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Expanding, Improving, and Understanding Behaviour Research and Therapy through Digital Mental Health

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The past two decades have brought increasing development, research, dissemination, and implementation of various technology-based interventions for the treatment of emotional and behavioral disorders. This includes the use of Internet websites, mobile devices and applications ("apps"), wearable devices, video games, and virtual reality (Mohr, Burns, Schueller, Clarke, & Klinkman, 2013). We refer to these interventions that leverage technology to create novel therapeutic interactions or affordances as digital mental health interventions (DMHIs) to differentiate them from other technology-facilitated interventions that merely use technology to provide traditional care - i.e., telepsychotherapy via phone or video platforms. Papers on DMHIs began to appear in *Behaviour Research and Therapy* (BRAT) as early as 1998 with a case report on virtual reality for treatment of claustrophobia (Botella et al., 1998), and by 2005 more rigorous, but small, randomized controlled trials of DMHIs were being conducted on treatments for panic disorder (Carlbring et al., 2005) and headaches (Devineni & Blanchard, 2005). Since then, the work published in the pages of BRAT has mirrored the progression that has occurred in the field - larger trials, more diverse target conditions, expanded methods of evaluation, and DMHIs that leverage ongoing technological advances. The goal of this special issue is to cover the contributions to the field of behaviour research and therapy made possible through various technologies. The papers included in this special provide examples of where the field is currently, while also previewing where it might be going. This overview aims to highlight some of these general themes while also advancing the thread of future directions of DMHIs to shape the treatment, and understanding of treatment, of emotional and behavioral disorders.

A considerable body of work has demonstrated that DMHIs are effective for a variety of emotional and behavioral disorders with perhaps the most robust evidence coming in the areas of depression (Karyotaki et al., 2021) and anxiety (Pauley, Cuijpers, Papola, Miguel, & Karyotaki, 2021). However, despite their effectiveness DMHIs are not without their limitations including: lack of sustained engagement, especially in real-world settings (Baumel, Edan, & Kane, 2019); limited dissemination, with very few products accounting for the majority of users (Wasil, Gillespie, Shingelton, Wilks, & Weisz, 2020); and most of the evaluation occurring with white females and few products considering the needs of racial, ethnic, sexual, and gender minorities (Schueller, Hunter, Figueroa, & Aguilera, 2019). Thus, although DMHIs hold the potential to significantly shape our understanding and dissemination of behaviour research and therapy, this potential has been largely unrealized. However, even with these limitations considerable investment is being made in DMHIs within the private sector. Venture capital investing in mental health companies has been high, hitting $637 million in 2019 which was a nearly 23 times increase since 2013 (Shah & Berry, 2020). As such, private investment and industry developers play an important role in this landscape and present a huge opportunity to advance understanding themselves and through academic-industry partnerships. This special issue brings together papers that address some of these issues. In our reading of the papers, we identified consistent themes of advancing methods, understanding what works, models of dissemination and implementation, and considering context, especially related to issues of diversity, equity, justice, and inclusion. We highlight each of these areas while touching on major takeaways from the papers.

Advancing Methods in Digital Mental Health

DMHIs provide opportunities to increase access, improve outcomes, and overcome obstacles to our understanding of both mental health disorders and their treatment. However, these novel interventions have struggled with issues of low engagement and increased dropout, with poor user experience often indicated as a significant barrier (Lattie et al., 2022). Clinical scientists are increasingly turning to other disciplines for the innovative methods that are needed to improve the design process for DMHIs. One such method comes from the development of technology, which has generally adopted the human-centered design (HCD) approach, in which stakeholders are engaged throughout the entire process of conceptualization, design, refinement, and evaluation (Lyon et al., 2019). One combination of HCD methods with those from intervention science is the Discover-Design-Build-Test (DDBT) model (Lyon et al., 2019). Jenness and colleagues (2022) present a case study of this DDBT model applied to the creation and evaluation of a prototype app for delivering behavioral activation to teens with depression. To help identify user needs and barriers to engagement, they recruited, in addition to their target patient population, mental health clinicians and expert app evaluators in a process of iterative co-design and evaluation, demonstrating how asynchronous remote communities (i.e., Slack) can facilitate both the creation and delivery of DMHIs.

