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Therapy by chatbot? The promise and challenges in using AI for Mental Health

Dr Japie Greeff

#DiscoverNWU

Who am I?

- Dr Japie Greeff
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- Optentia Research Unit Program Lead: Technology, Capability and Functioning
- Associate of the National Institute of Theoretical and Computational Science
- I am a technologist, not a clinician!


FAST COMPANY

1-21-23

'eople are using AI for therapy, vhether the tech is ready for it o ıot

lental-health counseling, text-based AI, and the future of your relationship with yc ıerapist.

Where are we?

- Therapy by Chatbot?
- At this point it is not so much about when this shift in paradigm is going to happen, but rather how big the impact is going to be…

But why a move to therapy by chatbot?

- Growing demand for mental health services
- Technological advancements
- Accessibility
- Cost-effectiveness
- Overcoming barriers associated with traditional therapy

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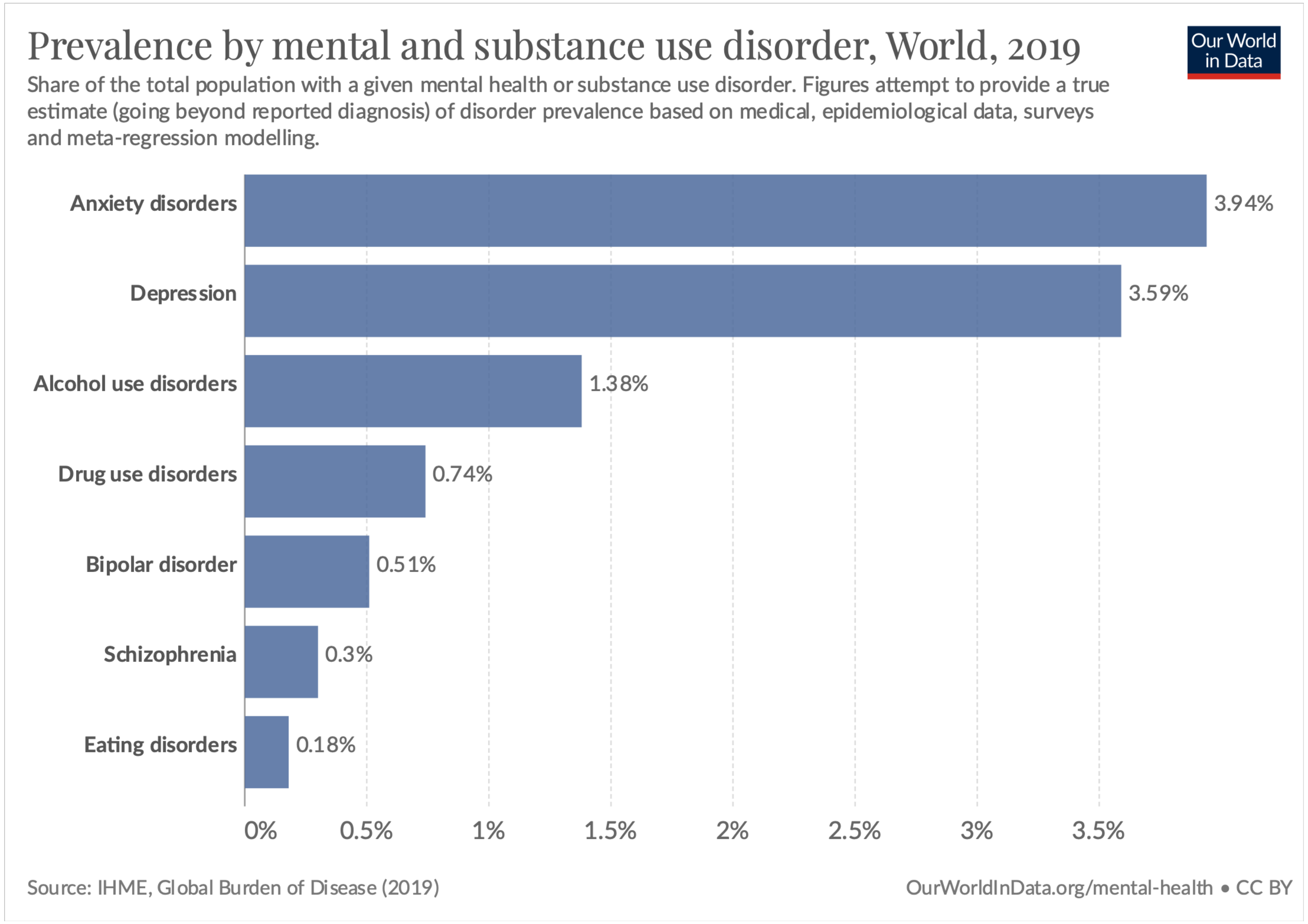
Worldwide prevalence of disorders

- Data from the WEF from 2019
- Research has shown that the first year of Covid-19 brought about a 25% increase in the number of cases of anxiety and depression alone



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History of chatbots in the therapy context

ELIZA (1965)
- Developed by Joseph Weizenbaum and was based on NLP pattern recognition
- Simulated Rogerian psychotherapy
- Source of the ELIZA effect

ALICE (1995)
- Developed by Richard Wallace
- Pioneered the use of AIML (Artificial Intelligence Markup Language) which also lead to SIML and EmotionML
- Won the Loebner Prize for conversational AI 3 times from 2000 (but would not pass the Turing Test)

Tess/Cass (2015 –)
- Two Randomised Controlled Trials
- +30 million users, 1st line support, paired with clinicians

