at risk of poor outcomes, after 4 weeks and 52 weeks of treatment.[13,14]

## How could machine learning help patients?

As previously explored, the scope for new ideas in eating disorder management is vast. Whilst artificial intelligence and machine learning are novel and interesting techniques, in such a morbid and complex disease, it raises the question as to how it could be used to benefit patients and carers.

### Detection and early intervention

Early intervention, based on prompt screening, assessment and diagnosis, improves prognosis and overall disease burden in virtually all mental illnesses, with EDs being no different.[15] Due to the significant mortality and morbidity associated with eating disorders, increasing early intervention is an urgent priority.

ML could be a useful tool in this area and has shown the ability to predict ED status from data sets, with good accuracy. Orru et al. demonstrated an accuracy of 70% when detecting patients with an ED (versus healthy controls) using retrospective interview and self-reported data.[16] Likewise Krug et al. were able to predict ED onset with an accuracy of 86% in emergency department patients using a range of risk factors, and differentiate ED type with 70% accuracy.[17] Social media and internet activity has also been a focus of research in the realm of early detection and intervention. Internet browsing history was volunteered by participants in one such study and was assessed for current ED status and additionally, the risk of a future ED. The machine learning algorithm produced increased the detection of EDs through browsing history by 38%, when compared with a randomised system.[18]

This strategy has the advantage of being both inexpensive in terms of data collection and immediate in terms of analysis. Importantly, in this specific population that can be complex and often vulnerable, it also has the benefit of being non-intrusive and requiring no active input from the individual. Stigma has been reported as one of the biggest obstacles to help-seeking in EDs, meaning an anonymous form of data collection (using retrospective self-reported data and volunteered social media and internet history), may be especially beneficial to identify at-risk individuals.[19] Therefore, this data could perhaps allow an opportunity for clinicians to intervene at an earlier stage of the disease and hence be a valuable tool in acting to reduce the unacceptably high time to diagnosis in EDs.

### Risk of poor outcomes/disease course

Once a diagnosis has been established, it is important for clinicians to identify those individuals who may be at greater risk of poor outcomes. This again allows for better risk planning and individualised care in an attempt to prevent potential morbidity in these patients. ML has been able to help identify and stratify those at risk of poor outcomes and identify important predictors that could be utilised in the clinical setting. A study was able to show that eating disorder outcomes could be predicted with good accuracy at 1 and 2 year follow-up. Likewise they were also able to identify the most important predictors of poor eating disorder outcomes, notably baseline diagnosis, psychiatric history and demographic characteristics.[20]

### Preventing harmful social media and internet content

As previously mentioned, it is well documented that individuals suffering the symptoms of eating disorders often go undiagnosed. Further to this, even with good quality screening identifying at-risk individuals, a large proportion of ED patients do not pursue further treatment or consult medical professionals despite being made aware of their diagnosis.[21] Instead, an extremely large percentage of patients utilise the internet as their primary source of information on eating disorders. In a study population of 1291, with a mean age of 22 years old, close to 87% reported that in the last 30 days their primary source of information was a website, compared with just 1.2% reporting use of medical professionals.[22] While there is a vast amount of supportive content available on reputable websites, Pro-eating disorder (pro-ED) websites are controversial and can be extremely problematic for sufferers. Pro-ED communities are those which refuse to view eating disorders as a 'disease', instead promoting their symptoms as a 'choice'. The content of these communities can differ, however they generally follow similar themes. They often present as being validating, reassuring and supportive, but concurrently act to reinforce disordered eating, discourage help-seeking behaviour and hence hinder recovery.[23] Their use is worryingly prevalent with almost half of the study population noted above reporting pro-ED (or 'pro-ANA') websites as their primary information source.[22] The dangers of pro-ED are evident; 96% of users reported that they learnt new weight loss techniques in a pilot study of 76 participants. Whilst health outcomes were similar here, those that used pro-ED were seen to have a longer duration of illness and were hospitalised more often than non-users.[24] Likewise, significantly poorer Disorder Examination Questionnaire (EDE-Q) and Eating Disorder Quality of Life (EDQOL) scores have been recorded in patients exposed to pro-ED content vs controls, with heavier use leading to worse scores.[22] Traditionally websites were the mainstay of pro-ED content, however now this information is shared widely on various social media platforms; a medium which is not just more accessible for users, but also much harder to regulate meaning this content is more available than ever.

