Digital Health & Care Innovation Centre

Emerging Innovations in Digital Mental Health: A Deeper Dive

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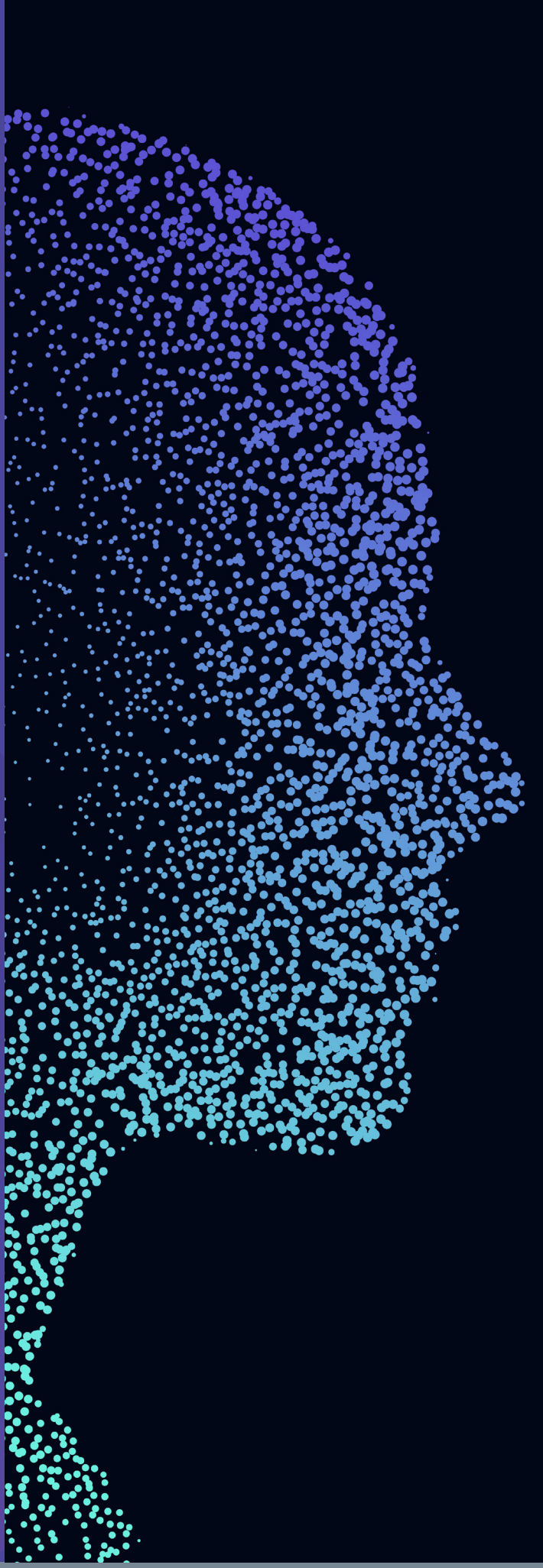

A collaboration between
INNOVATION SCHOOL THE GLASGOW SCHOOL OF ART
University of Strathclyde Glasgow

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Introduction

The Digital Health and Care Innovation Centre (DHI) has been funded by the Scottish Government to create an innovation cluster for digital mental health. In late 2021, the DHI released our "Digital Mental Health: Findings of a desktop horizon scan for Global Leaders & digital innovation opportunities" report [1].

This report was presented to the Scottish Government Digital Mental Health programme board in early 2022. The feedback on the report was particularly focused on the further exploration of the four innovation areas identified within the report. This report contains:

1. Artificial Intelligence,
2. Virtual Reality,
3. Gamification, and
4. Digital Phenotyping.

To better understand these emerging innovations in digital mental health, this report will examine:

- Who are key organisations, stakeholders etc. that are progressing these fields;
- What countries are leading this progress;
- Examples of any case studies;
- Relevant research literature; and
- Any further findings of significance.

Method

The findings of this report were identified through desktop research using standard online search engines, including Google, Google Scholar and PubMed, and through search functions within third party websites identified during the research process.

The purpose of this form of research is to identify and present a high-level overview of publicly available information; it does not include any in-depth cost-analyses or a review of technical specifications. A limitation of the methodology used is that all searches are limited to publications released in English, which could have a significant impact on the search results.

Artificial Intelligence

Since the early inception of Artificial Intelligence (AI), there have been many applications developed for health and care purpose. This was primarily observed in the knowledge-based systems; however, as the field has advanced, there has been a growing interest in machine learning techniques and predictive analytics [2].

AI largely refers to software and hardware that emulate mechanisms assisted by human intelligence and cognition, including deep learning, adaption, engagement, and sensory understanding [3&4]. In practice, this enables technology to perform functions similar to roles that typically require human interpretation and decision making. The techniques involved are multidisciplinary and have been applied across multiple fields [3].

However, whilst AI has become more prevalent in physical health and care, mental health services have been slower in adopting the technology [2-4]. The global burden of mental illnesses represents 32.4% of years lived with disability, placing mental illness on the first position in global burden of disease [5].

Furthermore, mental health challenges have increased in recent years with increased rates of suicide, substance abuse, and isolation, all of which have been worsened during the COVID-19 pandemic [6 & 7]. This is being compounded by a growing gap in supply and demand for NHS staff, with estimates for NHS England predicting 250,000 full-time equivalent posts being vacant by 2030 [8].

Similar trends have been observed by Audit Scotland with vacancy rates rising over the last 10 years [84]. AI is regarded to be a powerful and disruptive science that could fundamentally transform service delivery and overall practice, and address these key resource issues within the health sector and especially within mental health and care [4].

The immediate implication of AI in mental health is its potential in leveraging data to reveal the complex pathophysiology of mental health conditions and allow for informed decision making with regard to therapeutic applications in a citizen's care [9].

Further to this, AI could allow for streamlining tasks that do not require a 'human touch', providing complementary support (for example clinical decision support) that enables clinicians and other care providers to focus on delivering a more citizen-centred form of care [10].

As of 2021, there were no Food and Drug Administration (FDA) approved or cleared AI solutions in the field of psychiatry, and only a limited number of CE marked solutions [10 & 11]. The reasons behind this are multifaceted, but Lee et al. (2021) purport this to be due to the sensitive nature of data generated within mental health and the complex diagnostic criteria within the field [10]. Additionally, AI technologies require large amounts of data, and the field of mental health currently has limited access to large, well-structured datasets [10].

However, there are two core AI approaches – machine learning and Natural Language Processing – which may impact the field of mental health in the coming years.

Machine Learning

Machine learning (ML) is most common form of AI used in healthcare. This technique uses data-driven algorithms to learn from data for the purposes of estimating or predicting outcomes for new data and/or future events [8 & 11]. ML is enabling researchers to acquire important information from health data, to provide personalised care and to develop automated systems [12]. There are three approaches for learning from data: supervised, unsupervised and reinforcement learning.

Supervised learning in ML is the most widely applied method in the majority of studies and experiments, particularly for predicting illness in the health and care sector. Supervised learning algorithms are designed to learn by example. Training data (consisting of inputs that are paired with correct outputs) are used to predict a target attribute, and ML algorithms infer a model from labelled input data. This allows for trained algorithms to take in new data inputs and determine their classification based on the training data and make correct target predictions [12 & 13]. An example of this could be training algorithms with medical images of diagnosed conditions (e.g., X-rays of tumours) to detect tumours in new medical images.

Unsupervised learning in ML uses no form of supervision/training; instead it uses ML algorithms to analyse and cluster unlabelled data sets before identifying hidden patterns or data groupings without human intervention. This could be used in population health to categorise groups of patients with similar symptoms and/or background information to identify common causes [4, 12 & 13].

Reinforcement learning involves ML models using feedback that acts as a reward or punishment to learn and develop, which is a common gamification technique [12]. Over time, these algorithms optimise long-term rewards and learn the best response sequence. This could support ongoing dynamic treatment regimes for long-term conditions [14].

