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Component analysis of a synchronous and asynchronous blended care CBT intervention for symptoms of depression and anxiety: Pragmatic retrospective study

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ABSTRACT

Background: Depression and anxiety are leading causes of disability worldwide. Though effective treatments exist, depression and anxiety remain undertreated. Blended care psychotherapy, combining the scalability of online interventions with the personalization and engagement of a live therapist, is a promising approach for increasing access to evidence-based care.

Objectives: To evaluate the effectiveness and individual contribution of two components - i) digital tools and ii) video-based therapist-led sessions - in a blended care CBT-based intervention under real world conditions.

Methods: A retrospective cohort design was used to analyze N = 1372 US-based individuals who enrolled in blended care psychotherapy. Of these, at baseline, 761 participants had depression symptoms in the clinical range (based on PHQ-9), and 1254 had anxiety symptoms in the clinical range (based on GAD-7). Participants had access to the program as a mental health benefit offered by their employer. The CBT-based blended care psychotherapy program consisted of regular video sessions with therapists, complemented by digital lessons and digital exercises assigned by the clinician and completed in between sessions. Depression and anxiety levels and clients' treatment engagement were tracked throughout treatment. A 3-level individual growth curve model incorporating time-varying covariates was utilized to examine symptom trajectories of PHQ-9 scores (for those with clinical range of depression at baseline) and GAD-7 scores (for those with clinical range of anxiety at baseline).

Results: On average, individuals exhibited a significant decline in depression and anxiety symptoms during the initial weeks of treatment ($P < .001$), and a continued decline over subsequent weeks at a slower rate ($P < .001$). Engaging in a therapy session in a week was associated with lower GAD-7 ($b = -0.81$) and PHQ-9 ($b = -1.01$) scores in the same week, as well as lower GAD-7 ($b = -0.58$) and PHQ-9 ($b = -0.58$) scores the following week (all $P < .01$). Similarly, engaging with digital lessons was independently associated with lower GAD-7 ($b = -0.19$) and PHQ-9 ($b = -0.18$) scores during the same week, and lower GAD-7 ($b = -0.25$) and PHQ-9 ($b = -0.27$) the following week (all $P < .01$).

Conclusions: Therapist-led video sessions and digital lessons had separate contributions to improvements in symptoms of depression and anxiety over the course of treatment. Future research should investigate whether clients' characteristics are related to differential effects of therapist-led and digital components of care.

1. Introduction

According to the Substance Abuse and Mental Health Services Administration (SAMHSA), in 2017, 18.9% of US adults were suffering from mental illness, yet less than half of them (42.6%) had received any mental health treatment in the past year (Bose et al., 2018). Untreated

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and undertreated mental illness places a tremendous burden on individuals, their families, and society as a whole. In the US, it is estimated that 200 million workdays are lost annually due to depression alone (Gabriel and Liimatainen, 2000).

Anxiety and depression are the most common mental disorders in the US (Kessler et al., 2012) and over the past decades several effective psychotherapy treatments have emerged. Meta-analytic studies indicate that psychotherapy and medications exhibit similar efficacy in reducing depression and anxiety symptoms, with psychotherapy typically resulting in longer-lasting effects (Hofmann et al., 2012). However, traditional in-person psychotherapy has several limitations that may contribute to the undertreatment of mental illness. Specifically, psychotherapy is often costly (Benson and Song, 2020), which negatively impacts access for the more vulnerable and underserved populations. It also lacks convenience, requiring travel to a provider usually during work hours, which may be prohibitive for many. Additionally, in-person psychotherapy can be difficult to access, especially outside of large metropolitan areas (Zimmerman et al., 2020). Finally, stigma associated with going to mental health clinics may likewise prevent people from seeking care (Jennings et al., 2015). These barriers point to the necessity of developing innovative, confidential, widely accessible, and cost-effective treatment options.