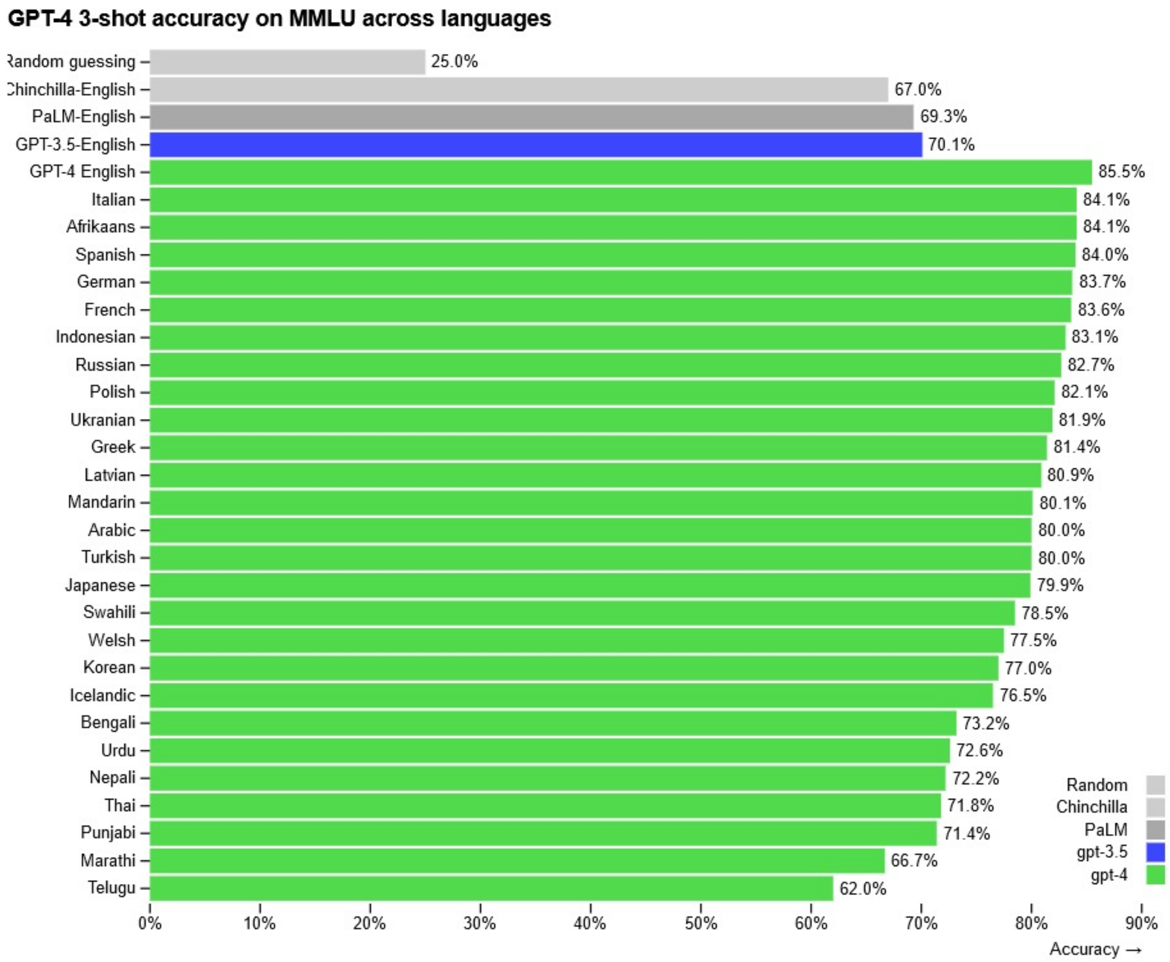
Replika (2017 -)
- Popularised the concept of a personalised relationship
- Offers many styles of interaction
- 2023 controversy relating to changes in the models reaction to sexual content

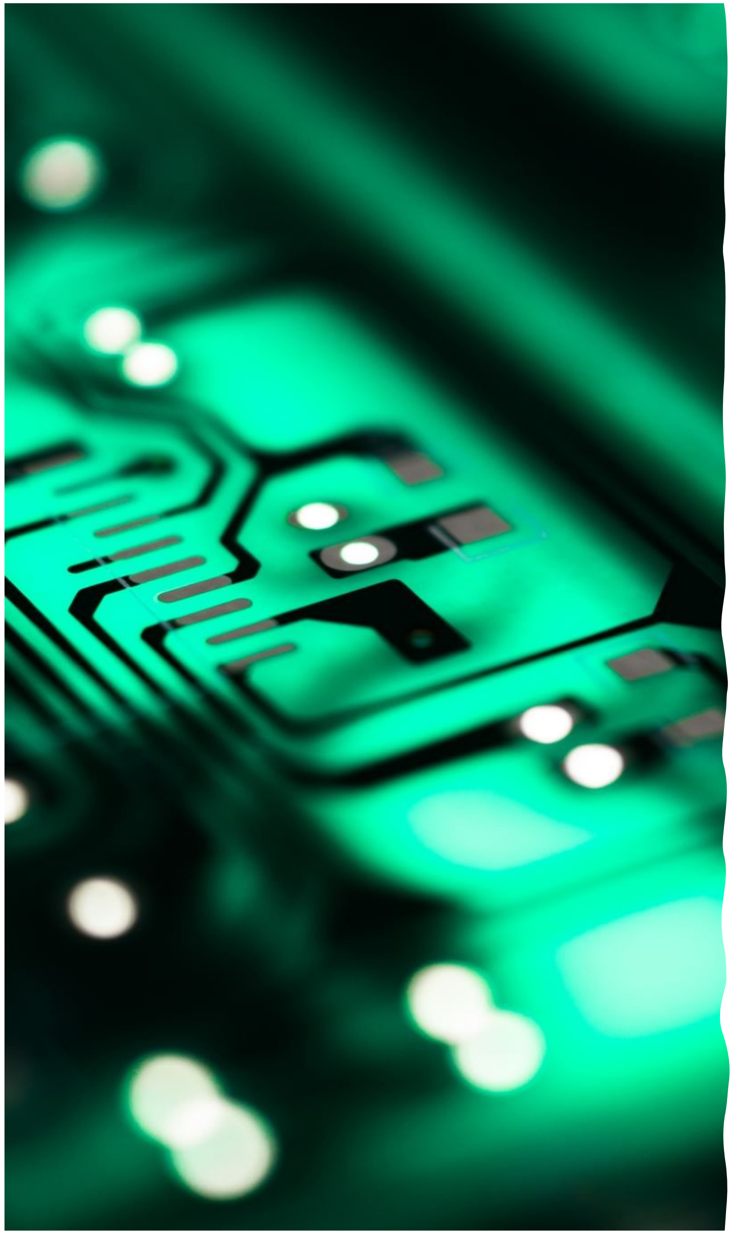
Woebot (2017 -)
- Founded by clinical research psychologist and technologist Alison Darcy
- Became famous due to the reaction to the Covid-19 pandemic in the way it assisted users

