Digital mental health: challenges and next steps

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APPENDIX

This appendix contains tables which highlight particular details about, or examples of, concepts relevant to the paper 'Digital mental health: challenges and next steps'. The explanations and examples are not exhaustive; instead they are presented to illustrate and to provide some examples of the concepts explained in the main paper.

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Table 1. EMA and digital phenotyping, definitions and examples.

EMA (ecological momentary assessment) in mental health describes, in its broadest sense, repeatedly collecting data in participants' daily lives using real-time measures [1,2]. **Digital phenotyping** can be defined as the 'moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices' [3]. Personal data gathered from mobile devices and sensors is analysed to provide health information (and can be used a basis for providing advice). This provides the opportunity to access continuous assessments of symptomatology in patients' daily lives, and therefore the potential to overcome some of the challenges in mental health [4]. There is some variability in the exact use of these individual terms. A detailed exploration is beyond the scope of this paper, but in some settings, EMA is used to refer to actively acquired data, and digital phenotyping to passive data (see for example [5]), whereas in others, digital phenotyping is used to cover both passively and actively acquired data as a whole [for example, [6]]. These differences may demonstrate the use of multiple terms to represent similar methodologies, which all have the common goal of using research to assess daily life [7]. Some examples to illustrate the potential uses of this type of data come from mood disorder research. Actively acquired data as described above involves active input from users: for example, in bipolar disorder patients can evaluate their level of symptoms, which map well onto clinical evaluations [8,9,10]. This active data has great potential for long-term monitoring or as outcome measures of the early effect of interventions. By contrast, passive data can be collected without active data entry from participants: for example, voice features collected during telephone calls may represent both a supplementary objective marker discriminating bipolar disorder from unipolar disorder and healthy individuals, and also serve as a state marker within bipolar disorder

[11,12]. Additionally, mobility patterns (from mobile location data) can contribute as a digital diagnostic marker in discriminating between patients with bipolar disorder and unipolar disorder, and serve as a state marker within bipolar disorder [13,14].

Table 2. An example of a transdiagnostic digital approach: adolescent mental health

In adolescence, prevalence of mental disorders is about one in four [15] but may be even higher for subthreshold conditions, which may then evolve into different psychiatric diagnoses [16]. As young people develop, their symptom presentation may change or evolve, either within a diagnostic category, or moving through several separate psychiatric diagnoses according to traditional classifications [17]. In addition, comorbidity is the norm rather than the exception in children and adolescents with mental health conditions [15]. Some underlying constructs, such as affect regulation, inhibitory executive control, or stress sensitivity, are also related to the onset and persistence of different psychiatric conditions in children and adolescents [18]. These factors taken together all suggest that the use of digital mental health in a transdiagnostic approach may help by integrating categorical and dimensional assessments. Tracking dynamic behavioural, physiological, cognitive, and symptom patterns (rather than solely episodes of categorised illness) may produce more meaningful data for the clinician and patient, such as prediction of episode onset or remission. This also has implications for treatment and is consistent with a wider consensus (led by the Neuroscience-based Nomenclature (NbN) task force, https://www.ecnp.eu/research-innovation/nomenclature) to move from traditional disease-based psychopharmacology classifications to those which categorise using factors such as the relevant neuroscientific evidence or mechanism of action. Perhaps the novel naturalistic and longitudinal data afforded by digital phenotyping could help in the development of such transdiagnostic approaches.

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Table 3. Machine learning methods in mental health: possible applications.

In parallel with the rapid development of digital phenotyping technology, machine learning methods have emerged as powerful tools to explore high-dimensional, time-series data (such as electroencephalography, resting-state functional magnetic resonance imaging, or natural language) [19]. Therefore, possible applications of machine learning in mental healthcare range from diagnostic and prognostic markers [20,21,22], to the potential use of generative deep learning models as conversational chatbots for broadly psychotherapeutic treatment delivery [23]. However, as highlighted by a recent review [24], these methods have so far rarely been used to extract predictive markers from digital data streams, and their application has mainly focused on the prediction of affective states in mood disorders [13,25,26]. Thus, it remains unclear if these mood-predictive models could be employed transdiagnostically to forecast abnormal affective and psychomotor states across other conditions such as schizophrenia, borderline personality disorder, or substance abuse disorders. In addition, the potential power of multimodal predictive information extracted across multiple parallel data streams, such as voice, geolocation, and EMA data, using machine learning methods, is only just beginning [27]. The use of these analytical methods requires large-scale and harmonised data collection efforts. This is not a trivial undertaking, as the technological basis of digital phenotyping, such as smartphone operating systems and the hardware itself, is rapidly evolving. Also, for the ultimate clinical translation of digital phenotyping-based prediction models into clinical care, evidence of out-of-sample generalisability, transdiagnostic generalisation, and therapeutic specificity must be submitted to regulatory bodies [19]. It is well-established that AI models themselves can be highly biased depending on the input data they have been trained upon, and so it is key that they use representative and diverse models in training. These requirements can only be met through