Another area where methodological innovation intersects with DMHIs is the field's increasing emphasis on precision and personalized mental health (Cohen & DeRubeis, 2018), which relies heavily on predictive modeling and other data-driven approaches (Cohen, Delgadillo & DeRubeis, 2021). Recent work has confirmed Meehl's (1954) findings on the limitations of clinician judgment (e.g., van Bronswijk et al., 2020) and demonstrated how clinical decision-making can be improved through the use of decision-support tools based on predictive modeling (Delgadillo et al., 2021). Although a recent study by Mullainathan & Obermeyer (2022) highlights how advanced modeling approaches can better account for the complexity of clinical phenomena, barriers such as flawed heuristics for powering predictive models (van Smeden et al., 2019) and existing randomized clinical trials' insufficiently small sample sizes (Lorenzo-Luaces et al., 2020) still stand in the way of the field's progress. New methods for calculating sample size requirements for developing and evaluating clinical prediction models have been proposed (Luedtke et al., 2019; Riley et al., 2021), but these efforts have focused on traditional clinician-delivered interventions. In their contribution to the special issue, McNamara and colleagues (2022) provide an accessible summary of this literature, highlighting opportunities and challenges for clinical prediction modeling in the context of DMHIs (e.g., Pearson et al., 2019). Building on existing work, they present simulations that explore the impact of noise variables, measurement error, complex interactions, and nonlinear effects on sample size requirements for classic (generalized linear models) and machine learning-based (elastic net regression, random forests, gradient boosting machines, and super learners) clinical prediction modeling efforts. The authors conclude with a discussion of how DMHIs are well-suited to provide the data needed for precision mental health, and the ways in which predictive algorithms can contribute to real-world clinical care.

DMHIs can generate large datasets not only by reaching people at scale, but also by leveraging repeated measures through intensive longitudinal designs. Such high-density datasets can advance the field by improving our ability to understand the inter- and intra-individual variability in peoples' experience with mental health and disorders. Network theory and associated network modeling approaches have shown promise for capturing the temporal variability and complex interactions between specific symptoms, as well as environmental and contextual factors (Bringmann et al., 2022). However, the ecological moment assessment (EMA) often employed to collect the intensive longitudinal measurements required by these approaches incurs a significant measurement burden, limiting both scalability and practicality in real-world clinical contexts. One approach to reducing measurement burden is to use passive digital data to pursue moment-by-moment quantification via digital phenotyping. Passive sensors can provide objective data on individuals' biology (e.g., heart rate), movement (e.g., actigraphy and GPS location), social interactions, and environment (e.g., light sensor).

Although a large and growing body of work speaks to the ability of these so-called "digital biomarkers" to predict depression (De Angel et al., 2022), less attention has been paid to their application in anxiety disorders. To explore this potential, Jacobson and Bhattacharya (2022) developed idiographic models using smartphone sensor data to predict momentary anxiety and avoidance in a sample of 32 undergraduates with generalized or social anxiety disorder. These personalized deep learning models accounted for the majority of total variation in anxiety symptoms ($R2 = 0.748$), and demonstrated the ability to predict hour-to-hour variability in momentary anxiety ($R2 = 0.385$). "Digital biomarkers" is just one example of how passive data collection can improve our understanding of behavioral and emotional disorders as well as treatments.

Ultimately, these data can support precision and data-driven personalization of DMHIs. As digital interventions they can provide interventions with near-perfect fidelity, and when structured as modular interventions, can break down treatment packages to isolate specific treatment components. The future of DMHIs might well involve sequences of interventions, perhaps even micro-intervention care (Baumel, Fleming, & Schueller, 2020). Importantly, however, we need to ensure that the methods for development, evaluation, and implementation do not remain static as the technologies, and as a result, the DMHIs, continue to innovate and advance.