Digital interventions delivered via the internet provide a promising approach for the improved treatment of mental health issues. Recent meta-analyses indicate that guided digital interventions are effective for common mental health problems, such as depression and anxiety (Harrer et al., 2019; Karyotaki et al., 2018; Königbauer et al., 2017; Păsărelu et al., 2017). Moreover, Internet interventions allow users to access care wherever and whenever it is convenient for them. However, digital interventions, and especially those without human support, have limitations, chief among them are low uptake and intervention adherence under real-world conditions (Baumel et al., 2019), difficulty to adapt in real time responding to crises or addressing idiosyncrasies in patients' clinical or cultural presentations, or inability to offer content beyond what has been pre-programmed. Indeed, prior work suggests that supported interventions perform better than unsupported ones (Andersson and Cuijpers, 2009), have higher adherence and retention (Baumeister et al., 2014; Christensen et al., 2006), and that the effect sizes of supported interventions are comparable to face-to-face treatment at a fraction of provider's time (Andrews et al., 2018).

Blended care interventions, or interventions where clients receive care delivered partially by a mental health professional, and partly by digital tools and exercises (e.g., internet-delivered intervention) are designed to address many of the limitations of internet-based interventions. By maintaining contact with a qualified provider who both treats the individual and assigns digital lessons or activities, blended care interventions allow for the flexibility and responsiveness of a live provider, while saving providers' time and offering clients more flexibility. Research evaluating the efficacy of blended care psychotherapy has shown promising results. In an initial review on blended care interventions that combined face-to-face psychotherapy with internet-based interventions, Erbe et al. (2017) identified 44 studies focused on adults with anxiety, depression, or substance abuse, concluding that such interventions are feasible and can be more effective than no-treatment controls. More recent blended care interventions have likewise been found efficacious in targeting both clinical levels of depression symptoms (Thase et al., 2018; Vernmark et al., 2019) and subclinical levels of depression and/or psychosis (van Aubel et al., 2020). Non-inferiority efficacy studies have found comparable outcomes between traditional therapy and blended care interventions with provider time reduced by up to 73% in blended care treatment (Marks et al., 2004; Thase et al., 2018).

Blended care interventions have been implemented across a diverse range of the clinical settings, including primary care (Høifødt et al., 2013), inpatient, general outpatient clinics (Schuster et al., 2020), specialized outpatient mental health clinics (Kooistra et al., 2016), and online clinics (Titov et al., 2018). However, large-scale effectiveness research for blended care interventions has been limited, and primarily focused on cost-effectiveness (Kleiboer et al., 2016) rather than clinical effectiveness.

Though current blended care interventions demonstrate their high promise in increasing access to cost-effective and efficient care, the science of blended care interventions is in its early stages. To advance the science of blended care interventions, we must evaluate the clinical effectiveness of blended care interventions at scale, as well as better understand the differential contributions of the provider and of digital components to clinical outcomes. Moreover, the most common form of blended care psychotherapy uses in-person treatment for the therapist component, along with digital supplementation. Unfortunately, by requiring the client to maintain regular face-to-face therapy sessions, the usual blended care interventions do not address the main limitations of traditional treatment, specifically, poor accessibility, availability, and likely privacy (given the need to visit a clinic). However, promising blended care interventions have recently emerged that utilize a video-based individual therapy model (Lungu et al., 2020), thereby retaining much of the benefits of internet interventions and of face-to-face therapy.

The present study utilized data collected as part of routine care for clients who received a blended care CBT intervention offered through their employer. We analyzed the differential contribution of the provider and digital elements of the blended care program on symptoms of depression and, in a separate analysis, on symptoms of anxiety. To our knowledge, to date, no study in the United States has performed a similar component analysis of blended care interventions delivered at a large scale under real-world conditions.

2. Methods

2.1. Study design

This study utilized a retrospective cohort design with data collected as part of routine quality control of a blended care CBT-based (BC-CBT) program that was offered to individuals residing in the United States as a mental health benefit from their employers. Informed consent was obtained from all participants to this research. Additional details on the BC-CBT program and its procedures are available elsewhere (Lungu et al., 2020). Participants were asked to complete weekly standardized measures of depression and anxiety. The length of care was not specified. This retrospective analysis of deidentified data collected as routine quality control for treatment offered by Lyra Clinical Associates was determined to be not human subject research by the Palo Alto University Institutional Review Board.