Transformers (2018 -)
- Various models are now in place after the initial model was presented by Google in 2018 with BERT
- Controversy arose in 2022 when it came out that the peer-support platform Koko incorporated GPT-3 in its responses to users
- GPT-4 is the current market leader and multiple projects are underway to use GPT-3.5 / GPT-4 in wellness and therapy apps…

Current levels of language model capability

- Current state of the art is GPT-4
- Scores 85.5% on MMLU
  - 14k problems spanning 57 areas
- Excellent on human tests
- Can process visual information
- Personality steerability (in dev)





Technological advancements in other areas

- Although the advancements in language models is huge, other advancements in technology also bring new potential
- Physiological data can be automatically obtained through wearables
- Mood tracking can be done in app
- Sleep patterns and food diaries can be integrated
- Chatbots can integrate with existing healthcare infrastructure
- Data science brings a whole new world of possibilities for individualized care approaches

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Accessibility of chatbot therapy

- Current incarnations offer a high level of personalisation
- Can integrate and switch between therapy styles easily
- Available 24/7
- Multilingual support for a variety of languages (SA context?)
- Available in areas where social services may not be available easily
- Can integrate with existing healthcare systems as 1st line support
- No need to physically travel to meet with therapist
- Note that online video and text therapy with traditional therapists has gained traction and can assist a large number of people when combined!

But why a move to therapy by chatbot?

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- **Cost-effectiveness**
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Cost-effectiveness

- Traditional therapy offers many benefits but the cost can be high
- Chatbot based therapy can in some cases be obtained for free
- Applications that incorporate AI scale well when taken on from an organizational perspective when combined with wellness programs
- No need to travel, and with text-based chat minimal data costs

But why a move to therapy by chatbot?

- Growing demand for mental health services
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- **Overcoming barriers associated with traditional therapy**

Overcoming barriers

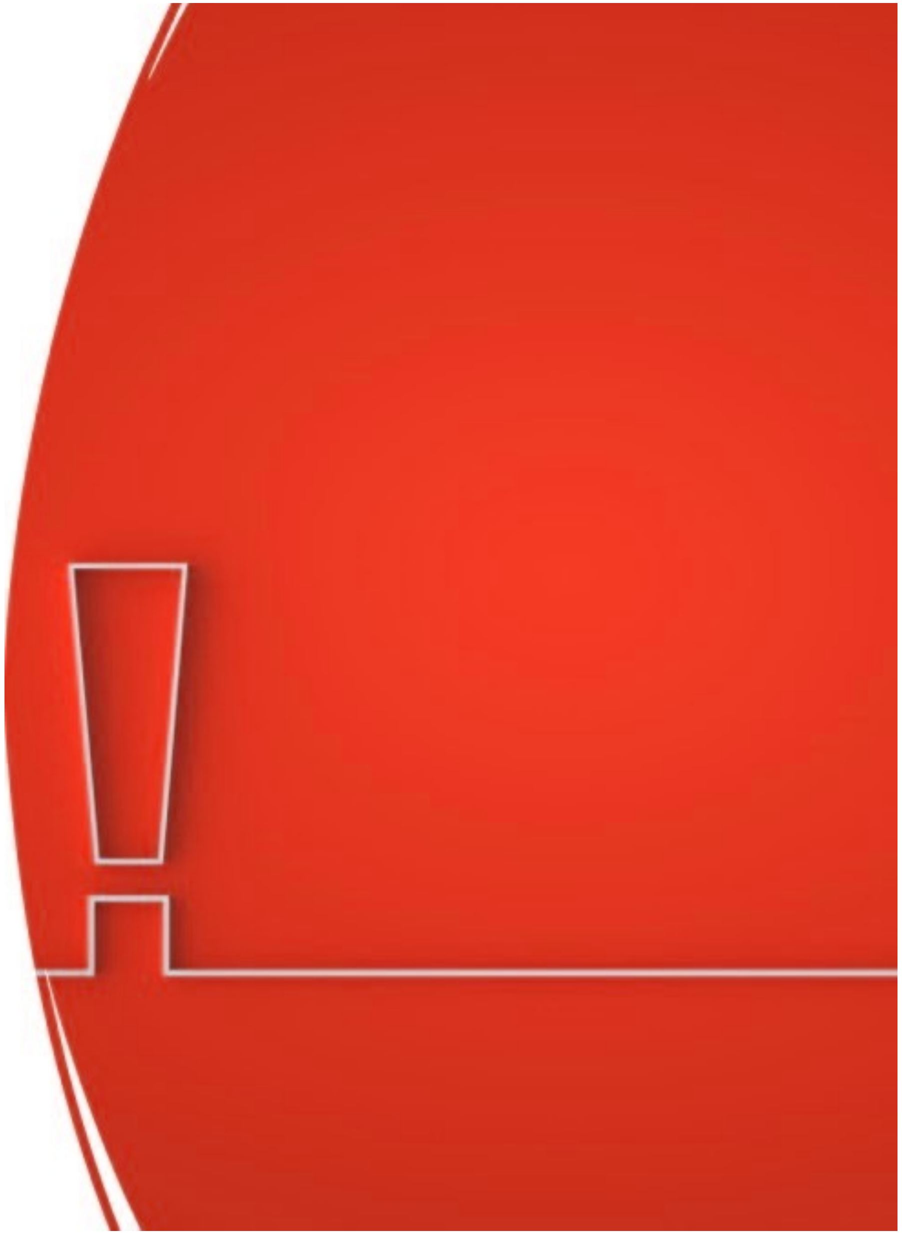
- When talking to an AI many people experience it as a more “anonymous” experience. People may share things in this context more easily than in the therapy context.
- Interacting with a chatbot does not carry with it the same stigma as seeing a therapist (in some cases)
- Chatbots tend to be written in such a way as to not judge, making them attractive alternative options to human interaction for some people

Which techniques seem to work?