internationally agreed standards that harmonise the data acquisition, training, and validation steps of models operating on digital phenotypes [19]. However, encouraging efforts towards these are now underway in large international projects involving digital phenotyping [28, https://www.nimh.nih.gov/research/research-funded-by-nimh/research-initiatives/accelerating-medicines-partnershipr-program-schizophrenia-ampr-scz]

Table 4. Choice of placebos in digital intervention studies

Placebos are needed to control for the considerable noise arising in clinical trials, including natural history, regression to the mean, response biases, Hawthorne effects (the potential for participants to change their behaviour when monitored), and placebo/nocebo effects (genuinely positive/adverse health changes arising as a result of psychobiological expectancy responses that a treatment will be effective/harmful) [29]. Without adequate placebo controls, researchers risk overestimating effect sizes of active interventions [30] leading to inaccurate inferences about the treatment's effectiveness. Placebos should therefore be matched to the active intervention on as many variables as possible (ideally all) except the hypothesised therapeutic component(s); the 'essence' of the intervention [29,31]. However, in digital intervention studies this is often not known, or not clearly described. This problem is not unique to digital interventions. For example, in drug studies, fewer than 10% report on placebo characteristics [30], and in psychotherapy studies there are additional challenges, as clinicians cannot be blinded to allocation [32,33]. An example of an approach addressing these complex issues would be the use of so-called 'dismantling' or 'additive' studies. For example, in studying a hybrid clinic that offers synchronous telehealth visits with a clinician, asynchronous support from a digital navigator, and real-time services from an app, it is important to assess the impact of each intervention, as well as their combinations, in order to understand the mechanisms behind efficacy and drive further improvement. To date, few if any studies report on the actual drivers of efficacy in hybrid care models [34] (for example therapeutic alliance with the clinician, coach or app, increased self-efficacy, increased emotional self-awareness) which has precluded both the development of new theories on engagement and the development of more effective services.

Table 5. Addressing the physical health needs of those with mental illness

The delivery of preventative/behavioural health interventions in the general population is increasingly relying on digital technologies, and there is currently a variety of research, innovation and investment towards using apps, wearables and remote support to create a physically fitter and healthier society [35]. Although people with severe mental illness (SMI) die approximately 15-20 years younger than the general population, primarily due to cardiovascular and metabolic diseases [36], the extent to which digital innovations for physical health can reach mental health populations has not been widely considered [37,38]. People with SMI may therefore be 'left behind', increasing pre-existing disparities. Psychiatric research has started to examine how digital technologies may be able to increase the accessibility and scalability of behavioral health interventions for people with mental illness, for instance through app-based approaches for smoking cessation [39], wearable or virtual reality-supported physical activity programs [40,41,42], and gamified mHealth platforms for healthy living [43]. Such innovations could improve not only physical health, but also mental health outcomes, as lifestyle interventions have been shown to have beneficial effects on cognitive and functional outcomes in people with mental illness [44].

Table 6. Examples of integrating intervention with real time assessment

Real-time analyses of mobile sensor technology can be used to increase adherence to interventions. For example, in the PROUD study (Prevention of comorbid depression and obesity in attention-deficit/ hyperactivity disorder), patients were treated preventively via light and exercise therapy [45]. Endurance training and strengthening exercises were implemented on a smartphone with short video clips. Real-time analyses of the completed training were performed, logging training videos and using accelerometers. Performance parameters were calculated in real time, for example steps per day, and sent to the participants as motivational cues to keep up the training or to motivate them for a certain physical activity of the day that had not yet been performed. Another example of integrating real-time analyses of mobile sensor technology into interventions is the Bipolife study [46], where digital phenotypes of patients with bipolar disorders are tracked and analysed in real time. A fully automated algorithm sends alarms to treating psychologists and psychiatrists, if a set of predefined parameters surpasses individualised, adapting thresholds. Just-in-time adaptive interventions (JITAIs) are interventions that adapt over time to an individual’s changing status and circumstances, to address the individual’s need for support, whenever this need arises [47]. They show great potential, but there is a lack of current real-world clinical examples in mental health [48,49].