While these different ML approaches appear to have numerous applications, they are limited to certain capacities. This is mostly due to their inherent reliance on datasets that may be incomplete, filled with unnecessary data or subject to systemic bias, all of which can lead to flawed predictions.

Natural Language Processing

Natural Language Processing (NLP) is a subdiscipline within AI that utilises the above algorithmic methods and focuses on helping computers to understand the way people write and speak. This involves large amounts of unstructured data and involves the use of different ML methods depending on the data being analysed [12]. In recent years, NLP has supported the analysis and management of large-scale text data, and facilitated various tasks such as information extraction, sentiment analysis, emotion detection, and mental health surveillance [15-18]. Its primary role in mental health is its ability to automatically identify early indicators of mental illness to support early detection, prevention, and treatment. NLPs are commonly deployed in everyday technologies, for example:

- voice-controlled assistants, e.g., Siri, Alexa, etc.;
- natural language generation for answering questions in chatbots, often for online customer service;
- grammar and vocabulary autocorrect tools; and
- pre-emptive text prompting.

The advantages of using NLP approaches to understand mental health through text and audio include high ecological validity, low subjectivity, low cost of frequent assessments, and faster administration of tasks compared to standard practice [19]. An additional benefit of analysis using NLP is that data can be collected remotely, meeting demand for remote cognitive and behavioural assessments in the post COVID-19 era [20].

Deep Learning

Deep learning is a subset of ML, which is essentially a neural network with three or more layers of nonlinear computational processing units [21]. These networks aim to simulate the behaviour of the human brain that allows them to learn from large amounts of data. Using the additional layers to support the optimisation and refinement for the purposes of accuracy.

These deep learning neural networks are made up of multiple layers of interconnected nodes, each building upon the previous layer to refine and optimize the prediction or categorization of input data. This computation through the networks is known as forward propagation, with the input and output layers being known as the visible layers where deep learning models ingest data and produce final predictions or classifications [22].

An alternate backpropagation process uses algorithms, to calculate errors in predictions and then adjusts the weights and biases of the function by moving backwards through the layers in an effort to train the model. When combined, forward propagation and backpropagation allow these neural networks to make predictions and correct errors [22]. This allows algorithms to become more accurate over time.

The deep learning algorithms are exceedingly complex, with different types of neural networks existing to address specific data and/or problems. In mental health, these are predominantly [21 & 22]:

- **Convolutional neural networks (CNNs)**, which are used primarily in computer vision and image classification applications. These networks can detect features and patterns within data, including images, allowing for object detection or recognition. CNNs have shown potential in detecting mental health conditions via the analysis of speech, specifically with regards to depression [23].
- **Recurrent neural networks (RNNs)**, which are used in natural language and speech recognition applications, leverage sequential or times series data. RNNs have been shown to have promise in identifying patients with schizophrenia through the analysis of functional MRI (fMRI) data [24]. Furthermore, RNNs have potential to analyse online behaviour to detect and support users in overcoming their mental health problems such as anxiety, phobia, depression, paranoia [25].

A large-scale scoping review of the use of deep learning in mental health advises that deep learning has incredible potential in improving mental health diagnosis and treatment in the future [21]. The study found that the amount of research into the use of deep learning is growing, and results to date have led to the development of multiple disease risk prediction models, using both clinical and non-clinical data, that show promising initial results.

There are still issues that need to be overcome in all aspects of AI in healthcare, such as overcoming the limited availability of large-scale health data (especially in the field of mental health) [21]. This in turn has restricted the validity of research outcomes meaning much more work is still required before implementing these technologies in mental health services.

All of the various subsets of AI have tremendous potential in supporting:

- diagnosis
- prediction of outcomes
- assessment
- treatment of mental health conditions

To ensure the true potential of AI within mental health, stakeholders from across the field of mental health care and research, citizens, governing bodies and AI specialists will need to work together to develop solutions. Collaboration is required to make sure to that human intelligence is combined with AI solutions to ensure product validity, appreciate the aspects of mental health that may not be observed or accounted for in data, to understand the impact of data biases and pre-empt and mitigate errors made by AI [26].

Leaders in Mental Health AI

The global AI in healthcare market size is estimated at $15.4bn in 2022 and is expected to grow at a compound annual growth rate (CAGR) of 38.4% to reach $208.2bn in 2030 [27]. North America (specifically USA tech regions) dominated the market in the last year, with over a 58% share of the current market. When observing research into ML and NLP by geographic location, we can infer that North America is leading the way in the academic world as well, with Europe and the UK also playing a significant role in the field (see figure 1).

Specific cities that lead this area of research include Boston, London, New York Cambridge, and San Francisco. In the coming years, the Asia Pacific region is expected to register faster growth due to rapid innovations and developments in infrastructure, which are expected to attract increased increase investments from private investors, venture capitalists and non-profits. Additionally, improved data analysis and data security, alongside reduced costs, are driving the adoption rates of AI in healthcare [27].

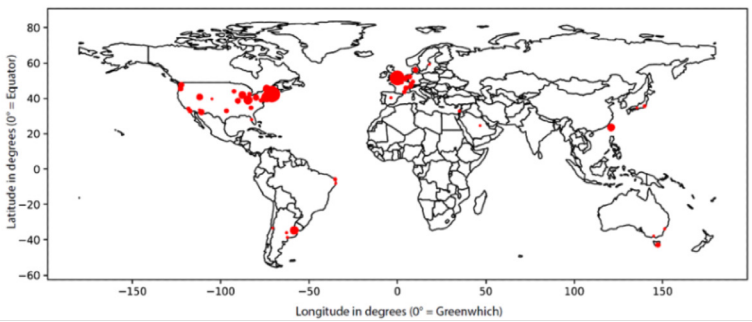

Figure 1. A distribution of research into Machine Learning and Natural Language Processing for mental health taken from Le Glaz *et al* (2021) [12]

Market leaders driving this growth in healthcare AI [27]:

- Nuance Communications
- IBM
- Microsoft
- NVIDIA Corporation
- Intel Corporation
- DeepMind Technologies Limited

Whilst these companies are all well established in the field of healthcare AI, very few of them are active in the field of mental health AI. For example, Nuance's Dragon Medical One is an AI solution that employs cloud-based clinical speech recognition to accurately capture the patient's story into their Electronic Patient Record (EPR); the Dragon Medical Workflow manager is a speech-enabled clinical workflow solution that integrates data and documentation into EPRs or other clinical information systems; and the Dragon Medical advisor provides clinicians with evidence-based decision support [28].

The Worcestershire Health and Care NHS Trust, one of NHS England's Global Digital Exemplars, invested in 200 licences of Dragon Medical to support their community and mental health team in overcoming their administrative backlog and burden of paperwork [29]. Specifically, in the Trust's Child and Adolescent Mental Health Services (CAMHS), the solution's speech recognition and integration with clinical documentation allowed for clinicians to capture their patients story and place it in their EPR much more efficiently.

This allowed health and care professionals to focus more on their patients and removes the administrative burden that inhibit this [29]. Meanwhile, online searches have shown that Microsoft and IBMs mental health AI activity has seemingly stalled as of 2020. In truth, the leaders of the field would appear to be in the field of academia and research, though this has potential to rapidly change.

Summary

AI for mental health is widely regarded to be in the early 'proof of concept' stage, with massive amounts of research investigating the many facets of mental healthcare. Very few solutions exist that are patient facing, with the majority of AI solutions being used to support and streamline mental health management services.

While this can have a positive impact upon patients, it will likely go unnoticed directly by them. The most common uses of AI in mental health will likely be in:

- **Image analysis** where machine learning and deep learning algorithms are trained to identify mental health conditions via image analysis. For example, a study by Just et al., (2017) used ML algorithms to identify individuals who engaged with suicidal ideation to a 91% accuracy via fMRI analysis [30].