- Cognitive Behavioural Therapy
- Dialectical Behaviour Therapy
- Mindfulness
- Acceptance and Commitment Therapy
- Motivational Interviewing
- Supportive Therapy with a supportive, non-judgmental environment
- Role play
- Self help exercises for immediate intervention (Anxiety, anger etc.)
- Etc.

But what are the risks?

- Although there is great potential, at this point in time chatbots are not a true replacement for professional mental health care just yet.
- There are not sufficient clinical trials that show the long term effectiveness and risks, however this is an active area of research
- Bias in large language models can be problematic
- Ethics and safety are being explored, but there are no standard frameworks (they are being developed)
- Ensuring safety and ethical performance of models can make discussing some subjects very difficult for a chatbot – for example discussing sexual assault



End of part 1!

After this point I will dive into some of the technical details of these systems

At this point though, are there any questions?

Thank you for your attention so far!

Mental health and technology

- Although therapy by chatbot is becoming more prevalent, it is by no means the only technique that is used to support mental health
- In this section we will dive a little deeper into the specific technologies that have been used and what literature says about it

Technologies that can assist

- Decision support systems
- Data analysis – post hoc
- AI and ML (various)
- Refining diagnosis with categorization
- Data collection
- mHealth and eHealth

Decision support systems

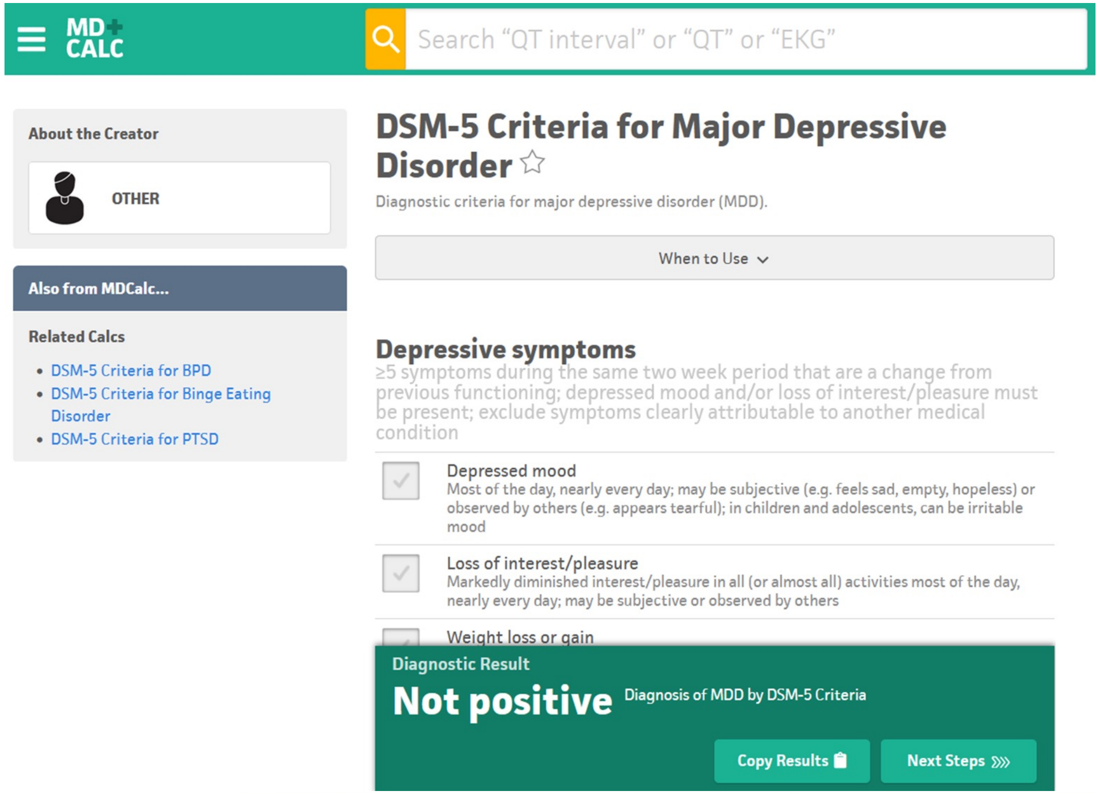
- Due to its very prescriptive nature, the DSM-V is very friendly to being translated into a DSS.

Table 9 DSM-IV to DSM-5 Major Depressive Episode/Disorder Comparison

Criteria[1]	DSM-IV	DSM-5[2]
Class: Mood **Disorders**	✓	
Class: **Depressive Disorders**		✓
Five or more of the following A Criteria (at least one includes A1 or A2)	✓	✓
A1 Depressed mood—indicated by subjective report or observation by others (in children and adolescents, can be irritable mood).	✓	✓
A2 Loss of interest or pleasure in almost all activities—indicated by subjective report or observation by others.	✓	✓
A3 Significant (more than 5 percent in a month) unintentional weight loss/gain or decrease/increase in appetite (in children, failure to make expected weight gains).	✓	✓
A4 Sleep disturbance (insomnia or hypersomnia).	✓	✓
A5 Psychomotor changes (agitation or retardation) severe enough to be observable by others.	✓	✓
A6 Tiredness, fatigue, or low energy, or decreased efficiency with which routine tasks are completed.	✓	✓
A7 A sense of worthlessness or excessive, inappropriate, or delusional guilt (not merely self-reproach or guilt about being sick).	✓	✓
A8 Impaired ability to think, concentrate, or make decisions—indicated by subjective report or observation by others.	✓	✓
A9 Recurrent thoughts of death (not just fear of dying), suicidal ideation, or suicide attempts.	✓	✓
The symptoms cause clinically significant distress or impairment in social, occupational, or other important areas of functioning.	✓	✓
The symptoms are not due to the direct physiological effects of a substance (e.g., drug abuse, a prescribed medication's side effects) or a medical condition (e.g., hypothyroidism).	✓	✓
The symptoms do not meet criteria for a mixed episode[3]	✓	
There has never been a manic episode or hypomanic episode.	✓	✓
MDE is not better explained by schizophrenia spectrum or other psychotic **disorders**.	✓	✓
The symptoms are not better accounted for by bereavement (i.e., after the loss of a loved one, the symptoms persist for longer than 2 months or are characterized by marked functional impairment, morbid preoccupation with worthlessness, suicidal ideation, psychotic symptoms, or psychomotor retardation).[4]	✓	

Decision support systems

- Due to its very prescriptive nature, the DSM-V is very friendly to being translated into a DSS.
- MD+CALC contains a number of calculators for many common disorders and is available on the web and in app form



Data analysis – post hoc

- Koppe, Meyer-Lindenberg and Durstewitz indicate in 2021 that the rise of big data, as opposed to clinical trials with statistically significant but small sample sizes could allow for a new a approach to person specific treatment in psychiatry.
- This concept has lead to some tools that seek to detect psychiatric disorders from sources of big data, like the study from 2020 by Wang et al. that aimed to detect depression from publicly available microblogs in China.
- This however raises all sorts of ethical questions – should we be analysing public data for diagnosis? What responsibility for treatment do you create when finding potential hits?