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Table 7. Clinical decision making using digital data: some concepts and examples

Using digital data in clinical decision-making not only allows for the addition of extra information, but as this extra information is generated in real time by the patient, it may also help to identify or confront the bias in information-gathering encountered via other routes [50]. This benefit in reduction of bias might occur at several levels: 1. At the 'micro-systemic' level (the clinical interaction with patients) this could reduce errors of judgment (in the patient or clinician) related to incomplete clinical information processing (for example memory bias, choice of salient information, influence of theoretical a priori knowledge). In addition, the patient/physician relationship could also be positively impacted by the increased emphasis on the patients' information, and act as a powerful empowerment tool. 2. At the 'meso-systemic' level (the organisation of care), the digital phenotype data may reduce heterogeneity in clinical practice and management, and therefore increase efficiency and reduce disparities in care. 3. At the 'macro-analytical' level (systems of care), these efficiencies and increased consistency could allow better acceptability by organisations in terms of financial support and implementation. An example of clinical decision making using digital data is in the so-called 'digital clinic' model of integration of asynchronous telehealth with apps into synchronous telehealth models of care through video (or in person) visits [51,52]. There are several potential advantages in this approach including both improved access and quality of care, as the use of digital tools can enhance evidence-based care and shared decision-making. Digital clinics can use a variety of asynchronous technologies (for example apps, and sensors) to collect comprehensive data and inform care decisions. These can supplement in-person or synchronous telehealth visits, and because of their asynchronicity, also allow for the potential to increase efficiency.

However, there are challenges in implementing digital tools in the clinical setting which go beyond any immediate technological difficulties [53]. In real world implementation, aspects such as the type of digital innovation (for example the complexity and utility of the app), the users (patients, carers, clinicians, and their familiarity and wish to use the digital tools), and the overall context (the healthcare system, reimbursement, and regulation policies) are also key areas to consider [51,52,54]. There are strategies which can facilitate implementation including: co-production of the technology with users (see Table 8), training for staff and patients, creation of new team members with complementary skills (such as 'digital navigators'), and re-design of the structure and flow through the clinic [55].

Table 8. Case studies highlighting co-design

Although initial engagement with digital interventions can be high, this is often not sustained. For example, the majority of users abandon apps within a few days [56,57]. Engagement can be improved by human support alongside app use [58], but this human interaction is often a limiting factor. To realise the full potential for interventions such as apps to expand access to care and enable scalability, there is increasing interest in co-design and co-production with users and stakeholders, to ensure that digital tools reflect their self-identified specific needs and preferences [59].

An example is in children and young people, where rates of mental illness and mental health difficulties are high, but rates of availability of intervention and support are much lower [60]. This may be an ideal population for digital intervention as a potential route to improve the reach and access to therapies. With 97% of teens reporting that they use the internet daily, and 46% saying they use the internet almost constantly [61], a digital approach could have a significant impact in this population. However, although there is some initial evidence to support this [62,63], engagement, uptake and adherence outside the research setting is a significant challenge and perhaps an "Achilles' heel" for the paradigm [62,64,65].

Co-design involves a process throughout the life and research cycle of the programme, involving all relevant stakeholders. For adolescents, these might include families, carers and friends, and also experts in youth services (for example in education, health, social care), experts in the content of the intervention (for example clinicians, researchers) and experts in digital technologies (for example designers, information technology specialists, animators) [64]. Parents' opinions and concerns about the use of technology, and the logistics of its use within families will highly impact the acceptability and utility of innovations and so it is key to include patients and families. It is especially important to encompass diverse populations and include those young people living in communities facing health and social disparities. Teens with socially complex needs may be more in need of mental health resources, but also experience the greatest systemic barriers to accessing care, and have previously been overlooked or excluded from collaborative research designs for mHealth [66].

Table 9. Ethical issues in digital interventions

There are a variety of potential ethical concerns in the use of digital mental health interventions [67]. Firstly, epistemology is deeply entwined with ethics. The quality of evidence on which digital interventions are based carries ethical consequences for clinical practice, both in terms of what diagnostic or treatment tools are employed, and what is conveyed to patients about these tools. In addition, due consideration must be given to informed consent when it comes to the inclusion of patient data in generating insights in the domain of digital mental health. There may be great scope for digital markers to improve the precision and timeliness of care; but establishing the benefits and balancing these against the potential harms of digital health interventions will be essential. Correlation does not imply causation: it is imperative to ensure that data collected are predictively valid and support safe and accurate diagnoses and prognoses [68]. Harms may arise if digital data lead to overdiagnoses or inaccurate predictions of mental health. Ensuring reliability and validity may require data to be collected from a diverse variety of populations [69]. For example, both individual and cultural differences may lead to differences in linguistic markers in digital phenotyping; analyses of content that use irony or sarcasm might incorrectly identify users as depressed or suicidal among some patients but be predictive among others. Without due caution and oversight, digital phenotyping could perpetuate or exacerbate health disparities via biases if trained on limited populations of patients [70]. Limitations with datasets combined with the opacity of some algorithms on which insights are based, might exacerbate healthcare inequalities, by restricting the usefulness of these tools among some patient populations or directly leading to harms via inaccuracies. Other ethical problems arise if the processes of collecting digital data incur adverse influences on patient behaviour [71]. For example, preoccupation with checking health tracking data via downloadable apps and wearable devices might increase anxiety or unwanted nocebo effects [72],