2.2. Participants and data inclusion

Participants in the study were individuals who began BC-CBT treatment between January 1st, 2019 and July 1st, 2020 and scored above the clinical cut-off for either the Patient Health Questionnaire-9 (PHQ-9 $\geq$ 10) or the Generalized Anxiety Disorder-7 (GAD-7 $\geq$ 8) on a valid baseline assessment (N = 1583). No additional diagnostic assessment was performed as part of the study, though therapists could perform individual assessments as clinically indicated. Exclusion criteria for the BC-CBT program were: not being open to seeing a provider via video, being under 18 years of age, manifesting active suicidality/self-harm or homicidality, having a current diagnosis of severe alcohol or substance use disorder, or a diagnosis of a mental health disorder with psychotic features not stabilized on medications, or unstable bipolar disorder.

We considered baseline assessments to be invalid if they were collected more than 2 weeks prior to the first therapy session or later than the 2nd therapy session with the provider. Based on this definition, we excluded 23 participants from the study. We considered participants to be missing a valid second assessment if no additional assessment (beyond the baseline) was completed by 5 weeks after the last therapy session. Based on this definition we excluded 32 participants from the study. We excluded assessments if they were collected more than 15.2 weeks after the first therapy session (representing the mean plus one standard deviation of the treatment duration for the sample). Based on this criterion we excluded 1 participant from the study (Fig. 1).

2.3. Self report measures

The PHQ-9 (Kroenke et al., 2001) and GAD-7 (Spitzer et al., 2006) were sent to participants as weekly assessments for depression and anxiety symptoms. Clinical cut-offs of PHQ-9 $\geq$ 10 and GAD-7 $\geq$ 8 were utilized for the baseline scores to determine inclusion in the analyses as research suggests individuals scoring above those thresholds are likely to meet diagnostic criteria for major depression (Kroenke et al., 2001) or anxiety disorders (Kroenke et al., 2007).

2.4. Treatment

The BC-CBT program was integrated with live video therapy sessions and digital care components delivered in an overlapping way throughout treatment. Furthermore, the program was *provider led*, with live video sessions with providers supplemented by provider-guided digital tools. Providers assigned digital lessons and exercises selected based on clients' evolving clinical presentation and provided written instructions and feedback on how the clients might specifically apply select skills given their needs. These digital lessons and exercises were assigned to be completed by clients in between therapy sessions. No specific length of care was defined for the BC-CBT program. Clients had access to a minimum of 12 therapy sessions, depending on the benefit offered by the sponsoring company.

A proprietary digital therapy platform was used by providers to assign personalized digital tools to clients, complete therapy notes and to track clients' engagement with the digital tools. Both clients and providers could review clients' progress on the weekly assessment measures (PHQ-9 and GAD-7) as part of the platform (Lungu et al., 2020).

2.4.1. Individual video psychotherapy

Individual video psychotherapy sessions were conducted via a secure HIPAA-compliant BC-CBT video platform developed by Lyra Health (Lungu et al., 2020). Therapy staff consisted of 131 licensed therapists (licensed clinical psychologists, licensed marriage and family therapists, licensed clinical social workers, or licensed professional counselors). 27.48% (n = 36) of the therapists had less than 5 years of experience, 41.98% (n = 55) had between 5 and 10 years of experience, and 30.53% (n = 40) had over 10 years of experience. Therapists were vetted for their commitment to and proficiency in CBT via extensive application reviews and clinical interviews. Therapists were employees and received no incentives to provide individual therapy sessions versus assigning digital tools to their clients. Therapists received extensive training in BC-CBT via two days of live training. The training included presentations on the digital tools available on the platform, integrating routine outcomes monitoring in care, refresher on suicide risk assessment and management, providing culturally responsive care as well as role plays and direct practice with the platform. Therapists were also engaged in ongoing individual and group consultations. The mean number of clinical cases for therapists was 10.47 (SD = 9.45).

