4-15-2024

Predictors of Adherence to a Publicly Available Self-Guided Digital Mental Health Intervention

Mercedes G. Woolley
Utah State University

Korena S. Klimczak
Utah State University

Carter H. Davis
Utah State University

Michael E. Levin
Utah State University

Recommended Citation

Woolley, M. G., Klimczak, K. S., Davis, C. H., & Levin, M. E. (2024). Predictors of adherence to a publicly available self-guided digital mental health intervention. *Cognitive Behaviour Therapy*, 1-15. https://doi.org/10.1080/16506073.2024.2341807

Predictors of Adherence to a Publicly Available Self-Guided Digital Mental Health Intervention

Mercedes G. Woolley

Korena S. Klimczak

Carter H. Davis

Michael E. Levin

Department of Psychology

Utah State University

Author for Correspondence:
Mercedes G. Woolley, Utah State University, Department of Psychology, 6430 Old Main Hill, Logan, Utah Mercedes.Woolley@usu.edu

Declarations of Interest: None

Abstract

Low adherence to self-guided digital mental health interventions (DMHIs) have raised concerns about their real-world effectiveness. Naturalistic data from self-guided DMHIs are often not available, hindering our ability to assess adherence among real-world users. This study aimed to analyze three years of user data from the public launch of an empirically supported 12-session self-guided DMHI, to assess overall program adherence rates and explore predictors of adherence. Data from 984 registered users were analyzed. Results showed that only 14.8% of users completed all 12 modules and 68.6% completed less than half of the modules. Users who were younger, had milder depression, had never seen a mental health provider, and who rejected signing-up for weekly program emails completed significantly more modules. Results add to concerns about the generalizability of controlled research on DMHIs due to lower adherence outside of research trials. This study highlights the potential of user data in identifying key factors that may be related to adherence. By examining adherence patterns among different sub-sets of users, we can pinpoint and focus on individuals who may adhere and benefit more from self-guided programs. Findings could also have implications for guiding intervention personalization for individuals who struggle to complete DMHIs.

Predictors of Adherence to a Publicly Available Self-Guided Digital Mental Health Intervention

Over two decades, more than 130 clinical trials have demonstrated the efficacy of DMHIs for anxiety and depression (Moshe et al., 2021; Pauley et al., 2021). As technology advances, DMHIs are becoming increasingly popular for scalable mental health care access. However, for empirically based DMHIs to realize their purpose and enhance treatment availability at the population level, naturalistic user research is essential. Significant gaps exist between research and the public marketplace. There are relatively few DMHIs available to the public that have been directly evaluated in research, compared to the thousands of available websites and mobile app programs which have never been tested in clinical trials (Fleming et al., 2018; Livingston et al., 2019). In general, programs with direct empirical support often do not reach the public market (Martinez-Perez, 2013). While the public dissemination of these tools is crucial, it may be equally important to monitor their usage, as meta-analytic findings from DMHI trials indicate program adherence is consistently related to symptom reduction post-program (Gan et al., 2021). Adherence to DMHIs in trial contexts has been a known challenge (see Forbes et al., 2023), and this problem could be both larger and different when shifting to the naturalistic use settings these programs aim to be deployed to.

Trial data from DMHIs grounded in evidence-based therapies, such as cognitive behavioral therapy and acceptance and commitment therapy (ACT), have shown that program completion rates often fall below 50%, and the majority of trial participants typically do not reach full completion of these programs (Lipschitz et al., 2022; Klimczak et al., 2023). Although there's a paucity of published data on the naturalistic usage of DMHIs, emerging concerns highlight the variable impact and adherence to self-help programs outside of controlled trial environments (Baumel et al., 2019). These insights particularly underscore the possibility that adherence rates may be markedly lower in naturalistic environments. Participants in a trial may benefit from assessment effects or face-to-face contact, which may be especially helpful for adherence and treatment success with unguided interventions. Additional researcher contact can increase adherence to online programs through processes such as those identified in the supportive accountability model (see Mohr et al., 2011). In addition, participants who successfully enroll in trials likely represent a subsample of individuals who will be more adherent to an online intervention, raising the question of whether results from samples in controlled trials generalize to the broader population online interventions aim to reach. A novel study by Baumel et al. 2019 leveraged aggregated user traffic data from ten online self-help websites to compare the extent of program use from clinical trial research of online self-help websites to data collected on the naturalistic use of the same programs. For programs involving contact, results showed adherence rates reported in published studies were just over four times higher than real-world usage of the same program, indicating a potential trial bias. Indeed, the emerging data on real-world use of DMHIs has shown that adherence is variable, with a few studies revealing that 21% to 88% of real-world users complete one program module or sign into the program at least once, and nearly half of users only complete between 40% and 60% of the program (Flemming et al., 2018). Adherence to DMHIs can be considered one aspect of dedicated engagement with the program (Perski et al., 2017), allowing users to derive benefits from newly acquired psychotherapeutic skills. The marked deficiencies in adherence to publicly available DMHIs therefore poses a significant barrier to the successful implementation of these services at the public health level.

Attempting to make sense of DMHI adherence issues, some researchers have opted to analyze trial data to identify predictors of adherence. For instance, a study on mobile mental health services found smartphone experience improved adherence, while higher depression led to lower adherence (Buck et al., 2020). Another study found older age, being a woman, experiencing barriers to mental health services, and concurrent therapy all predicted higher completion of an adjustment disorder intervention (Kazlauskas et al., 2020). However, predictors of adherence to DMHIs have varied across studies deeming this information potentially less useful (e.g., younger age was a predictor in one study and older age in another; Yeager & Benight, 2018). These mixed findings may be in part due to differences in types of DMHIs, such as those based in cognitive behavior therapy versus dialectical behavior therapy, and the target audience (e.g., users with depression vs. obsessive-compulsive disorder), as documented in the diverse DMHI literature (see Balcombe & De Leo, 2022 for a review). Thus, investigating predictors of adherence is still an important pursuit. Such predictors may be more specific to different types of DMHIs, offering opportunities for DMHI providers to personalize their interventions based on user characteristics. Moreover, trial-based adherence insights might differ for any one DMHI in real-world scenarios (Baumel et al., 2019). Therefore, examining adherence among real-world users is critical given the significantly lower adherence rates found in publicly available programs. Additionally, examining predictors of adherence is needed in bringing to light adherence challenges across contexts.