or lead to increased time spent online. Although the relationship between screen time and adverse mental health has not been fully resolved, there is a risk that under certain conditions, some social media platforms might be detrimental to mental health [73,74], displace more healthful behaviours, or be sources of misinformation.

Perhaps the most prominent ethical concerns with respect to digital mental health are patient privacy, confidentiality, and trust in healthcare. Data collection may involve tracking patients beyond traditional health information to include a variety of data embedded in (for example) social media posts, fitness trackers, telephone and text traffic, and geolocation. The secure storage and usage of this information including patient consent [75]and adequate data governance pose real and persistent challenges for healthcare, providers [76], and civic privacy laws. This is particularly relevant with the passive nature of data collection in digital phenotyping; ensuring patients are fully aware and consent to how data is collected, managed, and used, will be critical to preserving trust in clinicians.

Examples of ethical issues

Ethical challenges frequently appear, such as that around the Crisis Textline in the United States. In mid-2022 it was revealed the company had been sending all text messages (often about suicidal thoughts) to a partner company which used the messages for building AI-informed customer service software (https://www.bbc.co.uk/news/technology-60218894). Only when the public was made aware of this and amidst the subsequent outcry did the company stop this practice and agree that the prior terms of conditions of use were not ethical (agreeing to share data by texting for help).

Often, ethical challenges are difficult to track, as in the case of Facebook which, again in the United States, may send the police to a user’s door if they write messages around self-harm that are detected by natural language processing run by Facebook [77]. While there is no sharing of results to show if Facebook's approach prevents suicide and saves lives, or results in harm by sending police to people's homes, there is currently no means to opt in or out of this program.

Table 10: specific populations

Child and adolescent mental health is a public health priority worldwide [78]. Smartphone use among this population is high, suggesting that this could be an ideal mode of delivery for mental health interventions [79]. The desire for digital media is aligned with the biology of the adolescent brain, as it offers social connection, novelty and the potential for making choices with low failure cost during a developmental period in which there are extensive brain and neurotransmitter system changes [80]. However, the evidence of the effectiveness of digital mental health interventions for youth is still limited to short-term treatments for conditions such as anxiety or depression, with very few data on long-term outcomes, younger age groups, youth with developmental disorders, minimum dose required, and on the generalisability of findings to adolescents and young people with different socioeconomic, cultural, racial or other backgrounds [81,82]. This is not the only group which might be relevant for digital interventions. For example, the elderly are also an important population to target, but have so far been left out of many digital data studies even though innovations like digital phenotyping may be especially practical [83]. A recent systematic review identified factors such as ease of use, opportunities for social interactions, human support and having tailored interventions as related to the success of digital mental health interventions [84]. People with intellectual disability experience high rates of mental illness, but have also been excluded from the development and implementation of new interventions. Barriers to using digital technology could be overcome in many cases by appropriate support and adaptations, and there is some early evidence of the value of incorporating digital technologies for promoting health, educational, vocational and leisure opportunities in this population [85,86,87]. Those with chronic physical conditions also experience higher rates of mental illness, and digital health interventions might help to overcome barriers to accessing mental health support for these

individuals. However, there is still work to be done in assessing the design and implementation of digital health interventions in this population [88,89].

