ARTIFICIAL AND/OR INTELLIGENT?

MACHINE LEARNING, AI AND OTHER TECHNOLOGIES IN MENTAL HEALTH SERVICES...CHALLENGES AND OPPORTUNITIES...

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HONORARY CONSULTANT PSYCHIATRIST, HYMS AND HEALTH SCIENCES
What I plan to talk about....

- Predictive technologies in mental health
- CfFH/Wellcome Research Priming funded work
- Workforce selection/Development via predictive/playful technologies
What I plan to talk about....

• Where is prediction, via machine learning, likely to add values to a process [in mental health services]?
To use predictive modelling/machine learning effectively you need:

Right **task**
To use predictive modelling/machine learning effectively you need:

- Right task
- Right data
To use predictive modelling/machine learning effectively you need:

**Right task**

**Right data**

**Right method/s**
To use predictive modelling/machine learning effectively you need:

- Right task
- Right data
- Right context (HCI)
- Right method/s
To use predictive modelling/machine learning effectively you need:

Right **task**
Personalising Mental Health Treatments for Young People Using Machine Intelligence (ProMetheUs)

- Ran a (virtual) workshop with national leaders in Child and Adolescent Mental Health Services (CAMHS)
- Identified some potential tasks as well as key challenges to developing and implementing ML in CAMHS
- Follow up Delphi in October
- Working on scoping review of predictive modelling in CAMHS
- Identifying datasets for exploration/proof of concept
Potential tasks?

• Logistics and planning
  • Predicting risk of DNAs
  • Bed management and rostering
• Predicting relapse/crisis/self-harm
• Diagnosis
  • Biomarkers, imaging, integrating multi-source information
• Enhancing psychological therapies
  • Predictive feedback
  • ‘Chat bots’ [e.g. woebot] and AI therapists
Feedback-informed treatment versus usual psychological treatment for depression and anxiety: a multisite, open-label, cluster randomised controlled trial


Summary

Background Previous research suggests that the use of outcome feedback technology can enable psychological therapists to identify and resolve obstacles to clinical improvement. We aimed to assess the effectiveness of an outcome feedback quality assurance system applied in stepped care psychological services.

Methods This multisite, open-label, cluster randomised controlled trial was done at eight National Health Service (NHS) Trusts in England, involving therapists who were qualified to deliver evidence-based low-intensity or high-intensity psychological interventions. Adult patients (18 years or older) who accessed individual therapy with participating therapists were eligible for inclusion, except patients who accessed group therapies and those who attended less than two individual therapy sessions. Therapists were randomly assigned (1:1) to an outcome feedback intervention group or a treatment-as-usual control group by use of a computer-generated randomisation algorithm. The allocation of patients to therapists was quasi-random, whereby patients on waiting lists were allocated sequentially on the basis of therapist availability. All patients received low-intensity (less than eight sessions) or high-intensity (up to 20 sessions) psychological therapies for the duration of the 1-year study period. An automated computer algorithm alerted therapists in the outcome feedback group to patients who were not on track, and primed them to review these patients in clinical supervision. The primary outcome was symptom severity on validated depression (Patient Health Questionnaire-9 [PHQ-9]) and anxiety (Generalised Anxiety Disorder-7 [GAD-7]) measures after treatment of varying durations, which were compared between groups with multilevel modelling, controlling for cluster (therapist) effects. We used an intention-to-treat approach. This trial was prospectively registered with ISRCTN, number ISRCTN13458454.
Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning

Colin G. Walsh, Jessica D. Ribeiro, and Joseph C. Franklin
Vanderbilt University Medical Center, Nashville, TN; Florida State University, Tallahassee, FL, USA