Improving understanding of the effective of digital mental health

As mentioned previously, considerable evidence suggests that DMHIs are effective for various emotional and behavioral disorders (Karyotaki et al., 2021; Pauley et al., 2021). However, it has also been noted that many digital interventions lack supporting evidence (Larsen et al., 2019) and that in some areas, such as mental health apps, evidence only supports a few types of interventions (Goldberg et al., 2022). A major challenge for this field is that the number of products far outstrips the amount of evidence. Even the existence of hundreds of randomized controlled trials fails to be sufficient for the thousands of DMHIs that are available to consumers. Several papers in this special issue specifically investigate the evidence for various forms of DMHIs ranging from single-session online interventions (Dobias, Schleider, Jans, & Fox, 2021) to web-based cognitive-behavioral therapy (CBT, Karyotaki et al., 2022) to a suite of mobile applications (Mohr, Kwasny, Meyerhoff, Graham, & Lattie, 2021). In addition to indicating that DMHIs can be conceptualized quite differently in terms of expectations on the participants, these studies break down some traditional views on the use and benefits of these interventions.

Karyotaki and colleagues (2022) report on a guided transdiagnostic iCBT intervention intended to reduce anxiety and depression in college students. Given the interest in disseminating DMHIs broadly to provide low-threshold resources to those with common mental health issues, such an intervention could be extremely useful in reducing the burden of emotional and behavioral disorders. Unfortunately, in their randomized controlled trial enrolling 100 college students they found no evidence that the iCBT was more effective on symptoms of depression and/or anxiety than treatment as usual which consisted of detailed information about care services in the community. Null findings, such as these, are useful to ensure findings are not oversold and interventions not overextended to populations in which they might be beneficial. It also brings into question the care models that DMHIs can create and whether interventions consisting of seven weekly sessions through a web-based platform makes sense for those with mild to moderate symptoms. A very different intervention model was evaluated by Dobais and colleagues (2021) who created Project SAVE ("Stop Adolescent Violence Everywhere"), an approximately 30-minute self-administered web-based program intended to reduce self-injurious behaviors in youth. The intervention was brief, specific, and intended to be a stand-alone "single-session intervention", i.e., a youth would use the intervention once without returning later. This intervention was trialed among 565 adolescents and found to produce changes in short-term improvements of self-hatred and desire to stop future non-suicidal self-injury (NNSI) behavior but not 3-month outcomes of NSSI and suicidal ideation. Therefore, despite being acceptable and promising in the short-term, translation to more distal outcomes and long-term benefits requires additional consideration of building on promising short-term impacts. Mohr and colleagues (2021) conducted a meta-regression of three separate trials of a suite of app-based DMHIs for the treatment of depression and anxiety. The meta-regression combined 401 participants across these 3 trials that included different deployment settings and recruitment strategies (e.g., via social media or healthcare systems) but were consistent in the app interventions and human support strategy. Investigating whether effectiveness varied by symptom severity, they found that although users improved significantly across all levels of baseline severity, an ordinal pattern existed such that the participants with the lowest symptom severity at baseline experienced the smallest benefits. This contradicts a popular notion that DMHIs might be most appropriate as low-intensity treatments for those with minor impairments or the worried well. Instead, it suggests that DMHIs, when provided alongside human support, can be impactful interventions for those with more severe symptoms.

In sum, papers in this special issue highlight that some areas have clear and converging evidence, whereas other areas represent exciting new venues for DMHI. Clear evidence supports that digital CBT programs work, and that they work for populations with varying levels of symptoms. However, not all interventions might be effective as highlighted by the results from Karyotaki and colleagues (2022). Future efforts should explore the impact of DMHI dosing, and the potential to leverage models like single-session interventions.

Advancing Dissemination through Academic-Industry Partnerships

One appealing nature of DMHIs is the ability to reach those in need at scale. Academic interventions often end at the unit of the scientific publications, and even clinicians in practice can only help those who show up in their therapy offices. Although DMHIs offer to the potential to create new models of dissemination, academic endeavors often end at the unit of the scientific publications. For example, a systematic review of published RCTs of internet-based CBTs for depression found that the majority were not available at all, and only a quarter were available to the public (Buss et al., preprint). Relative to academics or clinicians themselves, industry might be better prepared to pursue impactful models for DMHI dissemination. With growing venture capital investment, industry's impact on the mental healthcare ecosystem has increased. Academic-industry partnerships will play an important role fulfilling DMHI's promise of accessibility.

