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Adapting Evidence-Based Treatments for Digital Technologies: a Critical Review of Functions, Tools, and the Use of Branded Solutions

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Abstract

Purpose of Review We provide a critical review of digital technologies in evidence-based treatments (EBTs) for mental health with a focus on the functions technologies are intended to serve. The review highlights issues related to clarity of purpose, usability, and assumptions related to EBT technology integration, branding, and packaging.

Recent Findings Developers continue to use technology in creative ways, often combining multiple functions to convey existing EBTs or to create new technology-enabled EBTs. Developers have a strong preference for creating and investigating whole-source, branded solutions related to specific EBTs, in comparison to developing or investigating technology tools related to specific components of behavior change, or developing specific clinical protocols that can be delivered via existing technologies.

Summary Default assumptions that new applications are required for each individual EBT, that EBTs are best served by the use of only one technology solution rather than multiple tools, and that an EBT-specific technology product should include or convey all portions of an EBT slow scientific progress and increase risk of usability issues that negatively impact uptake. We contend that a purposeful, functions-based approach should guide the selection, development, and application of technology in support of EBT delivery.

Keywords Evidence-based treatment · eHealth · Digital · Mental health · Mobile applications · Telehealth

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Introduction

Digital technologies have become part of everyday life and have a growing presence in mental health care. While digital technologies can be a useful tool in mental health care, there are several barriers to widespread adoption. The current paper provides a critical review of digital technology use in evidence-based treatments (EBTs) for mental health. The varied possibilities of mental health interventions in the digital age challenge both taxonomy-related review schemas and traditional scientific paradigms related to examining and validating treatment effects. Accordingly, the current review organizes this burgeoning and rapidly changing field by considering the specific functions technology is making possible in EBTs and the intentions of technology integration, rather than organizing by treatment type or technology platform. Indeed, different treatments can use similar technology platforms, and similar technology platforms can be used for different treatments and for vastly different reasons. By focusing on the functions of technology in EBTs, we hope to highlight issues

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related to clarity of purpose and usability, which are the ultimate gatekeepers of technology adoption. We will also discuss the concept of mental health-specific platforms related to particular EBTs, referred to here as "branded" solutions, as compared to tool-based approaches to EBT technology integration, referenced here as "non-branded" solutions.

Branded solutions rely on building new technology products to parallel existing EBTs or to establish new EBTs. This fairly dominant framework to EBT technology integration can be juxtaposed to a tool-based approach, which relies on readily available existing technologies to convey EBT protocols or portions of protocols, strategically. The distinctions between branded and tool-based solutions are rarely addressed head-on in the literature. This has led to under-examined assumptions that new treatment-specific digital tools are necessary to leverage technology for each individual EBT, contributing to both rapid proliferation of mental health applications and much innovation. However, this default mindset also contributes to confusion regarding specification of what the treatment is, what the tool is, and what the product is, as these three constructs merge into one technology-based entity. While there is often good reason to combine these constructs for truly stand-alone and innovative solutions, doing so by default can lead to reinventing the wheel in relation to common functions, importing unnecessary materials into digital formats, or other complicating factors that may impede usability.

Technology Use in Evidence-Based Mental Health Treatments

In considering the impact of digital technologies on mental health care, a number of recent reviews address the complexity and variety of the topic by highlighting examples across a broad range of categorical, technological, and content-oriented dimensions [1, 2]. Some reviews present one organizing taxonomy as a means to categorize all use cases. For example, Neary and Schueller [3•] describe a taxonomy for digital mental health stratified by user level of engagement with professionals, including unsupported self-help, supported self-help with some amount of synchronous or asynchronous provider communication, and fully supportive blended care models used within the context of traditional in-person treatments. Other mental health technology reviews published within the last 3 years narrow the field by focusing on the following: specific types of technologies, e.g., virtual reality [4]; specific treatments, e.g., mindfulness [5]; specific target populations, e.g., university students [6], adolescents [7], or children [8]; specific diagnoses, e.g., depression [9]; or specific modalities of treatment, e.g., serious games [10]. Still other reviews calibrate an even more explicit focus, describing the crossroads of identified technologies and specific interventions, e.g., internet-based treatments for PTSD [11]; mobile device-based applications for childhood anxiety [12]; or clinical videoconferencing-based treatment for anxiety and depression [13]. Indeed, the number of mental health technology reviews published in the last 3 years indicates a rapidly changing and growing field and a commensurate collective desire to organize and make sense of it.