Background: Adolescents have high rates of nonfatal suicide attempts, but clinically practical risk prediction remains a challenge. Screening can be time consuming to implement at scale, if it is done at all. Computational algorithms may predict suicide risk using only routinely collected clinical data. We used a machine learning approach validated on longitudinal clinical data in adults to address this challenge in adolescents. Methods: This is a retrospective, longitudinal cohort study. Data were collected from the Vanderbilt Synthetic Derivative from January 1998 to December 2015 and included 974 adolescents with nonfatal suicide attempts and multiple control comparisons: 496 adolescents with other self-injury (OSI), 7,059 adolescents with depressive symptoms, and 25,081 adolescent general hospital controls. Candidate predictors included diagnostic, demographic, medication, and socioeconomic factors. Outcome was determined by multiexpert review of electronic health records. Random forests were validated with optimism adjustment at multiple time points (from 1 week to 2 years). Recalibration was done via isotonic regression. Evaluation metrics included discrimination (AUC, sensitivity/specificity, precision/recall) and calibration (calibration plots, slope/intercept, Brier score). Results: Computational models performed well and did not require face-to-face screening. Performance improved as suicide attempts became more imminent. Discrimination was good in comparison with OSI controls (AUC = 0.83 [0.82–0.84] at 720 days; AUC = 0.85 [0.84–0.87] at 7 days) and depressed controls (AUC = 0.87 [95% CI 0.85–0.90] at 720 days; 0.90 [0.85–0.94] at 7 days) and best in comparison with general hospital controls (AUC 0.94 [0.92–0.96] at 720 days; 0.97 [0.95–0.98] at 7 days). Random forests significantly outperformed logistic regression in every comparison. Recalibration improved performance as much as ninefold – clinical recommendations with poorly calibrated predictions can lead to decision errors. Conclusions: Machine learning on longitudinal clinical data may provide a scalable approach to broaden screening for risk of nonfatal suicide attempts in adolescents. Keywords: Suicide; attempted; adolescent; machine learning; decision support techniques; electronic health records.
Detecting depression and mental illness on social media: an integrative review
Sharath Chandra Guntuku\textsuperscript{1}, David B Yaden\textsuperscript{1}, Margaret L Kern\textsuperscript{2}, Lyle H Ungar\textsuperscript{1} and Johannes C Eichstaedt\textsuperscript{1}

Although rates of diagnosing mental illness have improved over the past few decades, many cases remain undetected. Symptoms associated with mental illness are observable on Twitter, Facebook, and web forums, and automated methods are increasingly able to detect depression and other mental illnesses. In this paper, recent studies that aimed to predict mental illness using social media are reviewed. Mentally ill users have been identified using screening surveys, their public sharing of a diagnosis on Twitter, or by their membership in an online forum, and they were distinguishable from control users by patterns in their language and online activity. Automated detection methods may help to identify depressed or otherwise at-risk individuals through the large-scale passive monitoring of social media, and in the future may complement existing screening procedures.

Automated analysis of social media potentially provides methods for early detection. If an automated process could detect elevated depression scores in a user, that individual could be targeted for a more thorough assessment, and provided with further resources, support, and treatment. Studies to date have either examined how the use of social media sites correlates with mental illness in users \cite{3} or attempted to detect mental illness through analysis of the content created by users. This review focuses on the latter: studies aimed at predicting mental illness using social media. We first consider methods used to predict depression, and then consider four approaches that have been used in the literature. We compare the different approaches, provide direction for future studies, and consider ethical issues.

Prediction methods
Automated analysis of social media is accomplished by building predictive models, which use ‘features,’ or variables that have been extracted from social media data. For example, commonly used features include users’ language encoded as frequencies of each word, time of posts, and other variables (see Figure 2). Features are then treated as independent variables in an algorithm (e.g.
Can Machine Learning and Brain Imaging Create Better Diagnostics for Mental Illness?

MRI images like this one were screened by a machine learning computer algorithm designed by a research team at the University of Tokyo. The algorithm learned to identify the brains of nonpatients, patients diagnosed with autism, and patients diagnosed with schizophrenia based on subtle but statistically important differences in the thickness, volume, or surface area of certain regions of the brain. Credit: Image by Shinsuke Koike. CC-BY
Predicting persistent depressive symptoms in older adults: A machine learning approach to personalised mental healthcare

Christopher M. Hatton a, b, Lewis W. Paton a, b, Dean McMillan a, b, James Cussens c, Simon Gilbody a, b, Paul A. Tiffin a, b

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https://doi.org/10.1016/j.jad.2018.12.095

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Highlights

• Prediction of persistent depressive symptoms in older adults was superior using machine learning ('extreme gradient boosting'), compared to a traditional statistical approach (logistic regression).

• Using a machine learning approach ('extreme gradient boosting'), an average of 89% of those predicted to have PHQ-9 scores above threshold at 12 months, actually did, compared to 78% using logistic regression.

• These findings support the potential for machine learning approaches to support the development of personalised mental healthcare.
Personalized Medication Response Prediction for Attention-Deficit Hyperactivity Disorder: Learning in the Model Space vs. Learning in the Data Space

Hin K. Wong¹, Paul A. Tiffin²*, Michael J. Chappell³, Thomas E. Nichols¹, Patrick R. Welsh⁴, Orla M. Doyle⁵, Boryana C. Lopez-Kolkovska¹, Sarah K. Inglis⁶, David Coghill⁷, Yuan Shen⁸, and Peter Tiño⁸

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TABLE 1 | Rms errors for predicting symptom scores for inattentiveness (INA) and hyperactivity (HYP) using the (A) learning in model space and (B) conventional approaches.