Current Study

This study sought to help bridge this research-to-practice gap by examining user adherence rates and predictors of adherence within a real-world sample using a publicly available self-guided DMHI. Three years of program engagement data, with a total of 984 users, was examined from a publicly available program called Acceptance and Commitment Therapy (ACT) Guide. This study aims to (a) assess rates of user adherence to ACT Guide and (b) examine how user characteristics (sociodemographic and clinical) predict program use. This information will provide insights into potential differences across users, identifying those more or less likely to engage in publicly available DMHIs.

Method

Participants

The present study examined naturalistic data from the publicly available ACT Guide program. The program was primarily marketed through ACT research and therapist outlets (e.g., ACT for professional listserv, ACT resource lists, presentations to providers, word of mouth recommendations), and to the public more broadly through Utah State University's (USU) community outreach efforts (e.g., USU Extension, USU Sorenson Center for Clinical Excellence), as well as search-engine results. Three years of registration and program data were analyzed (10/16/2019 to 9/27/2022). All data in ACT Guide originated from program users who were at least 18 years of age and able to read English. Users who did not complete registration and duplicate signups from the same user were removed, yielding a total sample of 984 individuals who registered for ACT Guide over the three-year period. This excluded 32 users who had paid for the program but did not sign-up.

Procedures

To gain access to the program, users paid $10 for six months of access. After payment, users were directed to the program registration. Users were prompted to review and agree to a Privacy Policy, in which they agreed to their data being used for purposes including research. Demographic information including age, gender, race, and state or country of residence were collected from all users at the time of program registration. For summary purposes, home country was coded into continental categories. At the time of registration, participants were asked a series of questions regarding their history using mental health services, and whether they would like to sign up for one-month of weekly email tips about using ACT Guide. Email tips were added in September 2020 in an effort to increase program adherence; thus, 410 (41.7%) users were not asked this question. At the completion of registration, users were automatically directed to sign into and begin the program.

Self-guided Digital Program

ACT Guide (https://actguide.usu.edu/) is one of the few empirically supported self-guided digital ACT services currently available to the public. ACT Guide teaches core ACT skills (Hayes et al., 2006), which aim to increase quality of life for individuals struggling with a wide range of mental health challenges by promoting psychological flexibility. ACT Guide is based on over a decade of research from our team iteratively developing, testing, and refining digital ACT modules (Levin et al., 2016, 2017, 2020). Thus, ACT Guide is designed for a transdiagnostic population, with a series of modules broadly applicable to a range of mental health concerns.

The program is comprised of 14 modules, with 12 core modules and a welcome (e.g., orientation) and exit module. Each of the core module takes approximately 30 minutes to complete, and users are encouraged to complete one or two modules per week, thus providing 3-4 months of content for users who follow this pace. Users can navigate from session to session as desired but are recommended to complete the sessions in a linear fashion. The intervention was delivered through Qualtrics as an efficient way to develop and deploy interactive, tailored digital content.

Measures

Program Adherence

Program adherence was operationalized as the number of program modules users completed, ranging from 0-12. While the program is comprised of 14 total modules, including a welcome and exit module, these modules did not count towards adherence because they are short and not intended as stand-alone sessions teaching substantive skills. Module completion is recorded automatically in the Qualtrics platform. This data was used to determine whether participants reached the end of a module. If Qualtrics data showed a participant reaching at least 95% of a module, the module was recorded as completed. Full program completion was operationalized as completion of all 12 core modules. Users who registered but either never logged into the program, or logged in but did not complete any modules, were considered to have completed 0 modules and were still included in all analyses.

User Reported Anxiety and Depression

Self-reported anxiety and depression was assessed early on in the first program module using the anxiety and depression subscales of the Patient-Reported Outcomes Measurement Information System – Emotional Distress (PROMIS; Cella et al., 2007). PROMIS-Depression (4-items) and PROMIS-Anxiety (4-items) were administered during the first module of ACT Guide, in the “Welcome” session. Each item asked participants to rate their emotional experiences over the past 7 days on a scale from 1 (*never*) to 5 (*always*). Raw score totals are converted to T-scores. A T-score of 50 is the average for the United States general population with a standard deviation (SD) of 10.

Data Analysis

Statistical analyses were conducted with R (v 4.3.0; R Core Team, 2023) in RStudio (v 2023.03.1; Posit team, 2023). The R script for the present analyses is available online at https://osf.io/zh8f9/?view_only=03a223944eca4b6fa0dcfafafc1fa966. Descriptive statistics on demographic and clinically relevant information provided by program registrants were examined to characterize the sample. Additionally, descriptive statistics on program usage (i.e., login attempts and module completion) were used to assess program adherence as a whole. Finally, regression-based analyses were conducted to identify user characteristics as predictors of module completion. We took a pairwise deletion approach to missing data, in which participants who were missing data necessary to run any given analysis were excluded for that specific analysis.