Adapting EBTs for use with digital technologies could mean anything from using technology for implementation of existing treatments to whole paradigm shifts in treatment conception, construction, and delivery. A key distinction is between reformatting EBT materials for replication or partial replication on digital technology platforms (e.g., digital self-monitoring instead of paper-based monitoring), versus actually rethinking treatment dynamics, components, and EBT protocols to specifically leverage the native ecologies of interactive digital platforms (e.g., on-demand crowdsource support). Both frameworks have merit, and the reasons for both are rooted in the core question of why an identified technology is being employed in a specific EBT.

At the outset, this is often a straightforward question. Yet we note that the question of why a technology is being used in a particular EBT is often obscured by the possibilities, parameters, and branding of the technology or product under development. In branded solutions (i.e., technology platforms that are tied to specific EBT protocols or are branded mental health products in and of themselves), sometimes the "why" can be pushed off the canvass, as development teams orient to the technology as *the* framing or driving force in a treatment adaptation, rather than maintaining focus on the core innovation or originally desired behavioral solution. The result is often a product that is more complicated than it needs to be, less usable, and more difficult to test in scientific comparisons due to the inclusion of multiple non-critical components.

Limitations of Technology-Driven Framing: an Illustrative Example

To highlight this framing issue, consider a branded mobile application that will be developed and used in a particular EBT for self-tracking of specific behaviors. The target behavior occurs at multiple times during the course of a day and potentially at random or unpredictable intervals, so a mobile technology with tracking prompts could be a useful tool. This is a simple and elegant solution with a fairly high likelihood of success in service of the EBT. However, a branded solution will rarely stop there. During the planning process, the team—eager to take advantage of all the mobile platform has to offer—loads treatment psychoeducation materials onto the application as well and creates a user interface (UI) to enter in and edit a behavioral hierarchy. During the development process, the investigator gets an idea to deliver motivational messages along with the behavior tracking prompts and to provide informational resources for users in case of a mental health emergency.

In this example, the whole treatment protocol and additional materials end up being on the mobile application, solving a lot of problems that did not exist. There was no identified need for the psychoeducation materials to be in a mobile format; clinicians rarely think: “If only my clients had constant access to my psychoeducation materials this case would have gone better.” Similarly, there were no preliminary user data to test the rationale, benefits, or potential frustrations of constructing, arranging, and editing a behavioral hierarchy on a 2 × 3 in. mobile screen. Nor were there data to inform the urgency, effectiveness, or unintended consequences of conveying emergency numbers in this context, which originally was intended to facilitate tracking of ecologically occurring behaviors. The motivational messaging included with the prompts to track the target behaviors seems like a good idea, but in execution, the extra 3 s they take to read and the extra click required for users to get past the message may actually lead to lower tracking rates, which defeats the initial purpose of using the mobile platform. The result is a “solution” that is much less usable and less effective, with greater opportunities for bugs and a larger footprint than is necessary for bug, beta, usability, and efficacy testing. The process and decisions described in this example are not fanciful or uncommon. We need not include specific citations to make this point, because the vast majority of branded mental health technology products are guilty of at least some of these identified indulgences, including ones we have developed ourselves.

The inclusion of additional, peripheral, and untested functions is more problematic with branded mental health technologies, as opposed to non-branded technologies, and poses particular problems in mobile-oriented platforms. Non-branded solutions and functions, such as video telehealth products or reoccurring daily calendar alerts for self-tracking, are more parsimonious by nature, since they exist to facilitate self- or other communication rather than directly conveying content. Moreover, branded mobile device applications built from scratch to deliver information or be functionally interactive are particularly vulnerable to crowding and usability issues, due to small screens and interface areas [14, 15], ergonomics issues [16], likelihood of interruptions [17], and propensity/risk for user multitasking [18]. Regardless, the tendency to include untested and non-critical features in digital mental health solutions may be the natural consequence of a field coming to terms with the difference between what is possible versus what is effective. It may also likely be the result of a technology industry eager to please its clients in the clinical sciences, helping to create “kitchen sink” solutions rather than providing guided consultation on parsimony, usability, and clarity of purpose [19].