- **Chatbots** are currently the most common example of AI use in mental health. Using natural language processing and learning techniques, chatbots will continue to improve and provide users with 'virtual humans' to provide daily consultation and simplified therapy [31].

- **Voice and image recognition, and text analysis** are used to predict, monitor and prevent the onset of mental health conditions. For example, researchers have been able to classify schizophrenia patients and controls with an accuracy of 85.5% by extracting functional connectivity patterns from resting-state functional MRIs of schizophrenia patients and healthy controls [32].

It is important for stakeholders in the field to be realistic about AI in mental health and moving beyond clinical research towards implementation of solutions at scale. To date, AI applications have mainly been used to support diagnosis by helping determine whether individuals have a particular mental health condition.

AI technology has also been used to predict or assess the risk of having a mental illness. In terms of treatment, AI technologies have been used for a range of purposes:

- as platforms for interacting with clients;
- to predict if patients are more likely to respond to treatment;
- as a method of data collection that can be adapted;
- to provide mental health support using various styles and types of therapy in a conversational format.

These have all been predominantly in a research context. Further research is required to prove technical and clinical validation of AI solutions in both physical and mental healthcare. Health and care services also need to ensure that appropriate clinical guidelines are in place, that solutions have access to sufficient sets of data, and that the relevant infrastructure is in place to fully realise the potential of AI.

Virtual Reality

Virtual Reality (VR) is a computer-generated 3D simulation in which individuals can interact in a seemingly realistic manner via the use of specific hardware. Currently, the standard approach to VR technologies is the use of VR headsets with a head-mounted display. Certain VR solutions have made use of tactile and olfactory stimuli in addition to the standard visual and auditory stimuli [33]. While there is not a specific overview of the VR mental healthcare market, the overall VR healthcare market has been projected to grow from $240.91mn in 2018 to $2.38bn by 2026. The major factors driving this growth are believed to be;:

- an increase in the incidence of neurological disorders, which are being ranked as the leading cause of disability-adjusted life years (~276 million) [85],
- a growing demand for innovative diagnostic techniques,
- an increasing awareness of the potential for VR in the healthcare sector, as well as the overall advancement and uptake of VR tech within the sector [34].

As with the majority of digital health market segments, North America holds a dominant share of the VR healthcare market and is anticipated to continue to do so during this period of growth [34].

VR can transport users to simulated situations in which psychological or mental health issues occur. This allows for the precise, real-time data capture of a patient's reaction to certain stimuli in a safe and controlled virtual environment [35]. In turn, there is potential to drastically transform how health and care professionals assess mental health and provide alternative approaches to the delivery of mental health therapies.

VR has been applied in the delivery of exposure-based treatments, in which individuals can experience feared scenarios or contexts in a completely safe and controlled environment, something that has been shown to be effective [35].

Importantly, this has been in the research setting, where exposure therapy has been the dominant use of VR, and in which the quality of study methodologies has been noted to be low. The implementation of VR treatments outside of the research setting has yet to be examined [35].

Bell et al. (2020), suggest that VR for clinical assessment in mental health **is where the technology may have the most value** [35]. Through VRs ability to generate highly controllable real-world environments, clinicians can reduce the limitations in mental health assessment caused by the hospital setting and avoid the high costs of real-environment mental health assessments [36].

This is predicated on the knowledge that exposure to virtual environments has been shown to produce emotional responses that are consistent to exposure to real-world scenarios, including fear responses, anxiety, and paranoia [37].

The ability to control and manipulate these virtual environments and the objects within them further enhances the environmental validity of these virtual realities for the purposes of clinical assessment [36]. Research into assessment has predominantly focussed on:

- **Social functioning** this can be assessed using automatic data capture, such as eye gaze, recorded response to virtual social stimuli, and proximity to virtual reality avatars [38-39].

- **Cognition** where VR can be used to test memory and executive function (the mental skills for working memory, flexible thinking and self-control) using virtual mazes, attention tasks, etc. This has been used to assess attention and response inhibition in children and early teens with ADHD in comparison with a control population [40-42].
- **Symptomatology** VR environments can be used to elicit and assess symptoms of mental health conditions such as paranoia, psychosis, persecutory delusions, and have been used to study symptoms of auditory hallucinations, eating disorders and addiction [43-53].

The VR exposure therapies used in the treatment of mental health conditions, such as anxiety and depression, have been shown to effectively help patients overcome these conditions [54]. Scoping reviews of the literature surrounding VR for the treatment of anxiety and depression, in which VR Cognitive Behavioural Therapy (CBT) has been effective in supporting treatment, have recommended the use of VR in a clinical environment [54]. Despite the ever-growing academic evidence and support for the field, the commercialisation of VR mental health technologies is lacking [35].

Leaders in mental health VR

Global leaders in the VR healthcare market include [55]:

- Koninklijke Phillips
- Samsung
- EON Reality
- CAE Healthcare
- Microsoft
- Google
- Oculus Rift

However, while these are the leaders in VR technology overall and in VR for healthcare, their commercial offerings for mental health solutions are limited. For example, KoninKlijke Philips offer VR solutions that support their medical imaging technologies by enabling device guidance and training, but they do not offer any specific mental health solutions [56]. In 2017, Samsung worked with hospitals in Korea to roll out VR tech for CBT; however, results of this work and their recent activity in VR for mental health have not been publicised [57].

EON Reality collaborated with Danish health organisations in 2018 to use VR therapy to treat anxiety in children. However, their main use of VR in healthcare is in training and education via virtual environments and rendering of anatomy [58-59]. CAE Healthcare have collaborated with Microsoft HoloLens to develop healthcare training applications for clinical learners to engage with anatomy and physiology in a virtual environment [60].

Summary

VR for mental health appears some way from being used in clinical practice. The academic evidence base is well established (Appendix 1) and suggests that clinical trials of VR solutions for treatment and assessment of mental health will be the next step. Most likely, the use of VR in mental health will mirror the use of VR in wider health and care, which tends to be [61]:

- medical training
- patient education
- virtual therapies (both for physical and mental health)
- disease awareness, and
- patient experience

As is evident from the surrounding literature, more work is required to establish the clinical reliability and validity of VR-based solutions for mental health. Issues relating to access to both hardware and software solutions, as well as the ethical implications of the field require more attention, thought and research as the field develops.

The use of VR in mental health is reliant on the overall VR technology offering expanding. This is required to drive down hardware costs and increase the supply of hardware to ensure that any VR solutions are cost-effective for both health and care services and individual consumers.

Gamification

Gamification is a function of software development that uses the application of game design techniques and methods within non-game environments. It is an emerging trend across the entirety of digital health [62]. Gamification combines three components: gamefulness - the behavioural quality of games; gameful interaction - how users interact with games; and gameful design - the design of game elements for the non-game environment [63].

Gamification's potential in the field of digital mental health has been predicted to increase the effectiveness of solutions by extending the reach of online programs to users who may not otherwise use them. Games-based motivational techniques, such as rewards mechanisms are also used to increase user engagement with digital mental health solutions to produce better health outcomes for the user [64].

Several early studies into gamification have suggested that it can have possible benefits for psychological, cognitive, and behavioural changes and/or symptoms reductions in mental disorders, including mood disorders, autism spectrum disorders, attention disorders, substance abuse disorders, schizophrenia, conditions related to neurodegeneration and others [63]. The use of gamification in health and care has predominantly been applied in physical health and fitness to instil healthy behaviours in users [65-66].

While there are various gamified digital mental health solutions, they are not as common as their physical health counterparts. This could be due to the core principle of gamified solutions providing emotional rewards/compensation which could be detrimental to users with mental health conditions [63]. This is not to say that gamification methods may not have benefits in the context of psychological and behavioural modifications; rather, more work is required to enhance the reliability and validity of gamification for assessing, treating, and aiding mental health improvements in the future.

Underlying theories of gamification

The behavioural theories, and psychological and cognitive models that underpin behavioural change through gamification, are numerous. Figure 2 provides a brief snapshot of these with regards to mental health.