Given that number of modules completed is count data and appears to approximately follow a Poisson distribution in our dataset, we decided to run Poisson regression models. Analyses were conducted in a univariate fashion, in which a separate model with number of core modules completed as the outcome was run for each predictor, including gender, age, race, treatment status, and whether they enrolled in weekly email tips. Regarding the race model, American Indians/Alaska Natives and Native Hawaiians/Pacific Islanders were excluded from these analyses given there was a sample size of less than 5 for each. An additional model was run where depression and anxiety were both included as predictors in the same model, given that these two variables are highly associated with one another. We ran predictors in separate models as opposed to a single multiple regression model so that each user characteristic could be assessed individually, without using other variables as controls. We checked for potential model over or underdispersion (e.g., variance is below or greater than the mean) using the dispersiontest function from the AER package (Kleiber & Zeileis, 2008). All models were significantly overdispersed ($p < .05$ for all models), with dispersion values ranging from 3.92 to 4.33. This violates the Poisson regression assumption that the outcome mean is equal to the variance. Thus, models were re-run using negative binomial regression (Ver Hoef & Boveng, 2007) using the glm.nb() function from the MASS package (Venables & Ripley, 2022). Pseudo R^2 values were calculated for each model using the Nagelkerke index (a corrected version of the Cox & Snell index), using the RsqGLM() function from the modEvA package (Márcia Barbosa et al., 2013). To prevent family-wise error, all P-values were corrected using the Benjamini-Hochberg procedure for each of these sets of analyses.

Results

Demographic Characteristics

Table 1 displays sample characteristics. Those who signed-up for ACT Guide primarily identified as White (81.9%), and as a Woman (69.5%). The mean age for registrants was 36.6 (*SD* = 13.5), however the modal age was 23. A total of 83.5% of registrants reported living in the North America. For those located in the United States 39.5% reported living in Utah, which is where the university affiliated with the development of ACT Guide is located. Of the users who were asked about receiving email tips, 70% agreed to receive the weekly email tips. Regarding treatment status, 35.2% of registrants were working with a mental health professional at the time of sign-up, 5.1% had recently stopped working with a mental health professional, 33.9% had worked with a mental health professional at some point in the past but not currently, and 25.8% had never worked with a mental health professional.

Clinical Characteristics

With respect to mental health symptoms, only 65% of users had the opportunity to report depression and anxiety scores as the rest of the sample either never logged-in to the program after registering, did not progress far enough to encounter these items, or skipped the welcome module that contained these items. Of these users, 10% opted not to complete the depression and anxiety measures. Among the users who reported mental health symptoms, the mean raw score on the PROMIS-Depression was 10.8 (*SD* = 3.9; T-Score = 60.50, *SE* = 2.3), indicating that on average, users had moderate levels of depression. The mean raw score on the PROMIS-Anxiety was 12 (*SD* = 3.6; T-Score = 63.3, *SE* = 2.6), suggesting that on average users had moderate levels of anxiety. Descriptive statistics for each PROMIS-Depression and -Anxiety cut point can be found in Table 3.

Program Adherence

Of the 984 program registrants, 875 logged into ACT Guide at least once, meaning that 11.1% of users never used the program despite completing registration. Another 20.6% of users logged in at least once but did not complete any of the twelve core modules. A total of 68.3% of users completed at least one of the core modules, and approximately 31.4% completed at least half of the core modules. Only 14.8% completed all twelve core modules. On average, users completed 4.1 modules (*SD* = 4.5; *median* = 2). See Figure 1 for a histogram of the number of modules completed by users.

Predictors of Program Adherence

Negative binomial regressions are displayed in Table 2. Users who had never seen a mental health provider completed significantly more modules (*M* = 5.1, *SD* = 4.7) than those who had seen a mental health provider in the past (*M* = 3.6, *SD* = 4.4) and those who were seeing a mental health provider at the time of registration (*M* = 3.4, *SD* = 4). Specifically, users who saw a mental health provider in the past completed 30% fewer modules compared to users who had never seen a mental health provider ($p = .005$), while users currently working with a mental health provider completed 37% fewer modules ($p < .001$). Users who declined weekly email tips completed significantly more modules (*M* = 6.4, *SD* = 4.9) than those who opted to receive weekly emails tips (*M* = 3.5, *SD* = 4.1) and those who signed up before the feature was offered (*M* = 3.9, *SD* = 4.4). Specifically, those who signed-up for email tips completed 46% fewer modules than users who declined email tips ($p < .001$), and users who were not offered the weekly email tips completed 39% fewer modules ($p < .001$). Additionally, being younger in age ($p < .001$) and reporting fewer depressive symptoms (p=.001) significantly predicted greater module completion. Women completed more modules (*M* = 4.4, *SD* = 4.6) than men (*M* = 3.5, *SD* = 4.1), with men completing 19% fewer modules than women, however this effect was only trending towards significance (p = .056). Identifying as a non-binary gender, racial identity, having recently stopped working with a mental health provider, and level of anxiety at registration had no significant effect on number of modules completed (all $p > .05$).

Discussion

The present study sought to bridge the research-to-practice gap with understanding adherence to DMHIs by analyzing three years of user data from a publicly available program. Findings highlighted low adherence to the publicly available program as well as user characteristics that predicted higher adherence such as being younger, reporting lower depression, and having no past mental health treatment. To our knowledge, this is one of the first studies to leverage naturalistic data on user demographics and clinical characteristics to examine predictors of adherence in a DMHI. We discuss how our findings align with the broader digital health literature, and implications for intervention design.

Our results replicated previous findings that adherence to DMHIs among real-world users is notably low (Baumel et al., 2019). Almost one-third of users did not complete any of the twelve sessions, while another third completed at least half the program, and only 15%

completed the full program. The observed adherence levels echo findings from other naturalistic studies of DMHIs (see Fleming et al., 2018), yet they fall short of the higher adherence rates seen in versions of the ACT Guide during clinical trials, where module completion ranged from 25-78% (Ong et al., 2023; Levin et al., 2020). This discrepancy confirms broader concerns about the generalizability of DMHI clinical trial results.

Approximately one-tenth of users signed up for the program, but never logged-in. This is somewhat surprising given the associated program cost. For some users, the small $10 fee might not have justified the commitment required. Higher sign-up cost could potentially boost perceived value, encouraging higher completion (Hilvert-Bruce et al., 2012). While program should still consider cost in relation to accessibility, future programs might raise sign-up costs to improve adherence rates.