References

1. Hall M, Scherner PV, Kreidel Y, et al. A systematic review of momentary assessment designs for mood and anxiety symptoms. Frontiers in Psychology. 2021 May 17;12:642044.
2. Stone AA, Shiffman S. Ecological momentary assessment (EMA) in behavorial medicine. Annals of behavioral medicine. 1994.
3. Torous J, Kiang MV, Lorme J, et al. New Tools for New Research in Psychiatry: A Scalable and Customizable Platform to Empower Data Driven Smartphone Research. JMIR Ment Health. 2016 May 5;3(2):e16. doi: 10.2196/mental.5165. PMID: 27150677; PMCID: PMC4873624.
4. Insel, T. R. Digital phenotyping: a global tool for psychiatry. World Psychiatry 17, 276–277 (2018).
5. Maatoug R, Oudin A, Adrien V, et al. Digital phenotype of mood disorders: A conceptual and critical review. Frontiers in Psychiatry. 2022;13.
6. Melcher J, Hays R, Torous J. Digital phenotyping for mental health of college students: a clinical review. Evidence-Based Mental Health 2020;23:161-166.
7. Ebner-Priemer UW. Defining Ecological Momentary Assessment. Digital Phenotyping and Mobile Sensing: New Developments in Psychoinformatics. 2022 Jul 22:447.
8. Busk, J, Faurholt-Jepsen M, Frost M et al. Daily estimates of clinical severity of symptoms in bipolar disorder from smartphone-based self-assessments. Transl Psychiatry 10, 194 (2020a). https://doi.org/10.1038/s41398-020-00867-6
9. Ebner-Priemer UW, Mühlbauer E, Neubauer AB, et al. Digital phenotyping: towards replicable findings with comprehensive assessments and integrative models in bipolar disorders. International Journal of Bipolar Disorders. 2020 Dec;8(1):1-9.
10. Faurholt-Jepsen M, Vinberg M, Frost M, et al. Smartphone data as an electronic biomarker of illness activity in bipolar disorder. Bipolar disorders. 2015 Nov;17(7):715-28.
11. Faurholt-Jepsen M, Rohani DA, Busk J, et al. Voice analyses using smartphone-based data in patients with bipolar disorder, unaffected relatives and healthy control individuals, and during different affective states. International Journal of Bipolar Disorders. 2021 Dec;9:1-3.
12. Faurholt-Jepsen M, Rohani DA, Busk J, et al. Discriminating between patients with unipolar disorder, bipolar disorder, and healthy control individuals based on voice features collected from naturalistic smartphone calls. Acta Psychiatrica Scandinavica. 2022 Mar;145(3):255-67.
13. Faurholt-Jepsen M, Busk J, Rohani DA, et al. Differences in mobility patterns according to machine learning models in patients with bipolar disorder and patients with unipolar disorder. Journal of Affective Disorders. 2022 Jun 1;306:246-53.
14. Faurholt-Jepsen M, Busk J, Vinberg M, et al. Daily mobility patterns in patients with bipolar disorder and healthy individuals. Journal of Affective Disorders. 2021 Jan 1;278:413-22.
15. Merikangas KR, He JP, Burstein M, et al. Lifetime prevalence of mental disorders in US adolescents: results from the National Comorbidity Survey Replication–Adolescent Supplement (NCS-A). Journal of the American Academy of Child & Adolescent Psychiatry. 2010 Oct 1;49(10):980-9.
16. de Pablo GS, Besana F, Arienti V, et al. Longitudinal outcome of attenuated positive symptoms, negative symptoms, functioning and remission in people at clinical high risk for psychosis: a meta-analysis. EClinicalMedicine. 2021 Jun 1;36:100909.
17. Caspi A, Houts RM, Ambler A, et al. Longitudinal Assessment of Mental Health Disorders and Comorbidities Across 4 Decades Among Participants in the Dunedin Birth Cohort Study. JAMA Netw Open. 2020;3(4):e203221. doi:10.1001/jamanetworkopen.2020.3221
18. Cai RY, Hardan AY, Phillips JM, et al. Brief Report: Emotion Regulation Influences on Internalizing and Externalizing Symptoms Across the Normative-Clinical Continuum. Front Psychiatry. 2021 Jul 21;12:693570. doi: 10.3389/fpsyt.2021.693570. PMID: 34366922; PMCID: PMC8333703.
19. Koutsouleris N, Hauser TU, Skvortsova V, et al. From promise to practice: towards the realisation of AI-informed mental health care. The Lancet Digital Health. 2022 Oct 10