Data analysis – post hoc

- Researchers like Ewbank et al. (2020) have worked on relating the language that patients use in therapy (CBT) to try and predict clinical outcomes based on textual analysis

Table I. Response categories and guidelines (definitions and examples) used to tag patient utterances.

Category	Definition	Examples
Change-Talk Active	Patient responses that reflect a desire or commitment to change (including evidence that they have enacted some change such as doing their homework).	*"I don't want to live like this anymore"* *"Yes, I did fill in my thought record. I found it really helpful."*
Change-Talk Exploration	Patient responses that reflect a past, present or future state of mind and show evidence that the patient is using self-exploration and reflection of their problems.	*"So, I think that if I did that my heart would be racing, and I would get very nervous."*
Counter Change-Talk	Patient responses that move away from the target behaviour (including evidence of not-engaging in therapy).	*"I was unable to do the homework"* *"I don't think that would work"* *"I won't be able to"*
Follow/Neutral	Patient responses which do not favour either change or counter-change talk (including simple clarifications and non-therapeutic chit-chat).	*"Hello," "Ok," "I see"* *"Could you put that another way?" "What do you mean?"*
Describing Problems	Patient responses that describe external problems in their lives (i.e., not directly related to presenting problem).	*"I'm in a lot of debt and can't pay it off"* *"My mother has been very ill"*

Data analysis – post hoc

- Projects like this highlight the opportunities that exist to transform data that is collected from existing health and wellness platforms and transform it into predictive tools
- The ethical ramifications of this however need to be considered very carefully, while considering the tradeoff between group models and personal models
- For large population wide models data can be anonymized while analysing it and building the model making it more secure and less risky
- Personalised models however have more risk as data about the patient is stored in one place and traceable, but have the potential to allow for personalised treatment and much more descriptive models

AI and ML (various)

- A systematic lit review by Shatte et al. from 2019 gave an overview of the disorders that were being explored with ML techniques.
- Showed progress being made in the areas of diagnosis, treatment and support, research and clinical administration of 23 different aspects of mental health (disorders and problems) over 300 articles.
- Techniques considered included:
  - Random Forest
  - Support Vector Machines
  - Naïve Bayes
  - Neural Networks*
  - Latent Dirichlet Allocation
  - K- Nearest Neighbours
  - Hidden Markov Model
  - Bayesian Network
  - Association Rule Mining
  - Principal Component Analysis

AI and ML (various)

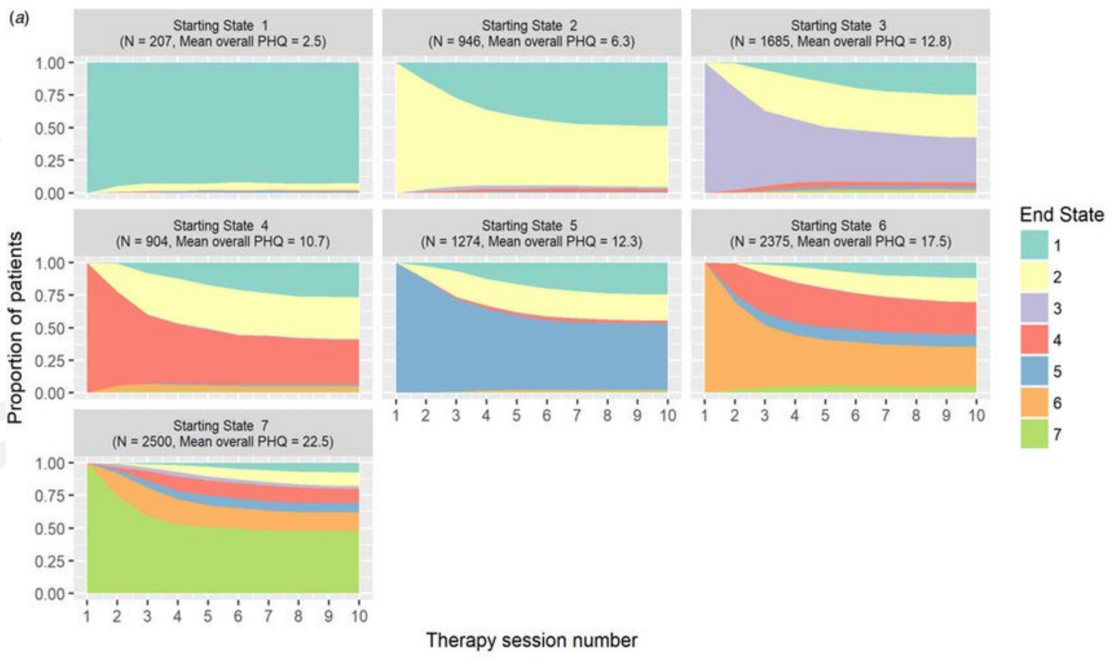
- In 2021 Chekroud et al. explored the promise of ML in predicting Psychiatric treatment outcomes and found that there are challenges to using these techniques in practice.
- They found that very few studies included external validation of their results, and even fewer tested the clinical feasibility of the proposed solution.
- They additionally cite the ethical challenges that studies face in going from concept stage to implementation.
- That said, they found that ML is an important approach to improving mental health care and that some clinical studies show it is working already.