Psychotherapy sessions occurred either weekly or bi-weekly

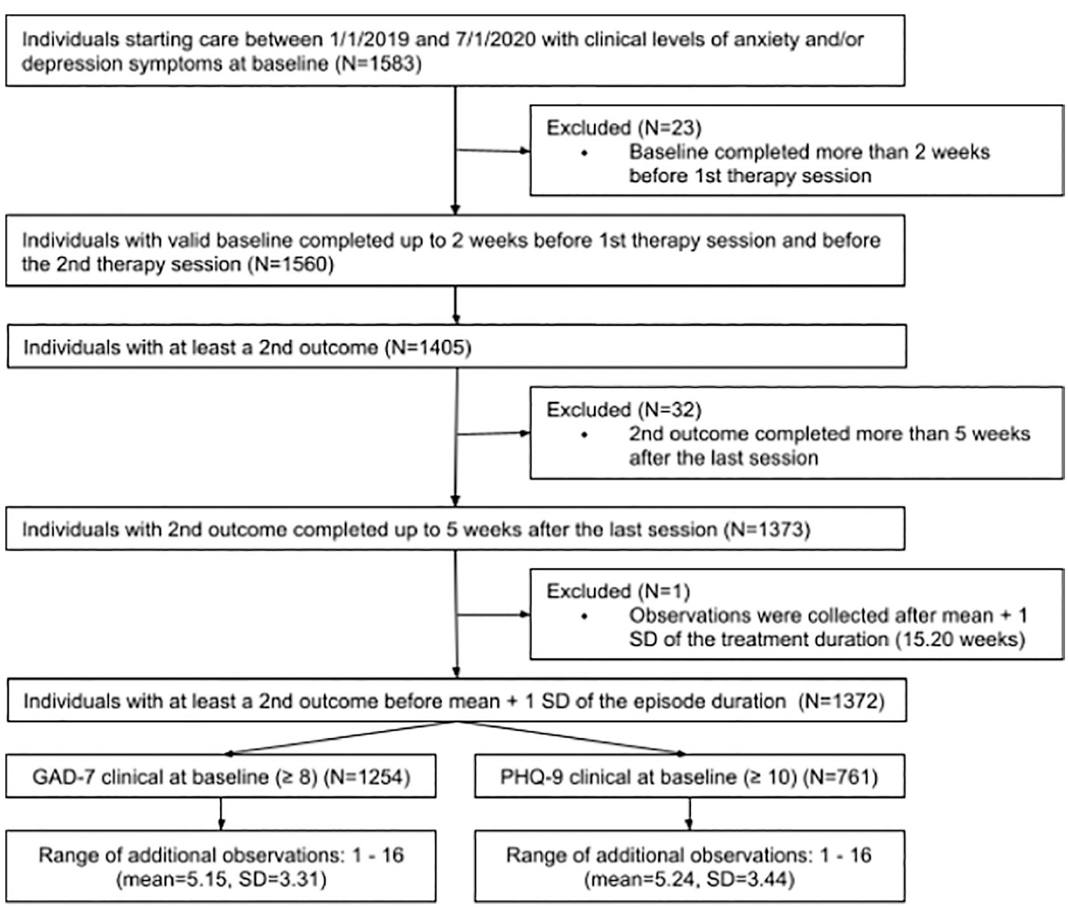

Fig. 1. Participant flow.

depending on the session number and symptom severity though bi-weekly sessions were encouraged in order to promote more time for in-between session skills practice via the digital lessons and digital exercises.

2.4.2. Digital lessons and digital exercises

The digital components of the BC-CBT interventions were developed by Lyra Health based on transdiagnostic treatment approaches like the Unified Treatment Protocol (Barlow et al., 2017), and other treatments rooted in CBT (Hofmann et al., 2010) like Acceptance and Commitment Therapy (Hayes et al., 2011), and Dialectical Behavior Therapy (Linehan, 2014). The digital lessons rely on storytelling, and were delivered via animated videos (mean length 9.48, SD = 3.71 min) that aimed to teach clinical skills in an engaging way (Lungu et al., 2020). A digital lesson concluded with a comprehension quiz based on the presented material.