A Functions-Based Review of EBT Digital Technology Development

The remainder of this review focuses on the functions that technology is intended to serve in EBTs. Mention of branded project names is specifically omitted to maintain a discussion geared toward ideas and not products. Moreover, the review is not primarily concerned with effect sizes or validating specific technology functions in EBTs. Although establishing the efficacy of broad strategies is important, whether or not a specific function can be clinically effective depends on many factors native to any one mental health technology project, and is not particularly well-defined by whether the concept or execution was effective in the past with a different context and user interface. Similarly, we are not primarily concerned with parsing out which treatments qualify as EBTs in this rapidly changing landscape. Instead, we identify the functions or intended purposes of technology use in relation to behavioral and cognitive behavioral treatments (CBT) under scientific investigation, focusing on the recent literature in the past 5 years. We limited case example citations to 100 to comply with publication guidelines; thus, cited examples of projects or reviews are not exhaustive within each identified category. Throughout the review, we highlight issues related to purpose and usability.

We identify eight non-mutually exclusive broad categories of basic functions or reasons why technology is being employed in EBTs. Mental health interventions often use digital tools for more than one reason within a given project. Sometimes the combination of functions is critical to the core treatment innovation, other times additional functions are used out of perceived convenience or in attempt to create a product that facilitates all portions of a treatment, whether the need is critical or not. We note that organizing the field by function or purpose creates categories that could be facilitated by several different types of technologies. In contrast to prior reviews, our organization was selected to highlight that the intention or purposes of technology integration, rather than what technological capabilities are possible, should guide design and implementation decisions. Moreover, this approach allows for highlighting which combinations of functions show particular promise in the implementation of EBTs.

Self-Tracking of Subjective Data

Self-monitoring is a highly utilized treatment component across EBTs. The potential benefits of self-monitoring with digital devices are face valid but have also been demonstrated in a range of treatment modalities [20], with recent findings indicating positive usability and clinical effects in diverse settings, from the treatment of eating disorders [21] to the provision of support for those with serious mental illness transitioning from inpatient services [22]. Current developments point to the increased use and benefits of self-monitoring when combined with asynchronous telehealth strategies, which enable automatic sharing of self-tracked data with therapists, to increase support, coaching, teamwork, or accountability [23].

Digital self-tracking can also be used to tailor interventions and deliver specific content or messages based on user input, either with or without ongoing support from clinicians. For example, a tailored behavioral strategy or cognitive reframe could be pushed to a user in response to particular tracked cognitive distortions or during a time of day that responses have indicated is particularly challenging. Recently dubbed "ecological momentary interventions (EMIs)," reviews are generally supportive of subjective user input guiding EMIs, demonstrating measurable effects for depression, anxiety, and stress with effect sizes in the small range [24, 25]. Notably, the majority of EMIs rely on user input and, thus, for the time being are limited by the subjective nature of self-report data [26•].

Objective Data Collection

Digital technology is also playing a role in advancing objective data capture relevant to treatment. Data capture can be broadly subclassified as either user-initiated approaches or passive data approaches. Passively collected objective data in particular can be analyzed and responded to using pattern recognition and prediction techniques.

User-Initiated Data Examples of user-initiated objective data capture include use of smartphone cameras to objectively document EBT homework assignments [27]; mobile audio recordings to document the completion of treatment-related behavioral prompts [28]; and patient video recordings within EMIs and asynchronous treatment modalities [23]. The availability of objective behavioral information will likely lead to continued optimization of and innovation within behavioral EBTs.

Passive Data Collection The use of digital tools to collect passive information is a rapidly growing type of objective data collection. Dubbed "digital phenotyping" [29, 30], passive data collection has been investigated in a wide variety of settings, populations, pathologies, and more recently, treatment models [2]. Many objective inputs are available to characterize behaviors and moods, including a range of factors associated with communications, e.g., phone call activity [31], tweeting activity [32], language content [33], and vocal characteristics [34]; a range of physical movements, e.g., activity levels [35], geographical locations [36], and sleep (see [37]); and a variety of physiological measures facilitated by wearable or smartphone sensors [38–41].

Passive data collection is enabling the development and implementation of a specific type of EMI, dubbed "just-in-time adaptive interventions," which are aimed at providing support, information, messaging, or behavior prompts precisely at moments when users need them or will be open to them [42]. Just-in-time adaptive interventions are in development for a range of health and mental health applications [43] and have the potential to facilitate new paradigms of EBTs for the management of chronic conditions in natural settings. For example, it is now feasible to use smartphones to facilitate automatic and early detection of markers of stability in individuals with bipolar disorder [44, 45] and to facilitate acceptable interventions for symptom management, mood regulation, and medication adherence for those with schizophrenia [46]. Accordingly, with continued development, research, and replication, such functionalities could easily grow into entirely new forms of EBTs. Currently, just-in-time functionality is also helping to optimize established EBTs. For example, geofencing is being used to automatically notify caregivers if their teens exhibiting conduct disorder are in the wrong places at the wrong times and to automatically reward teens for positive behaviors, such as arriving to school or work on time [47•].