The majority of users did not complete even half of the program, and many stopped using ACT Guide after the first few sessions, likely for a number of reasons that we were unable to investigate within the available data (e.g., low motivation and program dissatisfaction). User “drop-offs” in the current sample are similar to attrition rates after the first session of therapy (Swift & Greenberg, 2012; Simon et al., 2012), and studies suggests reasons for discontinuation are not always negative (e.g., clients felt like they ‘got-what-they-needed’ from treatment; O’Keeffe et al., 2019). Similarly, DMHI users may have positive reasons to disengage early, such as feeling satisfied with their improvement (i.e., a reduction of symptoms) or choosing to seek in-person services. Future studies should assess symptoms longitudinally to better assess discontinuation relative to symptom improvement or worsening, in addition to querying users about their reasons for discontinuation.

The majority of users signing up for the program were women (69.5%), who on average completed more modules than men, which is consistent with prior findings from DMHI clinical trials (e.g., Kazlauskas et al., 2020) and psychotherapy use more broadly (Albizu-Garcia et al., 2001). Even though we found that differences between adherence in men and women were only trending toward significance, this finding suggest a potential need to tailor programs towards a male audience. Similar to recommendations for gender-based customization for face-to-face psychotherapy (see Seidler et al., 2018 for a review), DMHIs might also emphasize content consistent with masculine socialization (e.g., male oriented treatment goals and metaphors).

Younger age significantly predicted adherence, possibly due to younger generations' familiarity with online interfaces which may help promote trust and willingness to use DMHIs. A step towards improving adherence across age groups might involve assessing the level assistance users require, then tailoring support features to meet users' unique needs (Pyvell et al., 2020).

Surprisingly, users without prior treatment completed more modules than those with treatment history, despite the expectation that individuals without prior mental health treatment might face ambivalence or struggle to learn new skills without therapist guidance.
This finding is encouraging, suggesting possibly strong motivation in those new to mental health services (Mojtabai et al., 2011). As a clinical application, self-guided DMHIs could function as part of a stepped-care model in which symptoms are either improved through a low intensity treatment or a more intensive treatment depending on client needs (van Straten, 2015).

ACT Guide appears to be reaching users with significant depression and anxiety symptoms. However, greater depression symptoms predicted lower adherence. With ACT Guide being entirely unguided, it is quite possible depression interfered with an ability to adhere to the program. Thus, individuals with elevated depression may ideally benefit from a higher level of care than self-guided DMHIs, such as therapist-assisted DMHIs. Alternatively, self-guided DMHIs could be tailored for users with elevated depression, such as incorporating more behavior activation techniques early (e.g., Krämer et al., 2022). Nevertheless, participants with elevated levels of depression may still benefit from unassisted DMHI use as has been documented in trial outcomes (Moshe et al., 2021). Moreover, although our findings align with multiple studies where greater depression predicts lower program adherence (e.g., Morgan et al., 2017), this relationship has not been consistently found in other studies. For instance, Fuhr et al., (2017) found greater depression predicted increased program use. Still, acknowledging that the conditions of clinical trials may not mirror the complexities of real-world use, it is vital to assess the robustness of these findings in naturalistic settings moving forward to optimally support public users with elevated depression.

The option to receive email reminders was added to ACT Guide in an attempt to increase program use. Surprisingly, those who opted out of weekly tips demonstrated significantly higher program adherence, contradicting prior research that suggests automated reminders help enhance adherence (e.g., Linardon & Fuller-Tyszkiewicz, 2020; Zarski et al., 2016). Perhaps among real-world DMHI users, opting out of reminders may reflect self-selection in which a subset of individuals felt capable of completing the program without external prompts, which appears accurate given their higher adherence rates.

Variability in adherence rates may be due in part to some individuals simply being a better fit for self-guided DMHIs (reflected in an ability to complete and benefit from these programs (irrespective of human contact and reminders), while others may not be well-suited (reflected in very low adherence). More research is needed in identifying individuals for whom self-guided DMHIs are well-suited for. In contrast, research is also needed to identifying individuals who DMHIs are well-suited for with relevant supports versus who might simply not be well-suited for DMHIs and would benefit from being referred to other services.

Findings should be interpreted with some considerations. First, poor adherence to DMHIs does not necessarily imply that the intervention had no impact. The “good enough level effect” suggests that participants may terminate therapy early when they begin to feel better (Owen et al., 2016), and it is plausible that this effect is also being observed in DMHIs. Indeed, a recent study highlighted sudden gains in DMHIs may be common, with as many as 51% of DMHI trial participants with social anxiety experiencing rapid symptom reduction in the first few weeks of program use (Threw et al., 2023) The reality that some users may terminate program use following early symptom reduction calls into question the importance of sustained program adherence. A fruitful area of future research will be to assess this phenomenon by tracking symptom change and reason for discontinuation among real-world DMHI users. This includes following up with users who signed up for the program but never logged in. It is currently unclear as to whether these users failed to start the program on account of low motivation, engagement, or interest in the program, or if signing up for the program improved mental health and engagement with other aspects of life (e.g., behavioral activation) and thus they no longer perceived a need or had time for the program. This study defined adherence as completing all 12 modules, but it is reasonable to assume a fewer number of sessions would be adequate to produce positive benefits and it is unclear if all 12 sessions are needed to gain maximal benefits. Future research is needed to better understand the adequate dosage of adherence for ACT Guide and similar ACT DMHIs as well as experimenting with briefer interventions that more efficiently teach ACT skills across fewer modules.