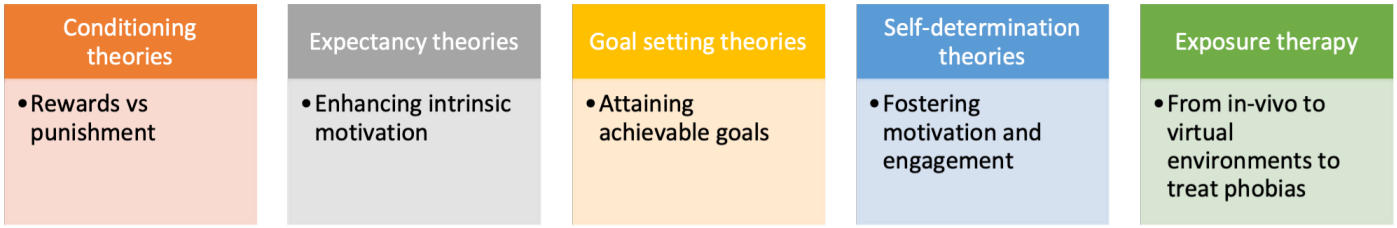

Figure 2. Psychological theories underlying gamification in mental health, taken from Nidhi (2021) [63]

- **Conditioning theories:** the most traditional form of psychological intervention is based on the principle of rewarding positive behaviour in citizens. In gamification for mental health, we apply the same thought process through the use of awards and scores. In some instances, users are provided with incentives for incremental goals to push towards overall change. This is a principal tenet of conditioning [63 & 67].

- **Expectancy theories:** people with mental health disorders often display a severe lack of intrinsic motivation. The role of a mental health professional is to provide these people with extrinsic motivation until they become intrinsically motivated over time. Applied games or gamification techniques can provide this extrinsic motivation using rewards mechanisms to motivate individuals to attain their behavioural change goals [63, 68 & 69].

- **Goal setting theories:** Fundamentally, gamification in mental health works on exploring ways to achieve realistic goals. This incorporates the SMART methodology of specific, measurable, attainable, realistic, and time bound goals for the purposes of enhancing the therapeutic process [63 & 70].
- **Self-determination theory:** Autonomy, competence and relatedness are factors that foster motivation and engagements of individuals. Self-determination theory purports that if these psychological needs are satisfied, it can have an incredible, positive impact on the wellness of individuals. Gamification in mental health attempts to capture these same factors [63 & 71].
- **Exposure therapy:** Virtual reality or augmented reality games use the frameworks of exposure therapy to guide behaviour change. VR games provide patients with the ability to interact with the stimuli or events they fear in a safe and secure virtual environment, with the goal of reducing their discomfort in a real-world context. For example, the use of VR therapy for patients with a fear of heights have shown promising results [63, 72 &73].

Beyond these core principals, gamification has applications in CBT-based therapy. These often employ a 'levelling up' function and incorporate conditioning theory through the use of incremental short-term goals over long-term periods [73]. There have also been multiple studies of gamification in mood assessment and mood tracking [74].

The advantages of gamification for mental health have been reported from both mental health service providers and citizens [63]. If used appropriately, gamification can help users in overcoming feelings of loneliness and a perceived lack of interpersonal skills through regularly engaging people in meaningful activities and helping them to familiarise with different users on the same platform.

For mental health service providers, gamification in mental health has helped improve the 'clinician-patient' relationship by encouraging the patient to assume greater responsibility for their own mental health and viewing their clinician as a coach rather than an instructor [63].

This could help to further the cause of remote mental health services; however, the individual patient and their needs must always be considered as certain people may need the ability to see and speak to their clinician as quickly and easily as possible [63].

Leaders in gamification for mental health

Whilst all the emerging trends in this report are in their infancy with regards to mental health, gamification is still an incredibly novel approach. This means that unlike AI and VR, gamification in healthcare does not have the same level of commercial leadership.

The global healthcare gamification market is predicted to surpass $47.2bn by 2026, though this anticipated to be mostly made up of casual healthcare-oriented games and not clinically validated digital therapies/therapeutics [75].

The use of gamification is still largely in the research space. A 2019 systematic review of gamification in apps and technologies for improving mental health and wellbeing found that the application of gamification is not driven by health behaviour change theory, but instead uses techniques of gamification without truly understanding the underlying theory and mechanisms [76].

The researchers called for a standardisation in how gamification is both applied and understood for both mental health and further afield [75]. Importantly, this was primarily in the academic context and the authors suggested commercial applications may not have the same issues.

There are several well-known commercial mobile applications including SuperBetter, Headspace, Calm and many more apps that utilise game design techniques for behaviour modification to improve users' mental health. A 2021 systematic review and meta-analysis of these mental health apps sought to determine whether these commercial solutions with gamification elements differ in their effectiveness in reducing symptoms of depression in comparison to those without gamification elements [77].

Their results showed that there was no significant difference in effectiveness of mental health applications with or without gamification elements. Mental health apps using gamification may provide a readily available option for mental health care; however, supplementary research is needed on their effectiveness before they can be reliably implemented into standard practice [77]. All of this highlights that despite great gains in the field of gamification for digital mental health, there is yet to be a leading region, health service or organisation that has emerged.

Summary

Gamification in mental health is not without its limitations and criticism. The costs alone in developing a game with the high complexity required to improve mental health could be extensive. This makes it incredibly difficult for researchers to venture into the field and establish the true efficacy and validity of these techniques without significant partnerships with industry. Similarly, the expertise required to build these games is a multidisciplinary effort that requires extensive skill sets on the part of each contributor (especially that of the mental health professionals) [63].

One of the core underlying components of gamification is that people are driven by intrinsic motivation to satisfy their base psychological needs. Mental health, however, is a highly complex domain in which users may lack some of these fundamental drivers. There is also a risk that, as with other digital mental health tools, these techniques can further isolate individuals and act as barriers to socialisation that may worsen certain mental health conditions [63]. Overall, there is still a clear lack of explicit interconnectedness between the application of gamification and the underlying psychological theory [63].

Going forward, there needs to be a greater focus on interdisciplinary and cross-sectoral approaches to improve the reliably and validity, as well as the user-centric components of gamified solutions. Combining traditional therapy methods with individualistically tailored gamification techniques, discussed above, could provide an opportunity to address mental health issues in the near future.

Digital Phenotyping

Digital phenotyping (a sub-sector of Big Data Analytics) refers to the constant mobile sensing and collection of data through smartphones, smartwatches, and other digital hardware [79]. It has been referred to as the "moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices, in particular smartphones" [80]. The development of this field has been driven by the modern collection of health data that is becoming more and more ubiquitous, unobtrusive, and continuous, and is no longer confined to lab or clinical environments or reliant on specialised medical instruments [81].

It is thought that as mental health conditions are diagnosed using symptoms identified from patient interviews and patient-reported experiences, digital phenotyping of mental health could expand the ability to identify and monitor mental health conditions though patient interactions with digital technologies [82]. Smartphones in particular allow researchers, and may allow health and care services, to collect a range of passive data from users/ patients. This data can potentially predict mental health problems. Figure 3 provides an example of the feature construction for mental health conditions from passive data [79].