Due to the vastness of social media, Machine learning is ideal to sift through and eliminate dangerous content such as this. This has been demonstrated in a number of studies already. One study analysed a million Tumblr photos and accompanying text that had previously been removed from the site for inappropriate pro-ED content. The machine learning model they produced using this data was able to identify pro-ED content with 89% accuracy.[25] Likewise, in a further study, 30,000 previously public Instagram posts with pro-ED content were analysed and classified. When applied to currently active Instagram posts, pro-ED content was detected with a respectable 69% accuracy.[26] These studies demonstrate the vast potential of machine learning approaches to aid in the removal of potential harmful posts which have been shown to reinforce disordered eating and contribute to poorer quality of life. This could be an important preventative strategy in both those with mild symptoms (where this content may promote progression to more severe disease) and also those with chronic or treatment resistant symptoms, where pro-ED content may sustain ambivalence and non-adherence with treatment.

## How could machine learning help carers?

Carers for ED patients have been seen to have high levels of anxiety and depression, illustrated by a reported incidence of 56% and 32% respectively, immediately after an established ED diagnosis. This was also reported to be largely unchanged at 1 year follow up. [27] Interestingly, caregiver anxiety was seen to improve with a reduction in perceived ED severity.[28] Therefore naturally, if the long term outcomes and severity of the eating disorder can be improved upon using machine learning, this can only act to reduce the associated morbidity amongst care givers.

## Conclusion

In conclusion, it is clear from available research that ED patients and their carers are in great need of innovative ways to tackle this complex pathology beyond the strategies employed thus far in healthcare and wider society. The current evidence supports that machine learning can offer a useful, quick and, importantly, cheap adjunct to improve various domains of ED diagnosis and care in which current measures are falling short to support patients and their carers.

**References**


1. Flynn M, Austin A, Lang K, Allen K, Bassi R, Brady G et al. Assessing the impact of First Episode Rapid Early Intervention for Eating Disorders on duration of untreated eating disorder: A multi-centre quasi-experimental study. European Eating Disorders Review. 2020;29(3):458-471

2. van Eeden A, van Hoeken D, Hoek H. Incidence, prevalence and mortality of anorexia nervosa and bulimia nervosa. Current Opinion in Psychiatry. 2021;34(6):515-524.

3. Forsén Mantilla E, Clinton D, Birgegård A. The unsafe haven: Eating disorders as attachment relationships. Psychology and Psychotherapy: Theory, Research and Practice. 2018;92(3):379-393.

4. McCulloch W, Pitts W. A logical calculus of the ideas immanent in nervous activity. The Bulletin of Mathematical Biophysics. 1943;5(4):115-133.

5. Shatte A, Hutchinson D, Teague S. Machine learning in mental health: a scoping review of methods and applications. Psychological Medicine. 2019;49(09):1426-1448.

6. Supervised vs. Unsupervised Learning: What's the Difference? [Internet]. Ibm.com. 2022 [cited 14 August 2022]. Available from: https://www.ibm.com/cloud/blog/supervised-vs-unsupervised-learning

7. 8. Le Glaz A, Haralambous Y, Kim-Dufor D, Lenca P, Billot R, Ryan T et al. Machine Learning and Natural Language Processing in Mental Health: Systematic Review. Journal of Medical Internet Research. 2021;23(5):e15708.

8. Mahabub A. A robust voting approach for diabetes prediction using traditional machine learning techniques. SN Applied Sciences. 2019;1(12).

9. Chen Q, Li H, Tang B, Wang X, Liu X, Liu Z et al. An automatic system to identify heart disease risk factors in clinical texts over time. Journal of Biomedical Informatics. 2015;58:S158-S163.

10. Fernandes A, Dutta R, Velupillai S, Sanyal J, Stewart R, Chandran D. Identifying Suicide Ideation and Suicidal Attempts in a Psychiatric Clinical Research Database using Natural Language Processing. Scientific Reports. 2018;8(1).