Digital technologies are also enabling objective psychophysiological measurement. Wearables and smartphone sensors are being investigated in a wide variety of treatment models for various pathologies in settings outside of treatment rooms [38–40]. A number of applications and firmware solutions have also dramatically decreased the expense, time commitment, and training required to implement reliable and research quality measurement of psychophysiological responses within treatment rooms [20]. Applied psychophysiology is now a common element in PTSD-related randomized controlled trials (RCTs; see [48–52]). Heart rate and electrodermal reactivity to treatment-related stimuli are emerging as high-quality objective markers of EBT treatment response and also as robust indicators of pretreatment prognosis for response to exposure-oriented protocols [53, 54•, 55]. Indeed, greater implementation of objective measurement in EBTs is leading to rapid discovery and potential synergies between distinct research platforms. For example, physiological measures have demonstrated similar prognostic ability in the treatment of OCD with CBT [56] and in the treatment of depression with psychopharmacology [57].

Enhanced Pattern Recognition and Prediction Passive data collection is also facilitating the development of machine learning models intended to perform a variety of tasks relevant to automated treatments, such as risk or symptom identification, decision-making, and behavioral suggestions. For example, natural language processing (NLP) models are being used to identify emotional states via user social media posts with the hopes of improving digitally delivered mental health interventions [58]. The use of passive data in combination with subjective user input is also rendering machine learning models that generate behavioral suggestions for individuals based on what has worked or not worked for that particular individual in the past [59]. As described by Schueller and colleagues [26•] given two behavioral strategies, such as deep breathing or progressive muscle relaxation, the one with evidence of being more helpful for the individual previously would be suggested by the application. Although promising, the efficacious application of these methods in standard mental health EBTs and their ability to solve common problems in EBT delivery or generate meaningful effect sizes is still mostly forthcoming.

Automated Conversations

Dubbed "conversational artificial intelligence," the ability to facilitate meaningful real-time exchange between humans and machines can be a core resource for scaling mental health EBTs with fidelity, improving access to care for particular populations or reducing concerns regarding stigma. These are overlapping, but different uses with different considerations for development. Conversations can be mediated by a variety of user interfaces including simple instant message chatbots, audio-only methods (e.g., Alexa and Siri), or by animated virtual agents. A recent review of conversational artificial intelligence (AI) in mental health [60] indicates low risk, high satisfaction, and notable clinical potential, especially for psychoeducational purposes and to promote adherence to treatments. There is evidence that conversational AI may lead to greater initial emotional self-disclosure in an experimental non-clinical manipulation [61] and that virtual agents can even play a role in delivering exposure therapies [62, 63].

Interestingly, technological capability is not the primary limiting factor in conversational AI. Voice recognition software and AI algorithms are now adequately sophisticated to handle the content of most context-specific conversations, especially therapy-related conversations, which are often goal-directed. The key need is for sufficient data to be collected to support engineering the therapeutic content. The effort and attention to recruit target populations for stepwise data collection and iterative development of specialized conversations are much more limiting resources than the bounds of technology. For example, a recent RCT [64] examined the use of conversational AI in a serious game to facilitate practice of social skills for children with social anxiety [65•]. Based on an exposure-oriented EBT [66], the platform includes a free-roam virtual school and 12 unique virtual characters with different personality traits for users to interact with. Following the EBT protocol, the program provides instruction and opportunities for goal-oriented practice of increasingly difficult social skills across 11 lessons, beginning with introductions and saying one's name (easiest); practicing open-ended questions to keep conversations going, joining conversations, and making tactful social invitations (moderately difficult); and appropriately standing up for oneself (most difficult).

The development team began with basic a priori conversation structures for each exchange. However, AI conversation streams that are based only on a priori guesses of what developers or clinicians think respondents might say will be stilted in all but the most basic contexts. User-oriented development is required to find the dead ends in conversations, improve AI understanding, expand or identify key triggering words and synonyms, discover how to handle unexpected sarcasm or boundary testing, and to ensure the goal that each exchange be retained through the conversation dynamics. Accordingly, the team spent 4 years in the development process improving the platform with interactive conversational data from 650 children and tens of thousands of utterances, before recruiting for a clinical trial. It is possible that machine learning may be used for development of therapeutic conversations in the future to minimize the need for data collection. However, currently, a surprisingly functional product can be rendered only with sufficient dedication, data collection, and iteration.