20. Chekroud AM, Bondar J, Delgadillo J, et al. The promise of machine learning in predicting treatment outcomes in psychiatry. World Psychiatry. 2021 Jun;20(2):154-70.
21. Dwyer DB, Falkai P, Koutsouleris N. Machine learning approaches for clinical psychology and psychiatry. Annual review of clinical psychology. 2018 May 7;14:91-118.
22. Dwyer D, Koutsouleris N. Annual Research Review: Translational machine learning for child and adolescent psychiatry. Journal of Child Psychology and Psychiatry. 2022 Apr;63(4):421-43.
23. Das A, Selek S, Warner AR, et al. Conversational Bots for Psychotherapy: A Study of Generative Transformer Models Using Domain-specific Dialogues. In Proceedings of the 21st Workshop on Biomedical Language Processing 2022 May (pp. 285-297).
24. Benoit J, Onyeaka H, Keshavan M, Torous J. Systematic review of digital phenotyping and machine learning in psychosis spectrum illnesses. Harvard Review of Psychiatry. 2020 Sep 1;28(5):296-304.
25. Mikus A, Hoogendoorn M, Rocha A, et al. Predicting short term mood developments among depressed patients using adherence and ecological momentary assessment data. Internet interventions. 2018 Jun 1;12:105-10
26. Busk J, Faurholt-Jepsen M, Frost M, et al. Forecasting mood in bipolar disorder from smartphone self-assessments: hierarchical bayesian approach. JMIR mHealth and uHealth. 2020b Apr 1;8(4):e15028.
27. Bianchi FM, Livi L, Mikalsen KØ, et al. Learning representations of multivariate time series with missing data. Pattern Recognition. 2019 Dec 1;96:106973.
28. Woods SW, Choi J, Mamah D. Full speed ahead on indicated prevention of psychosis. World Psychiatry. 2021 Jun;20(2):223-224.
29. Blease CR. The role of placebos in family medicine:'Implications of evidence and ethics for general practitioners'. Australian journal of general practice. 2019 Oct;48(10):700-5.
30. Howick J, Hoffmann T. How placebo characteristics can influence estimates of intervention effects in trials. Cmaj 2018;190:E908–11.
31. Blease C, Annoni M. Overcoming disagreement: a roadmap for placebo studies. Biology & Philosophy 2019;34:18.
32. Baskin TW, Tierney SC, Minami T, et al. Establishing specificity in psychotherapy: a meta-analysis of structural equivalence of placebo controls. Journal of consulting and clinical psychology 2003;71:973.
33. Locher C, Gaab J, Blease C. When a placebo is not a placebo: problems and solutions to the gold standard in psychotherapy research. Frontiers in Psychology 2018;9:2317.
34. Meyer A, Wisniewski H, Torous J. Coaching to Support Mental Health Apps: Exploratory Narrative Review. JMIR Hum Factors. 2022 Mar 8;9(1):e28301.
35. Piwek L, Ellis DA, Andrews S, Joinson A. The rise of consumer health wearables: promises and barriers. PLoS medicine. 2016 Feb 2;13(2):e1001953.
36. Firth J, Siddiqi N, Koyanagi AI, et al. The Lancet Psychiatry Commission: a blueprint for protecting physical health in people with mental illness. The Lancet Psychiatry. 2019 Aug 1;6(8):675-712.
37. Onyeaka H, Firth J, Kessler RC, et al. Use of smartphones, mobile apps and wearables for health promotion by people with anxiety or depression: An analysis of a nationally representative survey data. Psychiatry Research. 2021 Oct 1;304:114120.
38. Onyeaka H, Muoghalu C, Malekani M, et al. Use of wearable devices among individuals with depression and anxiety: A population level study. Psychiatry Research Communications. 2022 Dec 1;2(4):100081.
39. Sawyer C, Hassan L, Guinart D, et al. Smoking Cessation Apps for People with Schizophrenia: How Feasible Are m-Health Approaches?. Behavioral Sciences. 2022 Aug 1;12(8):265.