We must also consider that sustained adherence does not guarantee effectiveness (see Gan et al., 2021), potentially because actual engagement with the DMHI content in a meaningful way may lead to vastly different treatment effects than simple adherence (i.e., simply completing the program modules). Current conceptualizations of DMHI engagement suggest that it is a multifaceted construct involving not only program adherence but frequency and duration of use and user perceptions, interest and attention (Perski et al., 2017). While attention to variables of engagement is outside of the scope of the current study, this work is critically needed to improve the impact of DMHIs among real-world users. Finally, within DMHI trial literature there are inconsistencies across demographic and clinical predictors of adherence and engagement. Instead, a shift towards an examination of theoretically grounded psychological predictors, such as self-efficacy and motivation may provide additional insights (see Yeager & Benight, 2018 for a discussion). However, collecting such nuanced information may pose pragmatic challenges within real-world samples since these programs are frequently disseminated to the public without the primary goal of conducting research. Mitigating this necessitates a paradigm shift among providers of DMHIs to embed these data sources into publicly accessible programs. Embedding data sources to monitor symptoms during program use also poses a similar practical challenge, but it is still necessary to monitor the effects of DMHIs relative to program adherence. The absence of multiple assessment points to monitor gains is another limitation of the present study, and future work should involve efforts to embed these outcome measures.

Additionally, due to anxiety and depression scales being administered in the initial welcome module of the program, versus at initial signup, we were missing this data from approximately 41% of users. These users either did not log into ACT Guide, did not advance far enough to see these measures, skipped the welcome module in favor of proceeding directly to other sessions, or simply chose not to complete the measures when the opportunity was presented. As a result, the depression and anxiety levels reported for the sample may be an incomplete portrayal of the sample as a whole, only representing users who were engaged enough to start the program and use it for at least 5-10 minutes. Prior literature has found that higher anxiety and depression is associated with lower DMHI uptake (Cross et al., 2022), thus these mental health variables are likely biased towards higher values in our own study. Our findings that depression predicts poorer program adherence and anxiety is not a significant predictor should be interpreted cautiously given this bias. Future studies of real-world DMHI implementation should administer mental health scales earlier in the program (i.e., during program registration) to more fully assess clinical characteristics and their relationship to adherence.

Other limitations mainly relate to generalizability minoritized populations and other DMHIs. Results showed that neither race nor identifying as gender-nonbinary influenced program adherence. However, these results are very limited given that gender minorities and racial diversity were poorly represented. Further research necessitates specialized recruitment strategies to adequately explore the utilization and impact of DMHIs within gender minorities and marginalized racial identities. The program seems to have mainly reached users within North America, with approximately 40% of United States users residing in Utah, a historically homogenized state. However, this may be expected given that the program was developed at a public university in Utah, and many of our marketing strategies are targeted towards the local community. Additionally, program satisfaction was only measured in the final module of ACT Guide and thus could not be formally assessed in the present study, leaving the study’s generalizability to other DMHIs unclear. However, earlier iterations of the program have demonstrated adequate program satisfaction and usability (Levin et al., 2020), and we anticipate that satisfaction would be similar for the version of ACT Guide reported here given high overlap in structure, content, and design of the program.

Findings from the current study ultimately reaffirm the persistent challenge of sustaining user adherence to DMHIs when implemented in real-world contexts. Importantly, our findings also offer valuable insights into the relationship between users' characteristics and adherence patterns, emphasizing the need for targeted interventions and individualized approaches to address the diverse needs of users. Finally, given that some of the current findings on factors promoting adherence differ from those found in clinical trials (e.g., the effectiveness of reminders) this study highlights a need for more research on adherence to publicly available DMHIs.

References

Albizu-Garcia, C. E., Alegría, M., Freeman, D., & Vera, M. (2001). Gender and health services use for a mental health problem. *Social science & medicine (1982)*, *53*(7), 865–878. https://doi.org/10.1016/s0277-9536(00)00380-4

Baumel, A., Edan, S., & Kane, J. M. (2019). Is there a trial bias impacting user engagement with unguided e-mental health interventions? A systematic comparison of published reports and real-world usage of the same programs. *Translational Behavioral Medicine*, ibz147. https://doi.org/10.1093/tbm/ibz147

Balcombe, L., & de Leo, D. (2023). Evaluation of the Use of Digital Mental Health Platforms and Interventions: Scoping Review. In *International Journal of Environmental Research and Public Health* (Vol. 20, Issue 1). MDPI. https://doi.org/10.3390/ijerph20010362

Buck, B., Chander, A., & Ben-Zeev, D. (2020). Clinical and demographic predictors of engagement in mobile health vs. clinic-based interventions for serious mental illness. *Journal of Behavioral and Cognitive Therapy*, *30*(1), 3-11. https://doi.org/10.1016/j.jbct.2020.03.004

Cella, D., Choi, S. W., Condon, D. M., Schalet, B., Hays, R. D., Rothrock, N. E., Yount, S., Cook, K. F., Gershon, R. C., Amtmann, D., DeWalt, D. A., Pilkonis, P. A., Stone, A. A., Weinfurt, K., & Reeve, B. B. (2019). PROMIS® adult health profiles: Efficient short-form measures of seven health domains. *Value in health, 22*(5), 537-544. https://doi.org/10.1016/j.jval.2019.02.004

Christensen, H., Griffiths, K. M., & Farrer, L. (2009). Adherence in internet interventions for anxiety and depression. *Journal of medical Internet research*, *11*(2), e13. https://doi.org/10.2196/jmir.1194

Coxe, S., West, S. G., & Aiken, L. S. (2009). The analysis of count data: A gentle introduction to Poisson regression and its alternatives. *Journal of Personality Assessment, 91*(2), 121-136. https:/ /doi.org/10.1080/00223890802634175

Cross, S. P., Karin, E., Staples, L. G., Bisby, M. A., Ryan, K., Duke, G., Nielssen, O., Kayrouz, R., Fisher, A., Dear, B. F., & Titov, N. (2022). Factors associated with treatment uptake, completion, and subsequent symptom improvement in a national digital mental health service. *Internet Interventions, 27*, 100506. https://doi.org/10.1016/j.invent.2022.100506

Fleming, T., Bavin, L., Lucassen, M., Stasiak, K., Hopkins, S., & Merry, S. (2018). Beyond the Trial: Systematic Review of Real-World Uptake and Engagement With Digital Self-Help Interventions for Depression, Low Mood, or Anxiety. *Journal of medical Internet research*, *20*(6), e199. https://doi.org/10.2196/jmir.9275