Refining diagnoses with categorisation

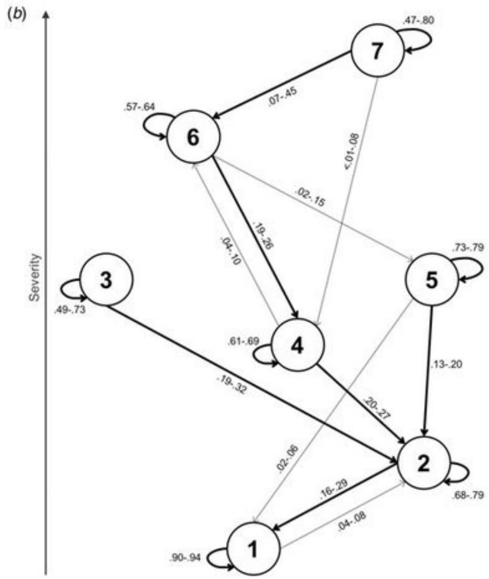
- In an overview of AI for Mental Health and Mental Illness from 2019 Graham et al. highlight the progress that has been made by a number of projects in the literature and explore sources of data that can be used.
- They highlight the fact that using a more data intensive approach can lead to a much more nuanced approach to classifying disorders than what is currently contained in the DSM-V criteria.
- An example of this can be found in Siegel et al. from 2021 where they use random forests to identify subtypes of PTSD in military veterans 6 to 10 years post-trauma.

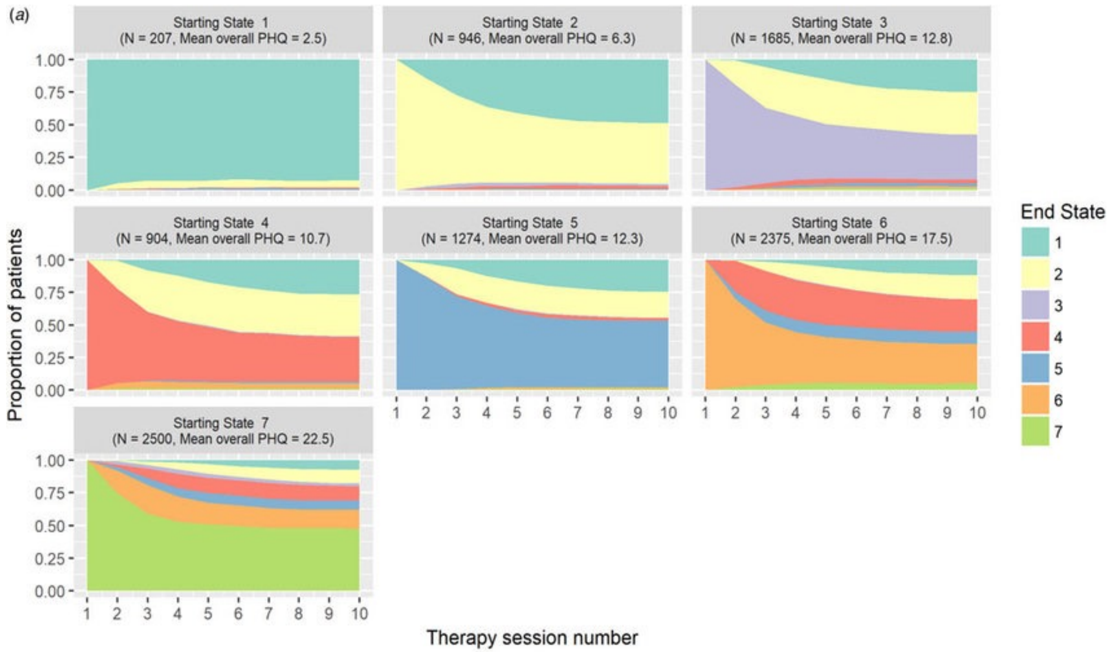
Refining diagnoses with categorisation

- Another example is found in Catarino et al. from 2020 where they used a small questionnaire regarding the past two weeks of a patient's life (N = 9891), and through latent Markov Modelling were able to define 7 different depressive states and transition probabilities



Refining diagnoses with categorisation





Data collection

- Although big data shows promise in the form of extracting large amounts of data from the internet, there is also the potential to gather large amounts of data from the individual.
- As indicated by Checkroud et al. there is the potential to gather:
  - text ,
  - electronic health records,
  - smart phone usage,
  - social media data,
  - Genetics data,
  - Electrophysiology data,
  - neuroimaging data and
  - cognitive testing.

But how to present it? mHealth!

But how to present it? mHealth!

- The WHO highlighted in 2018 the benefits of mHealth as a tool to reach the Sustainable Development Goals regarding access to healthcare. They go on to highlight:
  - The ease of use, broad reach and acceptance of mobile phones
  - The potential to revolutionize how people interact with services
  - The increasing proportion of the population accessing health services using mobile devices
  - The increase in the availability of apps that support health
  - The advent of wearables as data collection tools

But how to present it? mHealth!

- They do go on to highlights some challenges as well:
  - There are lots of pilots, but no clear plan for success
  - There is a lack of integration between different apps
  - An absence of standards and tools for comparison
  - A lack of a multisectoral approach that links together government agencies, donors, developers and researchers

mHealth and effectiveness in Mental Health

- In 2021 Wu et al. in did a systematic lit review of smartphone applications used for the treatment of Depression and Anxiety and found that although mental health apps can be effective in reducing symptoms of depression and anxiety, their usage is not generally sustained over time. They further explored characteristics of Persuasive System Design (PSD).
- Engagement in e-health and m-health interventions is an entire field of study, with instruments like the TWEETS that can be used to track engagement in a population over time.

The problem of insight

- In therapy situations, there are tools that are used to detect specific disorders and episodes that have been validated over a long time
- Some of these have been translated into mHealth tools, but there are limitations to what can be achieved due to the problem of insight

Detecting episodes and anomalies

- Detecting a Manic, Hypomanic or Major Depressive episode is normally done by a clinician in a controlled environment.
- For depression they use the Hamilton Depression Rating Scale (HDRS) which is administered with a semi-structured interview and the clinician marking 17 categories with a scale
- The Young Mania Rating scale (YMRS) is used for the detection of Mania and follows the same style of evaluation used in the HDRS.