One of our articles (Ritterband et al., 2022) presents on data from digital insomnia intervention developed through such an academic-industry partnership. SHUTi is the research precursor to the FDA-authorized Somryst, commercialized by Pear Therapeutics. Ritterband and colleagues' (2022) paper presents analyses of a large sample of "all-comer" population of users who purchased access to the SHUTi program. The authors demonstrate that SHUTi produces clinical impacts in real-world deployments consistent with clinical trials. They also report a dose-response effect such that those who completed more SHUTi modules experienced proportionately greater reductions in the Insomnia Severity Index. In addition to opportunities (e.g., large sample size), this paper highlights challenges associated with using naturalistic data from real-world deployments of commercialized interventions, such as potential biases in sample demographics (which were difficult to characterize due to the limited assessment) due to the pay-to-access nature of the intervention, and significant dropout and missing outcome data. Although analyses of naturalistic samples might be represented as counters to RCTs, it is worth thinking about how these are complementary evaluations that are both necessary and relevant to the process of bringing DMHIs to market. In addition to robust evidence demonstrating clinical benefit, products also need feasibility and engagement data to demonstrate that people will actually use them in the real-world, and that when they do, they can use them effectively. DMHIs offer enormous potential to evaluate interventions in context and it is important to note that in-context evaluations are likely necessary to provide the information we need to scale (Mohr, Weingardt, Reddy, & Schueller, 2017).

Advancing 'Tech-quity' in Digital Mental Health

DMHIs present both barriers and opportunities to addressing the needs of traditionally minoritized and underserved communities (Ramos & Chavira, 2019; Schueller et al., 2019; Munoz et al., 2018). Despite similar or higher rates of mental health problems, historically minoritized populations (e.g., people of color, sexual/gender minorities) often experience reduced access to care. Due to their scalability, DMHIs represent a key tool among the broader array of approaches being used to address these issues in minoritized and other underserved communities (e.g., rural and low-income populations)(Schleider et al., 2020; Singla et al., 2017). Unfortunately, the full potential of DMHIs has yet to be achieved, due in part to low engagement resulting from factors like language barriers or poor cultural fit (Borghouts et al., 2021), and reduced accessibility for those with disabilities (Bunyi et al., 2021). Additionally, despite the widespread availability of technologies, technology access is not ubiquitous and such access, at least in the US, often intersects with other factors that have minoritized individuals. A significant digital divide exists leading to challenges in achieving health equity through technologies. Promoting better 'tech-quity' requires considerations at multiple levels to ensure that DMHIs are designed (ideally co-designed), tested, and deployed with diverse populations and groups in mind.

Using data from a clinical trial of group cognitive-behavioral therapy in a sample of low-income, Spanish-speaking adults with depression (Aguilera et al., 2017), Hernandez-Ramos and colleagues (2021) evaluated the context of a daily text-messaging adjunct aimed to increase treatment engagement, adherence, and outcomes. In addition to a message reinforcing clinical content, clients completed ecological momentary assessments describing their mood, cognition, and behavior. The authors performed qualitative content analysis on clients' free text responses, revealing associations between mood and client's experiences with health, friends, religion, positive and negative emotions, dichotomous thinking, and behavioral activation. Their findings demonstrate how content generated by DMHIs can provide insights into the roles of sociocultural factors and core CBT elements in changes in mood among Latinxs.

For the promise of DMHIs to be achieved, increased attention to Diversity, Equity, and Inclusion (DEI) is needed. For example, involving end-users and other stakeholders during the development and adaptation of DMHIs can increase acceptability and reduce barriers to accessibility and effectiveness (Ospina-Pinillos et al., 2020; Perera et al., 2020; Salamanca-Sanabria et al., 2019, 2020). DMHI evaluation frameworks such as One Mind PsyberGuide (Neary & Schueller, 2018), American Psychiatric Association's App Evaluation Framework (Torous et al., 2018; Lagan et al., 2020), and mindApps.org (Lagan et al., 2021) are not only used to evaluate the quality of DMHIs and help determine fit, but they also guide development by identifying important criteria. To determine the extent to which such evaluation efforts capture DEI factors, Ramos and colleagues (2021) conducted a scoping review of app evaluation frameworks, identifying 44 unique frameworks, only 58% of which included at least one DEI criterion. With the goal of improving the effectiveness of DMHIs in marginalized communities and advancing the goals of DEI, the authors provide recommendations for increasing the cultural robustness and clinical utility of existing evaluation frameworks.