Immersive Experiences and Stimuli Presentation

Recent reviews of virtual reality (VR) and augmented reality (AR) in mental health treatments indicate positive clinical outcomes superior to waitlist controls and on par with conventional treatment effects [4, 67, 68]. There are many distinct reasons to use VR augmentation strategies in treatment protocols, including to increase emotional engagement in imaginal exposures for PTSD [69–71]; to readily access phobic stimuli not typically available in treatment contexts, e.g., crowded lecture halls [72], heights [73], or spiders [74]; to more easily manipulate body images for treating eating disorders [75]; to safely or easily present stimuli related to cue-induced craving in a variety of alcohol, drug, cigarette, and gambling scenarios (see [76]) or high-calorie food presentations [77]; or to assist those with serious mental health conditions to practice functional social and professional scenarios [78]. Recently, the use of VR in automated treatments that users can engage within their home [62, 72, 73] suggests that VR may also play a role in creating greater access to interactive EBTs. The combination of VR with conversational AI is a particularly attractive strategy for facilitating goal-directed learning and interactions.

Peer-to-Peer Sharing and Crowdsourcing

Peer to peer networking, either through social media outlets or mediated mental health platforms, has the potential to increase social support and augment intervention strategies [79]. Such technologies can facilitate paradigm shifting and disruptive innovations for EBTs, such as the use of crowdsourcing to receive real-time feedback on cognitive distortions as a way to promote reappraisals [80•]. A recent review and meta-analysis of mobile health (mHealth) interventions that utilized peer-to-peer functioning to increase physical activity indicates a potential to increase user engagement in treatment, but did not result in significant effects on primary behavioral outcomes [81]. User data indicated that while some felt motivated by peer comments, others expressed concerns about the usefulness of peer comparisons and appropriateness of content. Recent mental health-specific interventions implementing peer-to-peer networking and messaging for depression [80•] and self-help for bipolar disorder [82] attempt to address this issue by screening peer content prior to posting in order to ensure that comments are appropriately empathetic or content relevant. Of course, the potential or perceived need to mediate peer-to-peer or crowdsourced communications in digital EBTs compromises scalability. Although Morris and colleagues [80•] employed paid screeners, the model under investigation actually proposed to use peer crowdsourcing to screen originally crowdsourced responses. While this is not block chain technology (see [83]), the concept that a digital community has to agree with any one person's proposed contributions as a means of preventing iatrogenic posts or feedback is innovative in the mental health space.

Peer-to-peer networking and crowdsourcing also has the potential to connect providers to each other within the context of dissemination and implementation of specific EBTs [84] and could be operationalized to do so within the context of specific patient cases as well. Accordingly, perhaps as much as any other technology function, crowdsourcing has the potential to change the way EBTs are supervised, disseminated, and delivered. For example, an asynchronous telehealth platform currently under investigation [85•] allows providers to create and assign multimedia behaviorally interactive homework assignments to the mobile devices of patients who are receiving an EBT for childhood OCD [86]. The platform enables providers to operationalize EBTs and EBT homework/psychoeducation by ordering, combining, and mixing the presentation of custom therapist-generated content and stimuli (text, photo, video, audio, etc.) with behavioral requests for patient-side action (text, questions, responses, photo, video, audio, etc.), which automatically get tracked in a HIPAA-compliant system. However, once created, these activities or groups of activities can be shared with other providers to use with their clients. These assignments are searchable by key words, EBT titles, target symptoms, or authors. Thus, rather than giving patients predefined EBT worksheets or paper psychoeducation materials, clinicians can assign behaviorally interactive exercises or interactive psychoeducational video tasks created by expert clinicians and refined through therapist ratings, running dialogs related to each activity, and therapist-sourcing. This type of technology has the potential to be disruptive because it improves patient support and accountability, while also bending consultation models and blending dissemination and implementation for clinicians learning EBTs.

Facilitating Synchronous and Asynchronous Communication

Overall, strong evidence supports the safety and effectiveness of common EBTs for anxiety or depression delivered via synchronous clinical videoconferencing among diverse populations, age ranges, and care settings, with similar outcomes to in-person care and little need to alter protocol delivery or content [13]. In general, the replication of a typical in-person EBT effect size on a clinical videoconferencing platform is no longer scientifically interesting or necessary. Of course, there may always be specific indications for use or diagnoses that require careful investigation of at-distance or in-home care; however, without a compelling reason to think otherwise, a copious amount of evidence indicates that clinical videoconferencing can sufficiently support a typical EBT. What is needed now is a better understanding of how to address broader implementation challenges, such as logistics or client safety reporting and response, rather than more research on replicating a particular EBT protocol for clinical videoconferencing.