### (1A) Learning in model space

<table>
<thead>
<tr>
<th>Method</th>
<th>Inattentiveness</th>
<th>Hyperactivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Method 1</td>
<td>Method 2</td>
</tr>
<tr>
<td>AIR†</td>
<td>0.98</td>
<td>0.84</td>
</tr>
<tr>
<td>BRR†</td>
<td>0.82</td>
<td>0.82</td>
</tr>
<tr>
<td>BUR‡</td>
<td>0.99</td>
<td><strong>0.73</strong></td>
</tr>
</tbody>
</table>

*AIR: appointment-independent Bayesian linear prediction.
†BRR: retrospective Bayesian linear regression.
‡BUR: incremental Bayesian learning/update linear regression.

### (1B) Conventional approaches

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Inattentiveness</th>
<th>Hyperactivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear</td>
<td>Nonlinear</td>
</tr>
<tr>
<td>SVR*</td>
<td>0.73</td>
<td>0.74</td>
</tr>
<tr>
<td>GPR†</td>
<td>0.72</td>
<td>0.77</td>
</tr>
<tr>
<td>MER‡</td>
<td></td>
<td><strong>0.82</strong></td>
</tr>
</tbody>
</table>

*SVR: support vector machine regression.
†GPR: Gaussian processes regression.
‡MER: mixed effects regression.
Mental health Staff selection and development
Shortage of psychiatrists is threatening lives, we need government action

Baroness Parminter

3 min read | 22 October 2019

The Government must take action to address the shortage of psychiatrists, contributing to lengthy NHS waiting times and having devastating effects on people reaching out for support, writes Baroness Parminter.
Psychologists
Sen. Reg. Psychiatrists
SHO Psychiatrists
Snr Nurses
Nurses
N. Assts

Proportion of time spent in direct patient contact

Lots!

Relatively little...

The inverted pyramid of training
Situation judgment tests...to ‘scenario based learning’?
SCENARIO - You are working on an inpatient unit with a colleague who has used some derogatory terms about a patient. Your colleague was assaulted by the patient some time ago. Your colleague would not normally talk about patients in this manner, but this is becoming more frequent. Your colleague has been getting upset at work and seems frustrated with the job.

How appropriate would it be to respond in the following manner:

BEHAVIOUR - To advise your colleague that they should not be talking about patients in a derogatory manner, regardless of how they feel

- Very appropriate
- Appropriate, but not ideal
- Inappropriate, but not awful
- Very inappropriate
Question a39 (7 of 8)
SCENARIO - You are working on an inpatient unit with a colleague who has used some derogatory terms about a patient. **Your colleague was assaulted by the patient** some time ago. Your colleague would not normally talk about patients in this manner, but this is becoming more frequent. Your colleague has been getting upset at work and seems frustrated with the job.

How **important** is it to take into account the following consideration when deciding how to respond to the situation?

CONSIDERATION - That your colleague may be having difficulties at home

- [ ] Very important
- [ ] Important
- [ ] Of minor importance
- [ ] Not important at all
West Lane Hospital suspended staff 'still working'  

22 August 2019

Thirteen staff suspended over the alleged ill-treatment of patients at a mental health unit are still working for the trust, the BBC has learned.

The workers at West Lane Hospital in Middlesbrough faced claims they used techniques for moving people that were “not in line with trust policy”.

It has now emerged an inquiry has not led to any of them being dismissed.
• Can playful/immersive technology approaches be used to enhance ‘therapeutic skills’ in mental health staff?

• DBT-skills approach to training for staff promising (Haynos et al. 2016)

• Face to face training is challenging
  • Shift work, including nights
  • Staff churn
  • Need for interactive/emotive approach
  • Repeated training ‘top-ups’
  • Need for ongoing feedback
  • Low levels of literacy in some staff groups
• **Patient benefit?**
  • Reduced use of tranquillisation
  • Less frequent restraint
  • Shorter hospital stays
  • Better clinical outcomes

• **Staff benefits:**
  • Reduced burnout?/better morale
  • Less stigmatising attitudes towards ‘patients that challenge’
  • Better relations *between* staff
  • Improved relationships at home
  • Less sick leave
  • Reduced disciplinaries
THANK YOU!