Forbes, A., Keleher, M. R., Venditto, M., & DiBiasi, F. (2023). Assessing patient adherence to and engagement with digital interventions for depression in clinical trials: Systematic Literature Review. *Journal of Medical Internet Research*, *25*. https://doi.org/10.2196/43727

Gan, D. Z. Q., McGillivray, L., Han, J., Christensen, H., & Torok, M. (2021). Effect of Engagement With Digital Interventions on Mental Health Outcomes: A Systematic Review and Meta-Analysis. *Frontiers in digital health*, *3*, 764079. https://doi.org/10.3389/fdgth.2021.764079

Hayes, S. C., Luoma, J. B., Bond, F. W., Masuda, A., & Lillis, J. (2006). Acceptance and commitment therapy: Model, processes and outcomes. *Behaviour research and therapy*, *44*(1), 1-25. https://doi.org/10.1016/j.brat.2005.06.006

Hilvert-Bruce, Z., Rossouw, P. J., Wong, N., Sunderland, M., & Andrews, G. (2012). Adherence as a determinant of effectiveness of internet cognitive behavioural therapy for anxiety and depressive disorders. *Behaviour research and therapy*, *50*(7-8), 463–468. https://doi.org/10.1016/j.brat.2012.04.001

Kazlauskas, E., Eimontas, J., Olff, M., Zelviene, P., & Andersson, G. (2020). Adherence xPredictors in Internet-Delivered Self-Help Intervention for Life Stressors-Related Adjustment Disorder. *Frontiers in Psychiatry*, *11*. https://doi.org/10.3389/fpsyt.2020.00137

Kleiber, C. & Zeileis, A. (2008). *Applied Econometrics with R.* New York: Springer-Verlag. https://CRAN.R-project.org/package=AER

Klimczak, K. S., San Miguel, G. G., Mukasa, M. N., Twohig, M. P., & Levin, M. E. (2023). A systematic review and meta-analysis of self-guided online acceptance and commitment therapy as a transdiagnostic self-help intervention. *Cognitive behaviour therapy*, *52*(3), 269–294. https://doi.org/10.1080/16506073.2023.2178498

Krämer, L. V., Mueller-Weinitschke, C., Zeiss, T., Baumeister, H., Ebert, D. D., & Bengel, J. (2022). Effectiveness of a web-based behavioural activation intervention for individuals with depression based on the Health Action Process Approach: protocol for a randomised controlled trial with a 6-month follow-up. *BMJ open*, *12*(1), e054775. https://doi.org/10.1136/bmjopen-2021-054775

Levin, M. E., Haeger, J. A., Pierce, B. G., & Twohig, M. P. (2017). Web-based acceptance and commitment therapy for mental health problems in college students: A randomized controlled trial. *Behavior Modification*, *41*(1), 141–162. https://doi.org/10.1177/0145445516659645

Levin, M. E., Hayes, S. C., Pistorello, J., & Seeley, J. R. (2016). Web-based self-help for preventing mental health problems in universities: Comparing acceptance and commitment training to mental health education. *Journal of Clinical Psychology*, *72*(3), 207–225. https://doi.org/10.1002/jclp.22254

Levin, M.E., Krafft, J., Hicks, E.T., Pierce, B. & Twohig, M.P. (2020). A randomized dismantling trial of the open and engaged components of acceptance and commitment therapy in an online self-help program for distressed college students. *Behaviour Research & Therapy, 126,* 103557. https://doi.org/10.1016/j.brat.2020.103557

Linardon, J., & Fuller-Tyszkiewicz, M. (2020). Attrition and adherence in smartphone-delivered interventions for mental health problems: A systematic and meta-analytic review. *Journal of Consulting and Clinical Psychology, 88*(1), 1–13. https://doi.org/10.1037/ccp0000459

Lipschitz, J. M., Van Boxtel, R., Torous, J., Firth, J., Lebovitz, J. G., Burdick, K. E., & Hogan, T. P. (2022). Digital Mental Health Interventions for Depression: Scoping Review of User Engagement. *Journal of medical Internet research*, *24*(10), e39204. https://doi.org/10.2196/39204

Livingston, N. A., Shingleton, R., Heilman, M. E., & Brief, D. (2019). Self-help smartphone applications for alcohol use, PTSD, anxiety, and depression: addressing the new research-practice gap. *Journal of Technology in Behavioral Science*, *4*, 139-151. https://doi.org/10.1007/s41347-019-00099-6

Márcia Barbosa, A., Real, R., Muñoz, A. -Román, & Brown, J. A. (2013). New measures for assessing model equilibrium and prediction mismatch in species distribution models. *Diversity and Distributions, 19*(10), 1333–1338. https://doi.org/10.1111/ddi.12100

Martínez-Pérez, B., de la Torre-Díez, I., & López-Coronado, M. (2013). Mobile health applications for the most prevalent conditions by the World Health Organization: review and analysis. *Journal of medical Internet research*, *15*(6), e120. https://doi.org/10.2196/jmir.2600

Mohr, D. C., Cuijpers, P., & Lehman, K. (2011). Supportive accountability: a model for providing human support to enhance adherence to eHealth interventions. *Journal of medical Internet research*, *13*(1), e30. https://doi.org/10.2196/jmir.1602

Mojtabai, R., Olfson, M., Sampson, N. A., Jin, R., Druss, B., Wang, P. S., Wells, K. B., Pincus, H. A., & Kessler, R. C. (2010). Barriers to mental health treatment: Results from the National Comorbidity Survey Replication. *Psychological Medicine*, *41*(8), 1751–1761. https://doi.org/10.1017/s0033291710002291

Morgan, C., Mason, E., Newby, J. M., Mahoney, A. E. J., Hobbs, M. J., McAloon, J., & Andrews, G. (2017). The effectiveness of unguided internet cognitive behavioural therapy for mixed anxiety and depression. *Internet Interventions*, *10*, 47–53. https://doi.org/10.1016/j.invent.2017.10.003