Compared to clinical videoconferencing, asynchronous telehealth methods are more heterogeneous and have a wider range of complexity, from incorporating simple text messages into EBT delivery and client engagement strategies [87, 88] to using complex platforms for connecting clients, caregivers, and providers with stored multimedia exchanges (see [89]). Asynchronous telehealth strategies could be used to limit contact time for provider-side efficiency or to increase patient-side support from providers outside of the treatment room. Whether or not one is trying to limit or increase provider contact in relation to a traditional EBT necessarily influences research methods and models, i.e., non-inferiority versus superiority trials [90], and it should also influence the type(s) of technology selected and amount of contact specified for facilitating communication. However, earlier asynchronous telehealth projects were often defined by an opposite strategy; the technology was selected first or early (e.g., a texting intervention or a mobile app intervention). Accordingly, downstream functions and parameters of these projects were necessarily limited and defined by the technology solution. More recently, a variety of blended models often avoid this type of technology tunnel vision by not limiting tools to only one technology medium [3•]. A notable example is a recent case study investigating an asynchronous model supporting youth recovering from psychosis [91]. The authors bring together web content, asynchronous communication with a mental health moderator, peer-social networking, and a chatbot to address specifically identified needs, with tools suited to each task. Notably, the authors also identify two models that inform the project, a psychotherapy model informing the core intervention, but also a theory-driven model specifically related to and driving the delivery of online support and content [92•].

Whether or not the system will ultimately be determined to be usable or effective, we note that the intentionality of tool selection and theory-guided implementation are both positive aspects of this work worth highlighting.

Increasing Engagement, Acceptance, and Entertainment Value of Interventions

The use of serious games and gamification to make interventions more appealing and to leverage gaming elements for enhanced learning is a popular strategy. There can be fairly large differences between serious games, which are interventions packaged within a gaming framework, and gamification, which refers to the inclusion of some gaming elements in an otherwise non-gaming-oriented user interface (UI). For example, the use of points or badges to reinforce completion of content in an online CBT intervention is an example of gamification, whereas going on quests with an avatar that follows a story line would be considered a serious game. Recent evidence suggests that gamification can increase the time children spend using CBT-oriented mental health apps [93]. More generally, the feasibility and clinical potential of gamification and serious games have been demonstrated across several contexts [10]. While data to support clinical efficacy and implementation in any one specific domain is bourgeoning, a recent meta-analysis of serious games for mental health conditions, including 674 participants, revealed significant findings with about a half standard deviation effect compared to no treatment ($g = .55$; [94]). This finding obscures larger effects from individual investigations. Results from a multicenter non-inferiority trial of a CBT-oriented game for adolescent depression offer evidence that participants randomized to the game demonstrated close to a standard deviation improvement as compared to those randomized to treatment as usual who showed no differences [95•], though methodological issues prevent firm conclusions.

Overall, the advancement of both serious games and gamification science has the potential to impact and improve the usability and adoptability of digitally based interventions, perhaps in subtle but effective ways. Common gaming elements such as the use of reinforcing sounds, pleasant colors and movement, challenge tasks, and a mix of immediate and delayed gratification can all be incorporated subtly into almost any digitally mediated intervention to improve user experience, attention, and reinforcement.

Automatically Delivering Treatments

The ability to deliver treatments without the need for a provider is a major goal of many developers. Meta-analyses have demonstrated effect sizes between .77 and .88 standard deviations for a range of self-help computer-delivered treatments [96]. While these effects are not as robust as those of traditional EBTs or of EBTs delivered with some amount of provider contact [1], they are meaningful and have the potential for scaled impact.

Room for improvement in automatically delivered EBTs is also apparent, especially in addressing skeuomorphs and optimizing human/machine interactions for digital contexts. A skeuomorph is an aspect of content or an assumption about treatment dynamics that may be necessary for in-person treatments but not for digital contexts. The classic example of a skeuomorph is a digital camera that makes an audible shutter click [97]. While this example is innocuous and the function was included by developers on purpose for effect, counterproductive skeuomorphs in automated mental health interventions tend to be included by habit or from unexamined assumptions that users will be interacting with the content in a similar fashion to in-person protocols. Such examples include imposing a 50-min session, or weekly sessions, or even including the concept of a session at all in a digital intervention, when users tend to engage in briefer but more frequent interactions with their devices and software applications [98].