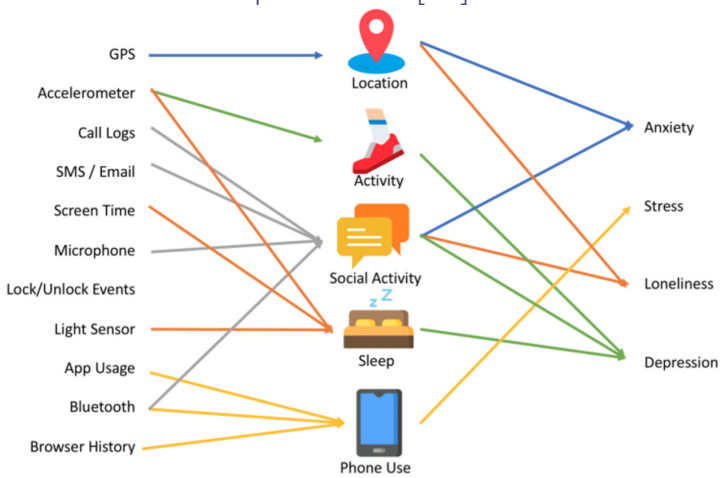

Figure 3 Mental health feature constructions from passive smartphone data streams [79]

A systematic review by Mendes et al. (2022) demonstrates that there are measurable features on smart devices that can act as proxies for mental status and well-being, but the overall evidence for high-quality features for mental states remains limited [82]. Furthermore, the ethical implications of the field especially regarding privacy and digital security of often vulnerable people with mental health issues need to be both clearly understood and considered at all stages of research and development for the technology.

In the research context 'patient' populations have consented to participate and have agreed what data is to be collected as well as how this data collection will occur. If digital phenotyping is employed at scale by mental health services, there needs to be established guidelines on the use of the technology, data usage consent.

At this early stage in the development of digital phenotyping, it is important to understand that its predicted use for moral good may overlook the social values embedded in the field, such as the wider ethical, social, clinical and economic values we may currently take for granted [83].

For digital phenotyping to have true benefit in mental health, there needs to be serious consideration about the practicalities of its future clinical application. If digital phenotyping is to be implemented, and to have true value, it must conform to the established norms of quality and safety, whilst being cost-effective and feasible. The research into these challenges will need to be multifaceted and multidisciplinary. This needs to include consumer and health stakeholder engagement, implementation science, technical development, intervention design and economic evaluation.

As mental health conditions are often first presented in youth, and this group is an enthusiastic adopter of consumer technologies, the successful development of digital phenotyping is of specific relevance to the future of mental healthcare. A concentrated effort is required to realise the benefits of digital phenotyping for today's citizens, and not for future generations.

If done properly we may see improved mental health care services that are more personalised with better diagnosis, monitoring, and overall treatment. To achieve this the field will require the development of global leadership and collaboration to tackle issues of trust and access to data, as well as increased research to better understand digital phenotyping and its potential impact for health and care services. As digital phenotyping is predicted to address genuine gaps in assessment and treatment of mental health issues, the field is well-placed to be a leader in this novel digital health discipline.

Conclusion

The identified innovations in digital mental health discussed in this report are all still in their infancy, with little to no clinically validated solutions operating in mental health and care services. Literature shows that these fields are expected to have tremendous impact in mental health, albeit it is likely that the true potential of each sub-sector may be realised in their interaction with one another (as well as other digital health solutions), rather than as individual technologies.

Digital phenotyping is and will continue to be reliant on Artificial Intelligence, particularly machine learning and predictive analytics, to develop the predictive models that diagnose mental health conditions from digital interactions, while AI is heavily reliant on 'Big Data' to learn and develop models for prediction. Gamification is intrinsically linked with Virtual Reality, with both technologies emerging from the gaming sector; the use of VR for the purposes of mental health therapies, in turn, is reliant on the underlying theories of gamification discussed above.

It is important to note that these technologies, especially in relation to digital mental health, have yet to be implemented at any scale and are likely to take several more years before they can penetrate the digital health and care market in a meaningful way.

However, there is an opportunity for Scotland to act as a test bed for some of these opportunities, expediting developments by creating multi-sectoral collaborations which help develop appropriate clinical and technical guidelines; informing appropriate data protection standards and processes; and supporting the piloting and refinement of solutions for mental health. These are aspects which could initially be progressed by the Digital Mental Health Innovation Cluster.

References

1. Morrison, C. (2021) Digital Mental Health: Findings of a desktop horizon scan for Global Leaders & digital innovation opportunities. Accessed from: https://doi.org/10.17868/79197
2. Martins, C. L., Martinho, D., Marreiros, G., Conceição, L., Faria, L., & de Almeida, R. S. (2022). Artificial Intelligence in Digital Mental Health. In Digital Therapies in Psychosocial Rehabilitation and Mental Health (pp. 201-225). IGI Global.
3. Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial intelligence in healthcare: a structured literature review. BMC Medical Informatics and Decision Making, 21(1), 1-23.
4. Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthcare Journal, 8(2), e188.
5. Vigo, D., Thornicroft, G., & Atun, R. (2016). Estimating the true global burden of mental illness. The Lancet Psychiatry, 3(2), 171-178.
6. Jeste, D. V., Lee, E. E., & Cacioppo, S. (2020). Battling the modern behavioral epidemic of loneliness: suggestions for research and interventions. JAMA psychiatry, 77(6), 553-554.
7. Iob, E., Frank, P., Steptoe, A., & Fancourt, D. (2020). Levels of severity of depressive symptoms among at-risk groups in the UK during the COVID-19 pandemic. JAMA network open, 3(10), e2026064-e2026064.
8. Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthcare Journal, 8(2), e188.
9. Lee, E. E., Torous, J., De Choudhury, M., Depp, C. A., Graham, S. A., Kim, H. C., ... & Jeste, D. V. (2021). Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging, 6(9), 856-864.
10. Topol, E. (2019). Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again. New York, NY: Basic Books
11. Benjamens, S., Dhunnoo, P., & Meskó, B. (2020). The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. NPJ digital medicine, 3(1), 1-8.
12. Le Glaz, A., Haralambous, Y., Kim-Dufor, D. H., Lenca, P., Billot, R., Ryan, T. C., ... & Lemey, C. (2021). Machine learning and natural language processing in mental health: Systematic review. Journal of Medical Internet Research, 23(5), e15708.
13. Chung, J., & Teo, J. (2022). Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges. Applied Computational Intelligence and Soft Computing, 2022.
14. Cape start (2022) Reinforcement Learning in Health Care: Why It's Important and How It Can Help. Accessed from: https://www.capestart.com/resources/blog/reinforcement-learning-in-health-care-why-its-important-and-how-it-can-help/
15. Nadkarni, P. M., Ohno-Machado, L. & Chapman, W. W. Natural language processing: an introduction. J. Am. Med. Inform. Assoc. 18, 544–551 (2011).
16. Ive, J. Generation and evaluation of artificial mental health records for natural language processing. NPJ Digital Med. 3, 1–9 (2020).
17. Mukherjee, S. S. et al. Natural language processing-based quantification of the mental state of psychiatric patients. Comput. Psychiatry 4, 76–106 (2020).
18. Jackson, R. G. Natural language processing to extract symptoms of severe mental illness from clinical text: the clinical record interactive search comprehensive data extraction (cris-code) project. BMJ Open 7, 012012 (2017).
19. DeSouza, D. D., Robin, J., Gumus, M., & Yeung, A. (2021). Natural language processing as an emerging tool to detect late-life depression. Frontiers in Psychiatry, 1525.
20. Geddes MR, O'Connell ME, Fisk JD, Gauthier S, Camicioli R, Ismail Z. For the alzheimer society of Canada task force on dementia care best practices for COVID-19. Remote cognitive and behavioral assessment: Report of the Alzheimer Society of Canada Task Force on dementia care best practices for COVID-19. Alzheimer's Dement. (2020) 12: e12111. doi: 10.1002/dad2.12111
21. Su, C., Xu, Z., Pathak, J., & Wang, F. (2020). Deep learning in mental health outcome research: a scoping review. Translational Psychiatry, 10(1), 1-26.
22. IBM Cloud Education (2020) Deep Learning. Accessed from: https://www.ibm.com/cloud/learn/deep-learning#toc-how-deep-l-vLJwLmX4