11. Berrouiguet S, Billot R, Larsen M, Lopez-Castroman J, Jaussent I, Walter M et al. An Approach for Data Mining of Electronic Health Record Data for Suicide Risk Management: Database Analysis for Clinical Decision Support. JMIR Mental Health. 2019;6(5):e9766.

12. Oh J, Yun K, Hwang J, Chae J. Classification of Suicide Attempts through a Machine Learning Algorithm Based on Multiple Systemic Psychiatric Scales. Frontiers in Psychiatry. 2017;8.

13. 12. Koutsouleris N, Kahn R, Chekroud A, Leucht S, Falkai P, Wobrock T et al. Multisite prediction of 4-week and 52-week treatment outcomes in patients with first-episode psychosis: a machine learning approach. The Lancet Psychiatry. 2016;3(10):935-946.

14. Kessler R, van Loo H, Wardenaar K, Bossarte R, Brenner L, Cai T et al. Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports. Molecular Psychiatry. 2016;21(10):1366-1371.

15. Bryant E, Spielman K, Le A, Marks P, Aouad P, Barakat S et al. Screening, assessment and diagnosis in the eating disorders: findings from a rapid review. Journal of Eating Disorders. 2022;10(1).

16. Orrù G, Miniati M, Conversano C et al. A machine learning analysis of psychopathological features of Eating Disorders: a retrospective study. Mediterranean Journal of Clinical Psychology. 2021; 9. 1-19

17. Krug I, Linardon J, Greenwood C, Youssef G, Treasure J, Fernandez-Aranda F et al. A proof-of-concept study applying machine learning methods to putative risk factors for eating disorders: results from the multi-centre European project on healthy eating. Psychological Medicine. 2021;:1-10.

18. 13. Sadeh-Sharvit S, Fitzsimmons-Craft E, Taylor C, Yom-Tov E. Predicting eating disorders from Internet activity. International Journal of Eating Disorders. 2020;53(9):1526-1533.

19. Hamilton A, Mitchison D, Basten C, Byrne S, Goldstein M, Hay P et al. Understanding treatment delay: Perceived barriers preventing treatment-seeking for eating disorders. Australian & New Zealand Journal of Psychiatry. 2021;56(3):248-259.

20. Haynos A, Wang S, Lipson S, Peterson C, Mitchell J, Halmi K et al. Machine learning enhances prediction of illness course: a longitudinal study in eating disorders. Psychological Medicine. 2020;51(8):1392-1402.

21. Fitzsimmons-Craft E, Eichen D, Monterubio G, Firebaugh M, Goel N, Taylor C et al. Longer-term follow-up of college students screening positive for anorexia nervosa: psychopathology, help seeking, and barriers to treatment. Eating Disorders. 2019;28(5-6):549-565.

22. Peebles R, Wilson J, Litt I, Hardy K, Lock J, Mann J et al. Disordered Eating in a Digital Age: Eating Behaviors, Health, and Quality of Life in Users of Websites With Pro-Eating Disorder Content. Journal of Medical Internet Research. 2012;14(5):e148.

23. Rouleau C, von Ranson K. Potential risks of pro-eating disorder websites. Clinical Psychology Review. 2011;31(4):525-531.

24. Wilson J, Peebles R, Hardy K, Litt I. Surfing for Thinness: A Pilot Study of Pro–Eating Disorder Web Site Usage in Adolescents With Eating Disorders. Pediatrics. 2006;118(6):e1635-e1643.

25. Chancellor S, Kalantidis Y, Pater J, De Choudhury M, Shamma D. Multimodal Classification of Moderated Online Pro-Eating Disorder Content. Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. 2017;.

26. Chancellor S, Lin Z, De Choudhury M. "This Post Will Just Get Taken Down". Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2016;.

27. Orive M, Padierna A, Martin J, Aguirre U, González N, Muñoz P et al. Anxiety and depression among caregivers of patients with eating disorders and their change over 1 year. Social Psychiatry and Psychiatric Epidemiology. 2013;48(9):1503-1512.

28. González N, Padierna A, Martín J, Aguirre U, Quintana J. Predictors of change in perceived burden among caregivers of patients with eating disorders. Journal of Affective Disorders. 2012;139(3):273-282.