Detecting episodes - HDRS

PLEASE COMPLETE THE SCALE BASED ON A STRUCTURED INTERVIEW

Instructions: for each item select the one "cue" which best characterizes the patient. Be sure to record the answers in the appropriate spaces (positions 0 through 4).

---

1 DEPRESSED MOOD *(sadness, hopeless, helpless, worthless)*

0 |__| Absent.
1 |__| These feeling states indicated only on questioning.
2 |__| These feeling states spontaneously reported verbally.
3 |__| Communicates feeling states non-verbally, i.e. through facial expression, posture, voice and tendency to weep.
4 |__| Patient reports virtually only these feeling states in his/her spontaneous verbal and non-verbal communication.

2 FEELINGS OF GUILT

0 |__| Absent.
1 |__| Self reproach, feels he/she has let people down.
2 |__| Ideas of guilt or rumination over past errors or sinful deeds.
3 |__| Present illness is a punishment. Delusions of guilt.
4 |__| Hears accusatory or denunciatory voices and/or experiences threatening visual hallucinations.

Detecting episodes - YMRS

GUIDE FOR SCORING ITEMS:
The purpose of each item is to rate the severity of that abnormality in the patient. When several keys are given for a particular grade of severity, the presence of only one is required to qualify for that rating.

The keys provided are guides. One can ignore the keys if that is necessary to indicate severity, although this should be the exception rather than the rule.

Scoring between the points given (whole or half points) is possible and encouraged after experience with the scale is acquired. This is particularly useful when severity of a particular item in a patient does not follow the progression indicated by the keys.

1. Elevated Mood

0 Absent
1 Mildly or possibly increased on questioning
2 Definite subjective elevation; optimistic, self-confident; cheerful; appropriate to content
3 Elevated; inappropriate to content; humorous
4 Euphoric; inappropriate laughter; singing

2. Increased Motor Activity-Energy

0 Absent
1 Subjectively increased
2 Animated; gestures increased
3 Excessive energy; hyperactive at times; restless (can be calmed)
4 Motor excitement; continuous hyperactivity (cannot be calmed)

The problem of insight

- Particularly the last question on both rating scales show the problem of subjectivity and patient insight on using these rating scales outside of the clinical setting.
- In many cases, even if the patient clearly has all the characteristics of an episode, they may still deny it or not have insight into their state of mind.
- Can a patient use such an instrument in a self-reporting way effectively?

17 INSIGHT

- 0 |__| Acknowledges being depressed and ill.
- 1 |__| Acknowledges illness but attributes cause to bad food, climate, overwork, virus, need for rest, etc.
- 2 |__| Denies being ill at all.

11. Insight

- 0 Present; admits illness; agrees with need for treatment
- 1 Possibly ill
- 2 Admits behavior change, but denies illness
- 3 Admits possible change in behavior, but denies illness
- 4 Denies any behavior change

Anomaly detection - physiological

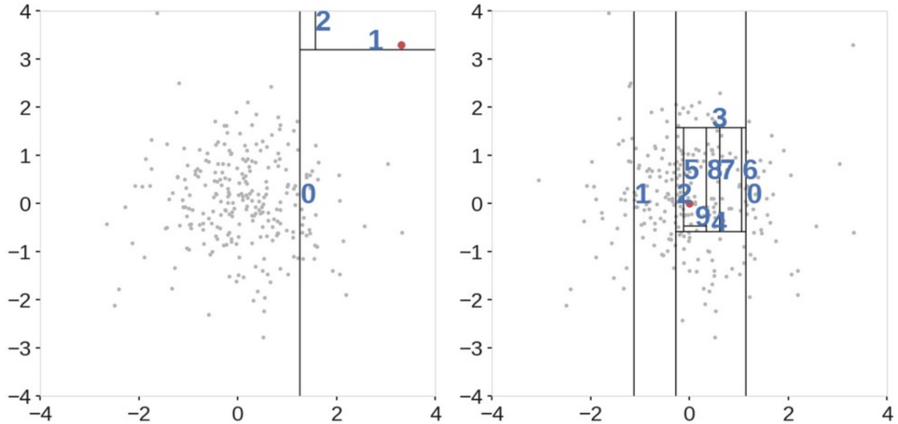
- Lots of data sources can be useful in detecting potential events
  - Sleep score
  - Sleep duration
  - Blood pressure
  - Pulse
  - Stress levels
  - Exercise levels
  - Mood recording
  - Sentiment classification
  - Medication tracking

Anomaly detection - physiological

- Lots of data sources can be useful in detecting potential events
  - Sleep score
  - Sleep duratio
  - Blood p
  - Pu
  - cording
  - timent classification
  - Medication tracking

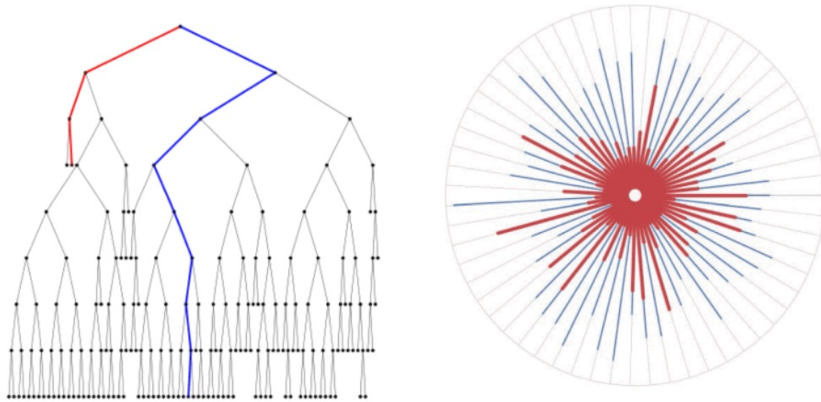
Quantitative

Anomaly detection – Isolation Forest



(a) Anomaly point

(b) Nominal point



(a) Representation of a single tree in a forest.

(b) Representation of a full forest where each radial line corresponds to a tree.