23. An, H., Lu, X., Shi, D., Yuan, J., Li, R., & Pan, T. (2019, December). Mental health detection from speech signal: A convolution neural networks approach. In 2019 International Joint Conference on Information, Media and Engineering (IJCIME) (pp. 436-439). IEEE.
24. Dakka, J., Bashivan, P., Gheiratmand, M., Rish, I., Jha, S., & Greiner, R. (2017). Learning neural markers of schizophrenia disorder using recurrent neural networks. arXiv preprint arXiv:1712.00512.
25. Bouarara, H. A. (2021). Recurrent neural network (RNN) to analyse mental behaviour in social media. International Journal of Software Science and Computational Intelligence (IJSSCI), 13(3), 1-11.
26. De Choudhury, M., & Kiciman, E. (2018). Integrating artificial and human intelligence in complex, sensitive problem domains: Experiences from mental health. AI Magazine, 39(3), 69-80.
27. Grand View Research (2022) Artificial Intelligence In Healthcare Market Size, Share, And Trends Analysis Report By Component (Software Solutions, Hardware, Services), By Application (Virtual Assistants, Connected Machines), By Region, And Segment Forecasts, 2022 – 2030. Accessed from: https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-healthcare-market
28. Nuance (2022) Clinical documentation solutions for community and mental health hospitals. Accessed from: https://www.nuance.com/en-gb/healthcare/care-settings-specialties/community-and-mental-health.html
29. Nuance (2021) Worcestershire Health and Care NHS Trust are leading by example. Case Study. Accessed from: https://www.nuance.com/content/dam/nuance/en_uk/collateral/healthcare/case-study/ss-worcester-uk-screen.pdf
30. just, M. A., Pan, L., Cherkassky, V. L., McMakin, D. L., Cha, C., Nock, M. K., & Brent, D. (2017). Machine learning of neural representations of suicide and emotion concepts identifies suicidal youth. Nature human behaviour, 1(12), 911-919.
31. Nexcode (2020) Designing with AI for Mental Health. Amygdala Case Study. Accessed from: https://nexocode.com/blog/posts/designing-with-ai-for-mental-health/#ai-solutions-for-mental-health
32. Pham, K. T., Nabizadeh, A., & Selek, S. (2022). Artificial intelligence and chatbots in psychiatry. Psychiatric Quarterly, 1-5.
33. Emmelkamp, P. M., & Meyerbröker, K. (2021). Virtual reality therapy in mental health. Annual Review of Clinical Psychology, 17, 495-519.
34. Allied Market Research (2020) VR in Healthcare Market by Product (VR Semiconductor Components, VR Devices, VR Sensors, and Others), Technology (Head-Mounted Technology, Gesture-Tracking Technology, and Projector & Display Walls Technology), and End User (Hospitals &Clinics, Research Laboratories, and Other End Users): Global Opportunity Analysis and Industry Forecast, 2019-2026. Accessed from: https://www.alliedmarketresearch.com/vr-in-healthcare-market-A06193
35. Bell, I. H., Nicholas, J., Alvarez-Jimenez, M., Thompson, A., & Valmaggia, L. (2020). Virtual reality as a clinical tool in mental health research and practice. Dialogues in clinical neuroscience.
36. Parsons, T. D. (2015). Virtual reality for enhanced ecological validity and experimental control in the clinical, affective and social neurosciences. Frontiers in human neuroscience, 9, 660.
37. Wechsler, T. F., Kümpers, F., & Mühlberger, A. (2019). Inferiority or even superiority of virtual reality exposure therapy in phobias?—A systematic review and quantitative meta-analysis on randomized controlled trials specifically comparing the efficacy of virtual reality exposure to gold standard in vivo exposure in agoraphobia, specific phobia, and social phobia. Frontiers in psychology, 1758.
38. Fornells-Ambrojo, M., Elenbaas, M., Barker, C., Swapp, D., Navarro, X., Rovira, A., ... & Slater, M. (2016). Hypersensitivity to contingent behavior in paranoia: a new virtual reality paradigm. The Journal of nervous and mental disease, 204(2), 148-152.
39. Koenig, S., Crucian, G., Dalrymple-Alford, J., & Dünser, A. (2011). Assessing navigation in real and virtual environments: A validation study.
40. Sorkin, A., Weinshall, D., Modai, I., & Peled, A. (2006). Improving the accuracy of the diagnosis of schizophrenia by means of virtual reality. American Journal of Psychiatry, 163(3), 512-520.
41. Ku, J., Cho, W., Kim, J. J., Peled, A., Wiederhold, B. K., Wiederhold, M. D., ... & Kim, S. I. (2003). A virtual environment for investigating schizophrenic patients' characteristics: assessment of cognitive and navigation ability. CyberPsychology & Behavior, 6(4), 397-404.
42. Spieker, E. A., Astur, R. S., West, J. T., Griego, J. A., & Rowland, L. M. (2012). Spatial memory deficits in a virtual reality eight-arm radial maze in schizophrenia. Schizophrenia Research, 135(1-3), 84-89.
43. Riches, S., Garety, P., Rus-Calafell, M., Stahl, D., Evans, C., Sarras, N., ... & Valmaggia, L. (2019). Using virtual reality to assess associations between paranoid ideation and components of social performance: A pilot validation study. Cyberpsychology, Behavior, and Social Networking, 22(1), 51-59.

44. Freeman, D. (2008). Studying and treating schizophrenia using virtual reality: a new paradigm. Schizophrenia bulletin, 34(4), 605-610.
45. Freeman, D., Pugh, K., Vorontsova, N., Antley, A., & Slater, M. (2010). Testing the continuum of delusional beliefs: an experimental study using virtual reality. Journal of abnormal psychology, 119(1), 83.
46. Valmaggia, L. R., Freeman, D., Green, C., Garety, P., Swapp, D., Antley, A., ... & McGuire, P. K. (2007). Virtual reality and paranoid ideations in people with an 'at-risk mental state'for psychosis. The British Journal of Psychiatry, 191(S51), s63-s68.
47. Valmaggia, L. R., Day, F., & Rus-Calafell, M. (2016). Using virtual reality to investigate psychological processes and mechanisms associated with the onset and maintenance of psychosis: a systematic review. Social psychiatry and psychiatric epidemiology, 51(7), 921-936.
48. Veling, W., Brinkman, W. P., Dorrestijn, E., & Van Der Gaag, M. (2014). Virtual reality experiments linking social environment and psychosis: a pilot study. Cyberpsychology, Behavior, and Social Networking, 17(3), 191-195.
49. Freeman, D., Pugh, K., Vorontsova, N., Antley, A., & Slater, M. (2010). Testing the continuum of delusional beliefs: an experimental study using virtual reality. Journal of abnormal psychology, 119(1), 83.
50. 50. Stinson, K., Valmaggia, L. R., Antley, A., Slater, M., & Freeman, D. (2010). Cognitive triggers of auditory hallucinations: An experimental investigation. Journal of behavior therapy and experimental psychiatry, 41(3), 179-184.
51. Ferrer Garcia, M., Gutierrez Maldonado, J., Treasure, J., & Vilalta Abella, F. (2015). Craving for food in virtual reality scenarios in non clinical sample: Analysis of its relationship with body mass index and eating disorder symptoms. European Eating Disorders Review, 23(5), 371-378.
52. Detez, L., Greenwood, L. M., Segrave, R., Wilson, E., Chandler, T., Ries, T., ... & Yücel, M. (2019). A psychophysiological and behavioural study of slot machine near-misses using immersive virtual reality. Journal of Gambling Studies, 35(3), 929-944.
53. Mühlberger, A., Sperber, M., Wieser, M. J., & Pauli, P. (2008). A virtual reality behavior avoidance test (VR-BAT) for the assessment of spider phobia. Journal of CyberTherapy and Rehabilitation, 1(2), 147-158.
54. Baghaei, N., Chitale, V., Hlasnik, A., Stemmet, L., Liang, H. N., & Porter, R. (2021). Virtual reality for supporting the treatment of depression and anxiety: Scoping review. JMIR mental health, 8(9), e29681.
55. Fortune Business Insights (2021) Virtual Reality (VR) in Healthcare Market Size, Share & COVID-19 Impact Analysis, By Component (Hardware, Software, and Content), By Application (Pain Management, Education & Training, Surgery, Patient Care Management, Rehabilitation Therapy Procedures, and Post-Treumatic Stress Disorder (PTSD)), and Regional Forecast, 2021-2028. Accessed from: https://www.fortunebusinessinsights.com/industry-reports/virtual-reality-vr-in-healthcare-market-101679
56. Philips (2022) Experience Virtual Reality. Accessed from: https://www.philips.co.uk/healthcare/resources/landing/vr
57. TechRadar (2017) Samsung Gear VR to be used in hospitals to diagnose mental health problems. Accessed from: https://www.techradar.com/news/samsung-gear-vr-to-be-used-in-hospitals-to-diagnose-mental-health-problems
58. EON-XR Technology is Helping Children With Anxiety in Denmark. Accessed from: https://eonreality.com/avr-technology-helping-children-anxiety-denmark/
59. Eon reality (2022) Application Examples. Accessed from: https://eonreality.com/application-examples/health-medical/
60. CAE (2020) HoloLens 2 and CAE: Making Healthcare Safer with Mixed Reality Solutions. Accessed from: https://www.caehealthcare.com/blog/hololens-2-and-cae-making-healthcare-safer-with-mixed-reality-solutions/
61. Visualise (2022) Virtual Reality in Healthcare. Accessed from: https://visualise.com/virtual-reality/virtual-reality-healthcare#:~:text=The%20Future%20of%20VR%20in%20Healthcare&text=In%20the%20coming%20years%2C%20VR,care%2Dgiver%20and%20the%20patient
62. Litvin, S., Saunders, R., Maier, M. A., & Lüttke, S. (2020). Gamification as an approach to improve resilience and reduce attrition in mobile mental health interventions: A randomized 1.controlled trial. PloS one, 15(9), e0237220. Accessed from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0237220
63. Sinha, N. (2021). Introducing Gamification for advancing current mental healthcare and treatment practices. In IoT in Healthcare and Ambient Assisted Living (pp. 223-241). Springer, Singapore.
64. Fleming, T. M., Bavin, L., Stasiak, K., Hermansson-Webb, E., Merry, S. N., Cheek, C., ... & Hetrick, S. (2017). Serious games and gamification for mental health: current status and promising directions. Frontiers in psychiatry, 7, 215.