Optimization of interventions for digital and mobile contexts has the potential to lead to more usable and likely more effective intervention. For example, weekly CBT often relies on after-the-fact appraisals of thoughts, behaviors, and feelings, but a well-specified and usable mobile application can facilitate behavioral experiments in real time, allowing users to predict outcomes prior to engaging in a behavior and then to assess those predictions immediately after or even during the behavior [99].

Notably, facilitating self-help is only one use for auto-delivered content; in some instances, the impetus may be geared more for ensuring standardized delivery than for improved access to care [100]. Automatically delivered content can help both self-care users and client/therapist duos adhere to protocols with fidelity. Current case use examples include strategies that allow therapists to learn how to employ specific protocols for exposure-oriented care as treatment unfolds [85•, 101].

Meeting Intended Functions With Non-branded Solutions

Several EBTs have been used to explore how aspects of protocols can be delivered using existing digital applications. Integrating non-branded off-the-shelf technology solutions to augment or deploy EBTs can be surprisingly effective and has the advantage of being immediately usable. For example, Bunnell and colleagues [102••] employed a variety of widely available and free mobile apps in the development of a behavioral hierarchy and exposure paradigm for the treatment of selective mutism. The brief protocol includes the use of a candle blowing app to initiate and gamify blowing behaviors, and then moves on to shape child blowing to create audible sounds, louder sounds, verbalizations, words, and question and answer responses using a variety of other non-mental health-specific apps (e.g., decibel meter, vowel sound flash cards, voice recorder). Published data related to the hierarchy and methods [102••, 103••] indicate rapid clinical responses. Anecdotally, although there are no formal dissemination efforts, we have become aware of several practices in geographically diverse regions adopting Bunnell's app-mediated protocol, perhaps specifically because it is accessible and the non-branded technology approach encourages low response-cost adoption.

The telehealth evidence base contains many other examples of providers forming testable protocols around non-mental health-specific technologies. For example, recent investigations explore the use of texting protocols to improve mental health services [104] and behavioral health outcomes [105] for specific populations of adolescents. Overall, however, the literature suggests that the scale of new mental health-specific technology development is far outpacing efforts to maximize use of existing and already highly utilized software products. Accordingly, we note that simply developing more and more patient-facing mental health-specific applications in some ways may be at cross purposes with paradigm shifts necessary to fully take advantage of digital tools in the service of EBTs (see [106]).

Strategies that incorporate non-branded solutions are typically more parsimonious, and hence usable, as they seek to develop protocols that can be implemented by digital tools rather than to develop custom digital tools to convey protocols. The trade-off between usability and customized content should be carefully weighed, as data suggest erring on the side of usability may be prudent. For example, in investigating an industry standard self-report instrument, the System Usability Scale (SUS [107]), in a sample of 500 new technology products, Sauro and colleagues [108•] found a median score of 68 out of 100 (50th percentile); yet, a score of 80 (90th percentile) is representative of the point where users will actually use and recommend a product [108•]. Accordingly, while evidence for the clinical efficacy of technology-assisted mental health products is of primary concern and often lacking [109–111], evidence for the usability of the products is equally important and often under-represented in mental health [112–114]. Although most reviews of mental health technologies include warnings to readers and innovators to carefully consider usability, the scale or importance of the issue is perhaps well-framed by inferences drawn from Sauro and colleagues [108•], namely, that 90% of new technology products are not usable enough to be adopted outside of initial development efforts and samples. Moreover, these data should be understood within the context of EBTs, which are already products with woeful adoption rates. Accordingly, while innovators seek to make EBTs more accessible and more adoptable with technology integration, integrating less than usable technologies into those EBTs may serve as additional barriers.

Measuring and attaining adequate usability on standardized instruments in mental health technology development is becoming more common. For example, recent examinations of treatments for depression using self-monitoring [22], in-person and on-line group intervention [115], and a mobile app with email support [116] have reported laudable SUS scores of between 80 and 86. Yet we note that just as there is a difference between treatment efficacy in controlled trials and treatment effectiveness in disseminated settings, we cannot assume usability ratings in product development research will necessarily convey during implementation. There is also a difference between assessing usability as an outcome of an already-completed product and baking in usability during development via step-wise user-centered design, with attention to content and functionality parsimony [117, 118]. To optimize usability, technology developers and clinical scientists may have to challenge the often ubiquitous assumption that one whole-source technology is ideal for implementation of one treatment.