Moshe, I., Terhorst, Y., Philippi, P., Domhardt, M., Cuijpers, P., Cristea, I., Pulkki-Råback, L., Baumeister, H., & Sander, L. B. (2021). Digital interventions for the treatment of depression: A meta-analytic review. *Psychological Bulletin, 147*(8), 749–786. https://doi.org/10.1037/bul0000334

Ong, C. W., Terry, C. L., Levin, M. E., & Twohig, M. P. (2023). Examining the feasibility and effectiveness of online acceptance and commitment therapy self-help in a quasi-stepped care model: A pilot study. *Psychological Services*, *20*(1), 166–177. https://doi.org/10.1037/ser0000596 https://doi.org/10.1016/j.invent.2017.10.003

O'Keeffe, S., Martin, P., Target, M., & Midgley, N. (2019). 'I just stopped going': A mixed methods investigation into types of therapy dropout in adolescents with depression. *Frontiers in Psychology*, *10*. https://doi-org.dist.lib.usu.edu/10.3389/fpsyg.2019.00075

Owen, J. J., Adelson, J., Budge, S., Kopta, S. M., & Reese, R. J. (2016). Good-enough level and dose-effect models: Variation among outcomes and therapists. *Psychotherapy research : journal of the Society for Psychotherapy Research*, *26*(1), 22–30. https://doi.org/10.1080/10503307.2014.966346

Pauley, D., Cuijpers, P., Papola, D., Miguel, C., & Karyotaki, E. (2021). Two decades of digital interventions for anxiety disorders: a systematic review and meta-analysis of treatment effectiveness. *Psychological medicine*, *53*(2), 567–579. https://doi.org/10.1017/S0033291721001999

Perski, O., Blandford, A., West, R., & Michie, S. (2017). Conceptualising engagement with digital behaviour change interventions: a systematic review using principles from critical interpretive synthesis. Translational behavioral medicine, 7(2), 254–267. https://doi.org/10.1007/s13142-016-0453-1

Posit team (2023). *RStudio: Integrated Development Environment for R.* Posit Software, PBC, Boston, MA. http://www.posit.co/

Pywell, J., Vijaykumar, S., Dodd, A., & Coventry, L. (2020). Barriers to older adults' uptake of mobile-based mental health interventions. *Digital health*, *6*, 2055207620905422. https://doi.org/10.1177/2055207620905422

R Core Team (2023). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Seidler, Z. E., Rice, S. M., Ogrodniczuk, J. S., Oliffe, J. L., & Dhillon, H. M. (2018). Engaging Men in Psychological Treatment: A Scoping Review. *American journal of men's health*, *12*(6), 1882–1900. https://doi.org/10.1177/1557988318792157

Simon, G. E., Imel, Z. E., Ludman, E. J., & Steinfeld, B. J. (2012). Is dropout after a first psychotherapy visit always a bad outcome?. *Psychiatric services (Washington, D.C.)*, *63*(7), 705–707. https://doi.org/10.1176/appi.ps.201100309

Solar, C., Halat, A. M., Maclean, R. R., Rajeevan, H., Williams, D. A., Krein, S. L., Heapy, A. A., Bair, M. J., Kerns, R. D., & Higgins, D. M. (2021). Predictors of engagement in an internet-based cognitive behavioral therapy program for veterans with chronic low back pain. *Translational Behavioral Medicine*, *11*(6), 1274–1282. https://doi.org/10.1093/tbm/ibaa098

Swift, J. K., & Greenberg, R. P. (2012). Premature discontinuation in adult psychotherapy: a meta-analysis. *Journal of consulting and clinical psychology*, *80*(4), 547–559. https://doi.org/10.1037/a0028226

van Straten, A., Hill, J., Richards, D. A., & Cuijpers, P. (2015). Stepped care treatment delivery for depression: a systematic review and meta-analysis. *Psychological Medicine, 45*(2), 231-246. https://doi.org/10.1017/s0033291714000701

Venables, W. N. & Ripley, B. D. (2002) *Modern Applied Statistics with S.* Fourth Edition. Springer, New York.

Ver Hoef, J. M., & Boveng, P. L. (2007). Quasi-Poisson vs. negative binomial regression: How should we model overdispersed count data? *Ecology, 88*(11), 2766-2772. https://doi.org/10.1890/07-0043.1

Yeager, C. M., & Benight, C. C. (2018). If we build it, will they come? Issues of engagement with digital health interventions for trauma recovery. *MHealth*, *4*, 37–37. https://doi.org/10.21037/mhealth.2018.08.04

Zarski, A. C., Lehr, D., Berking, M., Riper, H., Cuijpers, P., & Ebert, D. D. (2016). Adherence to internet-based mobile-supported stress management: A pooled analysis of individual participant data from three randomized controlled trials. *Journal of Medical Internet Research*, *18*(6). https://doi.org/10.2196/jmir.4493

Table 1

Sample Demographics

	Total Sample (n = 984)
Age (%)	
18 – 24	24.5
25 – 34	27.0
35 – 44	20.7
45 – 54	14.3
55 – 64	9.2
65 or older	3.4
Gender (%)	
Woman	69.5
Man	29.2
Other gender	1.2
Preferred not to answer	0.1
Race (%)	
White	81.9
Asian	4.4
Hispanic/Latinx	4.4
Black/African American	1.8
Native Hawaiian/Pacific Islander	0.4
American Indian/Alaska Native	0.1
Multiracial	2.5
Preferred not to answer	4.5
Continent (%)	
North America	83.5
Europe	5.7
Oceania (Australia; New Zealand)	4.1
Asia	1.7
South America	< 0.1
Transcontinental (Turkey)	< .01