65. Hoffmann, A., Christmann, C. A., & Bleser, G. (2017). Gamification in stress management apps: a critical app review. JMIR serious games, 5(2), e7216.
65. Sardi, L., Idri, A., & Fernández-Alemán, J. L. (2017). A systematic review of gamification in e-Health. Journal of biomedical informatics, 71, 31-48.
65. Wilson, G. T. (2005). Behavior therapy.
65. Taylor, S., & Fedoroff, I. C. (1999). The expectancy theory of fear, anxiety, and panic: A conceptual and empirical analysis. Anxiety sensitivity: Theory, research, and treatment of the fear of anxiety, 17-33.
65. Klingle, R. S. (1993). Bringing time into physician compliance-gaining research: Toward a reinforcement expectancy theory of strategy effectiveness. Health Communication, 5(4), 283-308.
65. Street, H. (2002). Exploring relationships between goal setting, goal pursuit and depression: A review. Australian Psychologist, 37(2), 95-103.
65. Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American psychologist, 55(1), 68.
65. Sinha, N. (2021). Using virtual reality in college student mental health treatment. In Current and Prospective Applications of Virtual Reality in Higher Education (pp. 257-273). IGI Global.
65. Riva, G., Baños, R. M., Botella, C., Mantovani, F., & Gaggioli, A. (2016). Transforming experience: the potential of augmented reality and virtual reality for enhancing personal and clinical change. Frontiers in psychiatry, 7, 164.
65. Feldmann, L. (2017). Positive Psychology Apps A systematic review of current positive psychological apps aiming to increase happiness (Master's thesis, University of Twente).
65. Global Newswire (2021) Global Healthcare Gamification Market Estimated to Surpass $47,281.5 Million by 2026, and Grow at a CAGR of 11.9% during the Forecast Period. Accessed from: https://www.globenewswire.com/news-release/2021/12/21/2356169/0/en/Global-Healthcare-Gamification-Market-Estimated-to-Surpass-47-281-5-Million-by-2026-and-Grow-at-a-CAGR-of-11-9-during-the-Forecast-Period-120-Pages-Divulge-by-Research-Dive.html
65. Cheng, V. W. S., Davenport, T., Johnson, D., Vella, K., & Hickie, I. B. (2019). Gamification in apps and technologies for improving mental health and well-being: systematic review. JMIR mental health, 6(6), e13717.
65. Vox (2020) These apps make a game out of relieving anxiety. They may be onto something. Accessed from: https://www.vox.com/the-highlight/2019/9/17/20863016/anxiety-app-phone-gamification#:~:text=SuperBetter%20may%20be%20the%20app,Think%2C%20to%20name%20a%20few.
65. Six, S. G., Byrne, K. A., Tibbett, T. P., & Pericot-Valverde, I. (2021). Examining the Effectiveness of Gamification in Mental Health Apps for Depression: Systematic Review and Meta-analysis. JMIR mental health, 8(11), e32199.
65. Melcher, J., Hays, R., & Torous, J. (2020). Digital phenotyping for mental health of college students: a clinical review. Evidence-based mental health, 23(4), 161-166.
65. Onnela, J. P. (2021). Opportunities and challenges in the collection and analysis of digital phenotyping data. Neuropsychopharmacology, 46(1), 45-54.
65. Spinazze, P., Rykov, Y., Bottle, A., & Car, J. (2019). Digital phenotyping for assessment and prediction of mental health outcomes: a scoping review protocol. BMJ open, 9(12), e032255.
65. Mendes, J. P., Moura, I. R., Van de Ven, P., Viana, D., Silva, F. J., Coutinho, L. R., ... & Teles, A. S. (2022). Sensing Apps and Public Data Sets for
65. Digital Phenotyping of Mental Health: Systematic Review. Journal of medical Internet research, 24(2), e28735.
65. Birk, R., Lavis, A., Lucivero, F., & Samuel, G. (2021). For what it's worth. Unearthing the values embedded in digital phenotyping for mental health. Big Data & Society, 8(2), 20539517211047319.
65. NHS Education for Scotland (2021) NHSScotland Workforce. Accessed from: https://turasdata.nes.nhs.scot/media/umdg5xnk/workforce-report-june-2021-final.pdf
65. Luo, Z., Lv, H., Chen, Y., Xu, X., Liu, K., Li, X., ... & Zhou, Y. (2021). Years of Life Lost Due to Premature Death and Their Trends in People With Selected Neurological Disorders in Shanghai, China, 1995–2018: A Population-Based Study. Frontiers in neurology, 12, 207.

Appendix 1

In the last 20 years a large body of clinical research into the use of immersive VR technologies to assess, understand and treat mental health. The below list is a number of key publications hosted on the University of Oxfords Medical Sciences Division website, that represent a sample of this evidence base.