40. Aschbrenner KA, Naslund JA, Gorin AA, et al. Group lifestyle intervention with mobile health for young adults with serious mental illness: A randomized controlled trial. Psychiatric Services. 2022 Feb 1;73(2):141-8.
41. Hargraves F, Armour M, Firth J, et al. The effect of an active virtual reality gaming intervention on physical activity and mood in young men with mild to moderate depression; a randomised controlled feasibility trial to improve physical and mental wellbeing during Covid-19. Digital Health Week; 2022; 16088.
42. Tang Y, Gierc M, Lam RW et al. The Effectiveness of Internet-Guided Self-help Interventions to Promote Physical Activity Among Individuals With Depression: Systematic Review. JMIR Mental Health. 2022 Dec 12;9(12):e38049.
43. Varnfield M, Rajesh K, Redd C, et al. Health-e minds: a participatory personalised and gamified mhealth platform to support healthy living behaviours for people with mental illness. In2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2019 Jul 23 (pp. 6943-6947). IEEE.
44. Firth J, Solmi M, Wootton RE, et al. A meta-review of "lifestyle psychiatry": the role of exercise, smoking, diet and sleep in the prevention and treatment of mental disorders. World Psychiatry 2020, 19, 360-380.
45. Mayer JS, Hees K, Medda J, et al. Bright light therapy versus physical exercise to prevent co-morbid depression and obesity in adolescents and young adults with attention-deficit/hyperactivity disorder: study protocol for a randomized controlled trial. Trials. 2018 Dec;19(1):1-9.
46. Mühlbauer E, Bauer M, Ebner-Priemer U, et al. Effectiveness of smartphone-based ambulatory assessment (SBAA-BD) including a predicting system for upcoming episodes in the long-term treatment of patients with bipolar disorders: study protocol for a randomized controlled single-blind trial. BMC psychiatry. 2018 Dec;18:1-9.
47. Nahum-Shani I, Hekler EB, Spruijt-Metz D. Building health behavior models to guide the development of just-in-time adaptive interventions: A pragmatic framework. Health psychology. 2015 Dec;34(S):1209.
48. Martinengo L, Stona AC, Griva K, et al. Self-guided Cognitive Behavioral Therapy Apps for Depression: Systematic Assessment of Features, Functionality, and Congruence With Evidence. Journal of Medical Internet Research. 2021 Jul 30;23(7):e27619.
49. Frank E, Wallace M, Matthews MJ, et al. Precision Digital Intervention for Depression Based on Social Rhythm Principles Adds Significantly to Outpatient Treatment. Frontiers in Digital Health. 2022 May 10:175.
50. Mouchabac S, Conejero I, Lakhlifi C, et al. Improving clinical decision-making in psychiatry: implementation of digital phenotyping could mitigate the influence of patient's and practitioner's individual cognitive biases. Dialogues in Clinical Neuroscience. 2021 Jan 1;23(1):52-61.
51. Rodriguez-Villa E, Rauseo-Ricupero N, Camacho E, et al. The digital clinic: implementing technology and augmenting care for mental health. General hospital psychiatry. 2020 Sep 1;66:59-66.
52. Connolly SL, Kuhn E, Possemato K, et al. Digital clinics and mobile technology implementation for mental health care. Current Psychiatry Reports. 2021 Jul;23(7):1-7.
53. Connolly SL, Hogan TP, Shimada SL, et al. Leveraging implementation science to understand factors influencing sustained use of mental health apps: a narrative review. Journal of technology in behavioral science. 2021 Jun;6(2):184-96.
54. Vis C, Mol M, Kleiboer A, et al. Improving Implementation of eMental Health for Mood Disorders in Routine Practice: Systematic Review of Barriers and Facilitating Factors. JMIR Ment Health. 2018 Mar 16;5(1):e20. doi: 10.2196/mental.9769. PMID: 29549072; PMCID: PMC5878369.

55. Torous J, Bucci S, Bell IH, Kessing LV, et al. The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. World Psychiatry. 2021 Oct;20(3):318-35.
56. Baumel A, Muench F, Edan S et al. Objective user engagement with mental health apps: systematic search and panel-based usage analysis. J Med Internet Res 2020;22:e17572.
57. Pratap A, Neto EC, Snyder P et al. Indicators of retention in remote digital health studies: a cross-study evaluation of 100,000 participants. NPJ Digit Med 2020;3:21.
58. Linardon J, Cuijpers P, Carlbring P et al. The efficacy of app-supported smartphone interventions for mental health problems: a meta-analysis of randomized controlled trials. World Psychiatry 2019;18:325-36.
59. Morton E, Barnes SJ, Michalak EE. Participatory digital health research: a new paradigm for mHealth tool development. Gen Hosp Psychiatry 2020;66: 67-9.
60. Rice F, Eyre O, Riglin L, Potter R. Adolescent depression and the treatment gap. Lancet Psychiatry. 2017 Feb;4(2):86-87.
61. Pew Research. Teens, Social Media and Technology 2022. https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/
62. Hollis C, Falconer CJ, Martin JL, et al. Annual Research Review: Digital health interventions for children and young people with mental health problems–a systematic and meta-review. Journal of Child Psychology and Psychiatry. 2017 Apr;58(4):474-503.
63. National Institute for Health and Care Excellence (2019). Depression in children and young people: Identification and management (NG134). https://www.nice.org.uk/guidance/ng134
64. Bevan Jones R, Stallard P, Agha SS, et al. Practitioner review: Co-design of digital mental health technologies with children and young people. Journal of child psychology and psychiatry. 2020 Aug;61(8):928-40.
65. Nwosu A, Boardman S, Husain MM, et al. Digital therapeutics for mental health: Is attrition the Achilles heel?. Frontiers in Psychiatry. 2022:1598.
66. Stiles-Shields C, Reyes KM, Archer J, et al. mHealth Uses and Opportunities for Teens from Communities with High Health Disparities: A Mixed-Methods Study. J Technol Behav Sci. 2022 Sep 13:1-13.
67. Martinez-Martin N, Greely HT, Cho MK. Ethical Development of Digital Phenotyping Tools for Mental Health Applications: Delphi Study. JMIR Mhealth Uhealth. 2021 Jul 28;9(7):e27343.
68. Stanghellini G, Leoni F. Digital phenotyping: ethical issues, opportunities, and threats. Frontiers in Psychiatry. 2020 May 27;11:473.
69. Benjamin R. Race after technology: Abolitionist tools for the new jim code. Social forces. 2019 Dec 23.
70. Birk RH, Samuel G. Can digital data diagnose mental health problems? A sociological exploration of 'digital phenotyping'. Sociology of Health & Illness. 2020 Nov;42(8):1873-87.
71. Loi M. The digital phenotype: A philosophical and ethical exploration. Philosophy & Technology. 2019 Mar 15;32(1):155-71.
72. Chang S, Torous J. Open notes and broader parallels in digital health: a commentary on C. Blease's 'Sharing online clinical notes with patients'. Journal of Medical Ethics. 2023 Jan 1;49(1):22-3.
73. Blease CR. Too many 'friends,'too few 'likes'? Evolutionary psychology and 'Facebook depression'. Review of General Psychology. 2015 Mar;19(1):1-3.
74. Yoon S, Kleinman M, Mertz J, et al. Is social network site usage related to depression? A meta-analysis of Facebook–depression relations. Journal of affective disorders. 2019 Apr 1;248:65-72.
75. Seltzer E, Goldshear J, Guntuku SC, et al. Patients' willingness to share digital health and non-health data for research: a cross-sectional study. BMC Medical Informatics and Decision Making. 2019 Dec;19(1):1-8.