Conclusions

In examining the recent scientific literature related to digital technologies used in the service of EBTs, we conclude that developers have a strong preference for creating and investigating whole-source, branded technologies related to specific EBTs, rather than developing, using, or investigating technology tools related to specific components of behavior change. Likewise, there is an emphasis on developing technologies to match protocols rather than developing new protocols that could be more easily deployed with technologies. We also note that these trends could be viewed as amounting to a meta-skeuomorphism, as a branded product approach assumes that a specific time-limited treatment follows a specifically derived mental health diagnosis—two concepts that are clearly more relevant to in-person health care utilization than digital contexts.

The branded EBT technology approach belies an inherent understanding of how humans prefer to interact with mobile technologies, e.g., we prefer rapid frequent interactions and simplicity [100]. We use mobile devices for texting, emailing, and calling, but these are not packaged in one all-encompassing communication app; they are packaged as three separate apps, rendered usable due to simplicity. Similarly, we do not use one application to check the weather and also buy a raincoat. Yet in the mental health realm, it is often the case that much more complex activities, such as increasing meta-awareness and changing behaviors in different contexts, are packaged together in one application under one brand name.

This is understandable, since the EBT protocols that the branded technology tools often represent do address all these functions. As noted, this default mindset leads to confusion regarding understanding what is the treatment, what is the tool, and what is the product, as these three constructs merge into one technology-based entity.

Accordingly, the decision to create one branded whole-source technology solution for a specific EBT should be made purposely, depending on the reason for EBT technology use, and not by default. Given estimations that 90% of new technologies fail, in part, due to usability issues, we propose that the simplest and most streamlined solutions are the best. Dismantling branded products and investigating specific tools would allow the EBT technology literature to grow more sequentially, as specific tools, technologies, and apps become validated for specific behavioral outcomes. This could mean breaking down multiple-function branded applications into a series of related but different branded applications [119], developing new behavioral protocols for use with existing non-branded technologies [102••, 103••], or taking care to be selective and parsimonious in how the technology is used, limiting its use to where it provides an advantage within a given EBT [69]. Ultimately, one might expect that more efficient methods than the one-treatment/one-technology mindset may be incentivized by the market. However, tool-based approaches could also be incentivized by institutions, for example, with matching funds for grant-developed behavioral technologies to be applicable to more than one research lab. Or, more directly, funding agencies could incentivize tool-based innovations via requests for proposals to develop and investigate intervention technologies for specific behavior domains rather than diagnoses, not unlike the movement and incentives for research domain criteria (RDoC) frameworks [120].

Another often under-addressed issue in EBT technology development is the identification of specific goals along with the worthwhile or expected compromises related to any particular strategy. For example, if the goal is to use an asynchronous strategy to improve EBT access to difficult to reach, geographically isolated, or stressed populations, then a potential face-valid compromise may be smaller overall effect sizes. If the goal is to make an EBT more convenient for families by offering in-home options, then drop outs or no-shows may increase compared to traditional treatment, as less patient investment required on the front end may select for less bought-in populations being served. Commensurately, if the goal is to provide an automated method for people to treat themselves, then less accuracy in diagnosis and treatment matching may be expected. Or, if the goal is to increase homework compliance via standard text messaging, then there may be a slightly increased—albeit acceptable—information security risk to clients. Our point is that nothing comes for free and the benefits of technology integration in mental health are most often accompanied by compromises, whether they are identified in research designs or not. Of course, higher levels of specification including the identification and measurement of expected compromises in research designs will allow for more rapid advancement and clearer interpretation of outcomes.

This is an exciting time in EBT development and implementation, as the scope of what technology can make possible expands. It is also a potentially hazardous time, as the proliferation of self-help and therapist-assisted technologies complicates the menu of options for individuals and families in need of help. While there is little doubt that cutting-edge technology-enabled methods, such as passive data collection and machine learning, will ultimately add great value to our treatment paradigms, it is also true that many of our more robust EBTs reduce down to relatively simple behavioral changes. In some cases, the trend toward one-source whole treatment technologies may risk violating Occam's razor and complicating otherwise straightforward interventions; in other cases, such products may end up propelling treatments forward. To protect against the former and encourage the latter, we suggest greater attention to tool-based approaches for EBT technology integration wherever possible and practical, and reserving branded whole treatment-based digital technology frameworks only for situations where there are necessary.

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- •• Of major importance

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