The State of Digital Mental Health in Behaviour Research and Therapy

If these papers are meant to act as representatives and exemplars of DMHIs in behaviour research and therapy, then they highlight some important lessons for the field. First, not only do clinical researchers and practitioners need to work outside of their silos by connecting with other areas - human-computer interaction, data science, industry, investing, and policy - as a few examples, but all these fields need to come together to form interdisciplinary and transdisciplinary partnerships. The field of DMHI is owned by no one field specifically and instead the unique expertises, backgrounds, methods, and models, need to come together to make a field that represents and combines all aligned areas. Second, a tension exists between agility and evidence. The current state of mental health service delivery is in serious need of re-design and innovation. Far too many people in need of support go without it and far too few people who receive care receive high-quality care. DMHI has the potential to fix this, but we cannot assume that something is always better than nothing. Indeed, a recent study showed iatrogenic effects of a brief digital intervention for those at risk through suicidal ideation (Simon et al., 2022). This brings us to our last point, we need far better evidence. Many of our studies are based on samples that are too small and too “WEIRD” (Western, educated, industrialized, rich and democratic). As mentioned earlier there is an evidence gap in that although many studies demonstrate that DMHI is effective, most DMHIs available to consumers have not been evaluated. As demonstrated in this issue (i.e., Karyotaki et al., 2022), and elsewhere (i.e., Simon et al., 2022) DMHI does not always work. Models of evaluation that can create knowledge faster and in real-world settings (i.e., Mohr, Cheung, Schueller, Brown, & Duan, 2013; Powell, Neary & Schueller, 2021) are necessary to accelerate translation and monitor DMHIs while deployed and available to consumers.

Nevertheless, these papers demonstrate how far the field has evolved since the early papers published in this journal in the late 1990s. They begin to break down some of the challenges identified before - larger samples, combining multiple studies, addressing diversity, equity, and inclusion, and bringing together clinical scientists with human-computer interaction specialists. Building on and correcting this work can offer a bright potential for the future and the opportunity for the potential of digital mental health to be realized.

Moving Forward - The Future of Digital Mental Health

We would like to close to note a few areas where we had hoped to see more scholarship as that might lead to some suggestions for future directions for DMHI. Although effective DMHIs exist, far too few make it into the hands of those who might benefit from them. The “if you build it, they will come” approach to DMHI has obviously failed as well as the line of thinking that DMHIs are simply technological products that can be acquired and plugged into service systems. Leveraging implementation science to support the clinical integration of DMHIs is a growing area of research (Schueller & Torous, 2020), and we would expect many lessons to be shared from such projects in the coming years. One critical concern though related to implementation is reimbursement and given that the mental health service system is largely built on pay-for service reimbursement models this leaves it an open question of where DMHIs fit in. Indeed, current models of reimbursement have been found to be insufficient for the different ways systems are attempting to use DMHIs or reimburse for current mental health services (Powell, Bowman, & Harbin, 2019). We also expected to see more DMHIs using various technological innovations to create new forms of interventions including chatbots, virtual reality, and augmented reality. The early DMHIs used fairly basic forms of interaction style and in some instances DMHIs have not broken that mode. As we previously suggested, combining expertise across disciplines might help solve some of this, but it will also require validating truly new interventions that are based on understanding from our field but on interactions made possible through technology.

We noted earlier that DMHIs are not meeting their full potential. Yet tackling many of the issues started in this special issue - advanced methods, better understanding of effectiveness (and its limits), partnering with industry, and pursuing ‘tech-quity’ - all provide pathways to advance that potential. We hope these papers are as inspiring to other readers as they were to us, and that the future of the field will be shaped and informed by their learnings. Ultimately, at the end of the day, the value of technology will be whether we can better understand behaviour research and therapies - how they work, who they work for, and how to create better treatments - as well as whether we can move the needle in terms of improving the lives of those who are impacted by behavioral and emotional disorders.

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