76. Perez-Pozuelo I, Spathis D, et al. Digital phenotyping and sensitive health data: Implications for data governance. Journal of the American Medical Informatics Association. 2021 Aug 13;28(9):2002-8.
77. Barnett I, Torous J. Ethics, Transparency, and Public Health at the Intersection of Innovation and Facebook's Suicide Prevention Efforts. Ann Intern Med. 2019 Apr 16;170(8):565-566.
78. World Health Organization. Adolescent mental health. https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health. Geneva: World Health Organization, 2021.
79. Punukollu M, Marques M. Use of mobile apps and technologies in child and adolescent mental health: a systematic review. Evid Based Ment Health 2019;22:161-6.
80. Giedd JN. Adolescent brain and the natural allure of digital media. Dialogues Clin Neurosci. 2020 Jun;22(2):127-133.
81. Lehtimaki S, Martic J, Wahl B, et al. Evidence on Digital Mental Health Interventions for Adolescents and Young People: Systematic Overview. JMIR Ment Health. 2021 Apr 29;8(4):e25847.
82. Pandina G. The role of digital medicine in autism spectrum disorder. Eur Neuropsychopharmacol. 2021 Jul;48:42-44
83. Fortuna KL, Torous J, Depp CA, et al. A Future Research Agenda for Digital Geriatric Mental Healthcare. Am J Geriatr Psychiatry. 2019 Nov;27(11):1277-1285.
84. Riadi I, Kervin L, Dhillon S, et al. Digital interventions for depression and anxiety in older adults: a systematic review of randomised controlled trials. The Lancet Healthy Longevity. 2022 Aug 1;3(8):e558-71.
85. Sheehan R, Hassiotis A. Digital mental health and intellectual disabilities: state of the evidence and future directions. Evidence-Based Mental Health. 2017 Nov 1;20(4):107-11.
86. Krysta K, Romańczyk M, Diefenbacher A, et al. Telemedicine treatment and care for patients with intellectual disability. International Journal of Environmental Research and Public Health. 2021 Feb;18(4):1746.
87. Oudshoorn CE, Frielink N, Nijs SL, et al. Psychological eHealth interventions for people with intellectual disabilities: A scoping review. Journal of Applied Research in Intellectual Disabilities. 2021 Jul;34(4):950-72.
88. Shah A, Hussain-Shamsy N, Strudwick G, et al. Digital Health Interventions for Depression and Anxiety Among People With Chronic Conditions: Scoping Review. Journal of medical Internet research. 2022 Sep 26;24(9):e38030.
89. Sasseville M, LeBlanc A, Boucher M, et al. Digital health interventions for the management of mental health in people with chronic diseases: a rapid review. BMJ open. 2021 Apr 5;11(4):e044437.

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