Table 2

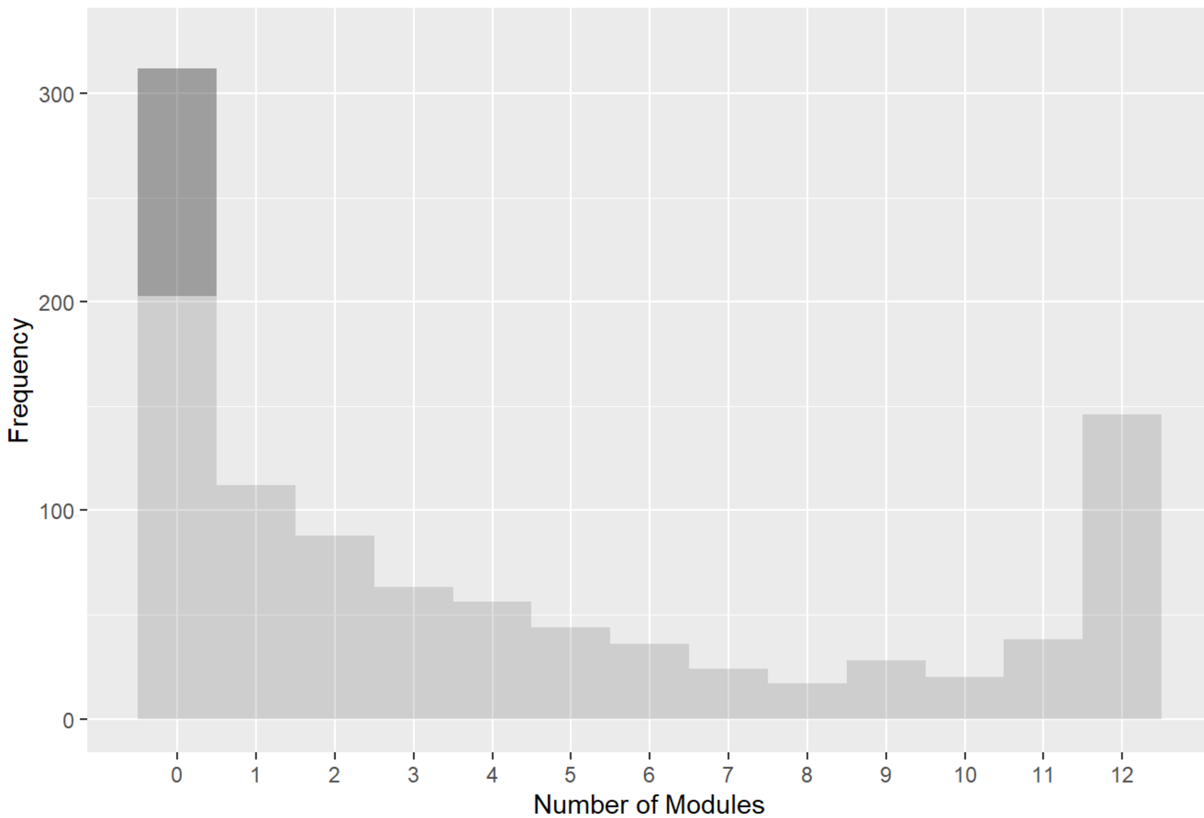
Treatment and Clinical Status

	Total Sample (n = 984)
Treatment status (%)	
Currently working with a mental health professional	35.2
Recently stopped working with a mental health professional	5.1
Has worked with a mental health professional in the past (not currently)	33.9
Has never worked with a mental health professional	25.8
Preferred not to answer	4.0
Depression* (%)	
Below normed average	11.5
Normal to Mild (0 - 1 SD above average)	32.9
Moderate (1 - 2 SD above average)	50.5
Severe (2 – 3 SD above average)	5.1
Anxiety* (%)	
Below normed average	4.2
Normal to Mild (0 - 1 SD above average)	30.7
Moderate (1 - 2 SD above average)	46.2
Severe (2 – 3 SD above average)	18.9

Note. * *Does not include users who did not progress far enough into ACT Guide to complete the depression and anxiety measures. Depression includes 572 users and anxiety includes 576 users.*

Figure 1

Distribution of Number of Core Modules Completed



Note. Dark grey shaded portion of the "0" bar represents users who never logged into the program. Only the completion of the 12 core modules are represented here.

Table 3

Negative Binomial Regression Models Predicting Program Adherence.

Covariate (Reference group)	Nagelkerk Pseudo R^2	β	Standard error	Incidence Rate ratio	Lower 95% CI	Upper 95% CI	P-value
Gender (Woman)	.005						
Man		-0.21	0.10	0.81	0.67	0.98	.056
Other gender		0.15	0.39	1.12	0.58	2.73	.808
Age	.040	-0.02	0.00	0.98	0.98	0.99	< .001***
Race (White)	.002						
Asian		0.23	0.21	1.25	0.85	1.95	.415
Black		-0.15	0.33	0.86	0.47	1.73	.808
Hispanic/Latinx		0.00	0.21	1.00	0.67	1.55	.988
Multiracial		-0.11	0.28	0.89	0.53	1.60	.808
Treatment status (Has never worked with an MHP)	.015						
Currently working with an MHP		-0.40	0.11	0.67	0.54	0.84	.001**
Recently stopped working with an MHP		-0.31	0.22	0.74	0.49	1.14	.270
Has worked with an MHP in the past (not currently)		-0.35	0.09	0.70	0.56	0.88	.005**
Weekly email-tips (Declined email-tips)	.029						
Signed up for email-tips		-0.61	0.12	0.54	0.43	0.69	< .001***
Was not offered email-tips		-0.50	0.12	0.61	0.48	0.77	< .001***
Depression	.038	-0.06	0.02	0.94	0.91	0.98	.001**
Anxiety		0.00	0.02	1.00	0.97	1.04	.840

Note. *$p < .05$; **$p < .01$; ***$p < .001$. MHP = Mental health professional. Each covariate was modeled separately from one another, except for depression and anxiety which were included in one model.