Key Publications
Gorisse, G., Senel, G., Banakou, D., Beacco, A., Oliva, R., Freeman, D., & Slater, M. (2021). Self-observation of a virtual body-double engaged in social interaction reduces persecutory thoughts. Scientific Reports, 11, 23923.
Knight, I., West, J., Matthews, E., Kabir, T., Lambe, S., Waite, F., & Freeman, D. (2021). Participatory design to create a VR therapy for psychosis. Design for Health, 5, 98-119.
McInerney, J., Brown, P., Bird, J.C., Nickless, A., Brown, G., & Freeman, D. (2021). Does raising heart rate prior to a behavioural test enhance learning in cognitive therapy for anxiety? An experimental test for the treatment of fear of heights using virtual reality. Behaviour Research and Therapy, 144, 103928
Bond, J., Robotham, D., Kenny, A., Pinfold, V., Kabir, T., Andleeb, H., Larkin, M., Martin, J., Brown, S., Bergin, A., Petit, A., Rosebrock, L., Lambe, S., Freeman, D., & Waite, F. (2021). Automated virtual reality cognitive therapy for people with psychosis: protocol for a qualitative investigation using peer research methods. JMIR Research Protocols, 10(10):e31742.
Halldorsson, B., Hill, C., Waite, P., Partridge, K., Freeman, D., & Creswell, C. (2021). Immersive virtual reality and digital applied gaming interventions for the treatment of mental health problems in children and young people: the need for rigorous treatment development and clinical evaluation. Journal of Child Psychology and Psychiatry, 62, 584-605.
Brown, P., Waite, F., Rovira, A., Nickless, A., & Freeman, D. (2020). Virtual reality clinical-experimental tests of compassion treatment techniques to reduce paranoia. Scientific Reports, 10: 8547.
Brown, P., Waite, F., Rovira, A., & Freeman, D. (2020). Power posing for paranoia: a double-blind randomized controlled experimental test using virtual reality. Behaviour Research and Therapy, 132, 103691.
Brown, P., Waite, F., Lambe, S., Rosebrock, L., & Freeman, D. (2020). Virtual Reality Cognitive Therapy in Inpatient Psychiatric Wards: Protocol for a Qualitative Investigation of Staff and Patient Views Across Multiple National Health Service Sites. JMIR Research Protocols, 9(8), e20300.
Lambe, S., Knight, I., Kabir, T., West, J., Patel, R., Lister R., Rosebrock, L., Rovira, A., Garnish, B., Freeman, J., Clark, D., Waite, F., & Freeman, D. (2020). Developing an automated VR cognitive treatment for psychosis: gameChange VR therapy. Journal of Behavioural and Cognitive Therapy, 30, 33-40.
Freeman, D., Yu, L-M., Kabir, T., Martin, J., Craven, M., Leal, J., Lambe, S., Brown, S., Morrison, A., Chapman, K., Dudley, R., O'Regan, E., Rovira, A., Goodsell, A., Rosebrock, L., Bergin, A., Cryer, T., Robotham, D., Andleeb, H., Geddes, J., Hollis, C., Clark, D., & Waite, F. (2019). Automated virtual reality (VR) cognitive therapy for patients with psychosis: study protocol for a single-blind parallel group randomised controlled trial (gameChange). BMJ Open, 9:e031606.
Freeman, D., Lister, R., Waite, F., Yu, L.-M., Slater, M., Dunn, G., & Clark, D. (2019). Automated psychological therapy using virtual reality (VR) for patients with persecutory delusions: study protocol for a single-blind parallel-group randomised controlled trial (THRIVE). Trials, 20: 87.
Martens, M., Antley, A., Freeman, D., Slater, M., Harrison, P., Tunbridge, E. (2019). It feels real: physiological responses to a stressful virtual reality environment and its impact on working memory. Journal of Psychopharmacology.
Freeman D., Haselton P., Freeman J., Spanlang B., Kishore S., Albery E., Denne M., Brown P., Slater M., Nickless A. (2018). Automated psychological therapy using immersive virtual reality for the treatment of the fear of heights: a single-blind parallel-group randomised controlled trial. Lancet Psychiatry. 5: 625-632.
Freeman, D., Reeve, S., Robinson, A., Ehlers, A., Clark, D., Spanlang, B., & Slater, M. (2017). Virtual reality in the assessment, understanding, and treatment of mental health disorders. Psychological Medicine. 47: 2393-2400

Key Publications

Freeman, D., Bradley, J., Antley, A., Bourke, E., DeWeever, N., Evans, N., Černis, E., Sheaves, B., Waite, F., Dunn, G., Slater, M., & Clark, D. (2016). Virtual reality in the treatment of persecutory delusions. British Journal of Psychiatry, 209, 62-67.

Atherton, S., Antley, A., Evans, N., Cernis, E., Lister, R., Dunn, G., Slater, M. & Freeman, D. (2016). Self-confidence and paranoia: an experimental study using an immersive virtual reality social situation. Behavioural and Cognitive Psychotherapy, 44, 56-64.

Freeman, D., Dunn, G., Murray, R., Evans, N., Lister, R., Antley, A., Slater, M., Godlewska, B., Cornish, R., Williams, J., Di Simplicio, M., Igoumenou, A., Brenneisen, R., Tunbridge, E., Harrison, P., Harmer, C., Cowen, P., Morrison, P. (2015). How cannabis causes paranoia: Using the intravenous administration of Δ9-tetrahydrocannabinol (THC) to identify key cognitive mechanisms leading to paranoia. Schizophrenia Bulletin, 41, 391-399.

Freeman, D., Evans, N., Lister, R., Antley, A., Dunn, G., & Slater, M. (2014). Height, social comparison, and paranoia: an immersive virtual reality experimental study. Psychiatry Research, 30, 348-352.

Freeman, D., Antley, A., Ehlers, A., Dunn, G., Thompson, C., Vorontsova, N., Garety, P., Kuipers, E., Glucksman, E., & Slater, M. (2014). The use of immersive virtual reality (VR) to predict the occurrence 6 months later of paranoid thinking and posttraumatic stress symptoms assessed by self-report and interviewer methods. Psychological Assessment, 36, 841-847.

Freeman, D., Thompson, C., Vorontsova, N., Dunn, G., Carter, L-A., Garety, P., Kuipers, E., Slater, M., Antley, A., Glucksman, E., & Ehlers, A. (2013). Paranoia and post-traumatic stress disorder in the months after a physical assault: a longitudinal study examining shared and differential predictors. Psychological Medicine, 43, 2673-2684.

Freeman, D., Pugh, K., Vorontsova, N., Antley, A. & Slater, M. (2010). Testing the continuum of delusional beliefs: an experimental study using virtual reality. Journal of Abnormal Psychology, 119, 83–92.

Stinson, K., Valmaggia, L., Antley, A., Slater, M. & Freeman, D. (2010). Cognitive triggers of auditory hallucinations: an experimental investigation. Journal of Behavior Therapy and Experimental Psychiatry, 41, 179–184.

Freeman, D. (2008). Studying and treating schizophrenia using virtual reality (vr): a new paradigm. Schizophrenia Bulletin, 34, 605-610.

Freeman, D., Gittins, M., Pugh, K., Antley, A., Slater, M., & Dunn, G. (2008). What makes one person paranoid and another person anxious? The differential prediction of social anxiety and persecutory ideation in an experimental situation. Psychological Medicine, 38, 1121-1132.

Freeman, D., Pugh, K., Antley, A., Slater, M., Bebbington, P., Gittins, M., Dunn, G., Kuipers, E., Fowler, D., & Garety, P. A (2008). A virtual reality study of paranoid thinking in the general population. British Journal of Psychiatry, 192, 258-263.

Fornells-Ambrojo, M., Barker, C., Swapp, D., Slater, M., Antley, A. & Freeman, D. (2008). Virtual reality and persecutory delusions: safety and feasibility. Schizophrenia Research, 104, 228-236.

Freeman, D., Pugh, K., Green, C., Valmaggia, L., Dunn, G., & Garety, P. (2007). A measure of state persecutory ideation for experimental studies. Journal of Nervous and Mental Disease, 195, 781-784.

Freeman, D., Garety, P.A., Bebbington, P., Slater, M., Kuipers, E., Fowler, D., Green, C., Jordan, J., & Ray, K & Dunn, G., (2005). The psychology of persecutory ideation II: A virtual reality experimental study. Journal of Nervous and Mental Disease, 193, 309-315.

Freeman, D., Slater, M., Bebbington, P.E., Garety, P.A., Kuipers, E., Fowler, D., Met, A., Read, C., Jordan, J., & Vinayagamoorthy, V. (2003). Can virtual reality be used to investigate persecutory ideation? The Journal of Nervous and Mental Disease, 191, 509-514.