Anomaly detection - text

- This is a little bit harder to collect than integrating with wearables as this needs to either be taken from other sources (social media?), or be added manually (diary)
- The format is largely text or voice though leading to opportunities for evaluation by LLM (also sentiment classification), or TF-IDF to detect if there are trigger words that identify state change or correlations with mood (correlated word clouds)
- Voice has been identified as a possible source of state detection as cadence (among other features) seems to be a potential predictor

The new world of ALPACA?

Alpaca.cpp

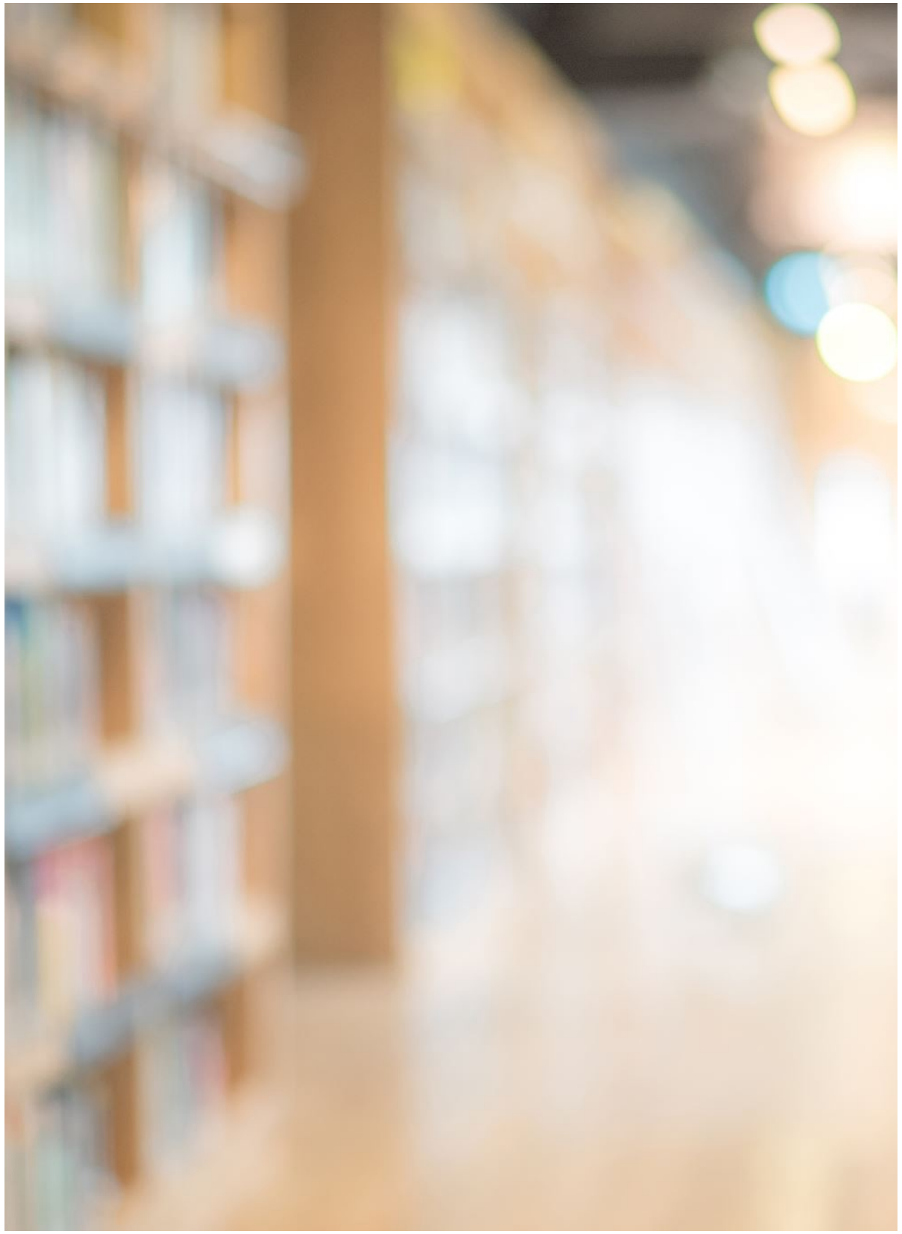
Run a fast ChatGPT-like model locally on your device. The screencast below is not sped up and running on an M2 Macbook Air with 4GB of weights.

```
kevin@Kevins-Air ~/G/llama.cpp (master)> ./chat
main: seed = 1678970541
llama_model_load: loading model from 'ggml-alpaca-7b-q4.bin' - please wait ...
llama_model_load: ggml ctx size = 4529.34 MB
llama_model_load: memory_size =   512.00 MB, n_mem = 16384
llama_model_load: loading model part 1/1 from 'ggml-alpaca-7b-q4.bin'
llama_model_load: .................................... done
llama_model_load: model size =  4017.27 MB / num tensors = 291

system_info: n_threads = 4 / 8 | AVX = 0 | AVX2 = 0 | AVX512 = 0 | FMA = 0 | NEON = 1 | ARM_FMA = 1 | F16C = 0 | FP16_VA = 1 | WAS
M_SIMD = 0 | BLAS = 1 | SSE3 = 0 | VSX = 0 |
main: interactive mode on.
sampling parameters: temp = 0.100000, top_k = 40, top_p = 0.950000, repeat_last_n = 64, repeat_penalty = 1.300000


== Running in chat mode. ==
 - Press Ctrl+C to interject at any time.
 - Press Return to return control to LLaMa.
 - If you want to submit another line, end your input in '\'.

> tell me about alpacas
Alpacas are members of the camelid family, which includes llamas and vicuÒas as well. They originate from South America but have b
een domesticated for thousands of years in Peru and Bolivia where they were used to produce wool that was prized by Incan civiliza
tion. Along with their distinctive fleece (which is warmer than sheep'
```

This combines the LLaMA foundation model with an open reproduction of Stanford Alpaca a fine-tuning of the base model to obey instructions (akin to the RLHF used to train ChatGPT) and a set of modifications to llama.cpp to add a chat interface.

Conclusions

- There is a large amount of research that has been done regarding the use of AI and related technologies in the mental health space
- Some techniques are quite established, but need sufficient (clean) data which is not always easy to obtain
- The emergence of accessible large language models is bound to have a huge impact on this field – watch this space!



End of part 2!

At this point, are there any questions?

Thank you for your attention!

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