The digital exercises were developed based on traditional CBT worksheets to help guide clients in practicing therapy skills taught as part of the therapy sessions or digital lessons. Example topics covered in the digital lessons and exercises include psychoeducation on depression and anxiety symptoms, clarifying values, mindful awareness, engaging in exposure for decreasing anxiety and in behavioral activation for decreasing depression, psychoeducation on sleep and sleep hygiene, assertiveness and self-compassion.

In-session, therapists played an active role in introducing and facilitating the comprehension of therapeutic skills via the use of digital lessons and exercises. Therapists personalized homework by selecting the digital tools that matched the clients' case formulation and were most relevant to the clients' presenting issues and treatment goals. Therapists decided the number of lessons to be assigned and which lessons would be most useful, if any, for each session. Session time was spent on collaboratively reviewing clients' experiences with the previous homework, discussing future homework, and assessing clients' willingness and ability to engage with homework outside the therapy session. Through the platform's screen share feature, therapists previewed the digital lessons and exercises, which allowed them to fill out sample digital exercises with the client. In-between sessions, BC-CBT put emphasis on client's independent practice and engagement with the digital lessons and exercises via email and text reminders to complete homework. As clients completed the digital exercises, therapists reinforced the practice by reviewing the submitted entries and providing personalized feedback of encouragement or addressing difficulties that the client was facing in completing the homework. On average, two homework assignments were assigned after each session: 1 digital lesson, and 1 digital exercise.

2.5. Statistical analyses

The current study analyzed the differential contribution of the blended care intervention's provider and digital elements on symptoms of anxiety and, in a separate analysis, on symptoms of depression. The intervention was personalized by providers to clients' presenting concerns. Thus, for clients presenting with elevated symptoms of depression but mild symptoms of anxiety, presumably the therapy session, digital lessons and digital exercises had a strong anti-depression focus and less of an anti-anxiety focus. Conversely, for clients presenting with elevated symptoms of anxiety but mild symptoms of depression, the intervention presumably had an anti-anxiety focus and less of an anti-depression focus. To reflect this, we excluded from the analysis on depression symptoms individuals who scored below the clinical cut-off on depression symptoms at baseline (PHQ-9 $<$ 10), and from the analysis on anxiety symptoms individuals who scored below the clinical cut-off on anxiety symptoms at baseline (GAD-7 $<$ 8). Individuals scoring above clinical cut-offs on both depression and anxiety symptoms were retained in both analyses.

Each observed GAD-7 or PHQ-9 response (level 1) is nested within clients (level 2), who are also nested within treatment providers (level 3), resulting in a 3-level hierarchical design. As a result, we used a mixed effects modeling to examine growth trajectories of anxiety and depression scores over the course of treatment (Bollen and Curran, 2005; Fitzmaurice et al., 2011; Singer and Willett, 2003). In addition to accounting for provider-level variability in client-level symptom trajectories, the growth curve modeling (GCM) approach also allowed us to incorporate predictor variables at both the response and participant levels. The results for each outcome are presented in a stepwise fashion, beginning with a null model containing only fixed and random effects corresponding to the growth function, followed by a series of conditional models incorporating response and participant level predictors.

The time variable used in the GCM was operationalized as Weeks (or fractions thereof) since the first therapy session. For example, if a client completed a GAD-7 assessment 10 days after their first therapy session, the Week variable value for that observation would be 10/7 = 1.43. To calculate values for the time varying covariates, we counted the number of Therapy Session (sessions), digital Lessons (lessons), and digital Exercises (exercises) recorded during the last week (previous 7 days), as well as the number of each that occurred during the week before last (prior 8 to 14 days).

We began by fitting an unconditional quadratic growth curve model, featuring random effects for intercept and linear at the Client level and a random effect for the intercept at the Provider level (Model 1). Next, we introduced a block of level 1 predictors representing the effect of completing therapy sessions, digital exercises, and digital lessons during the last week (Model 2), followed by a model that also includes the number of therapy sessions, digital exercises, and digital lessons completed during the week before last (Model 3). Finally, several covariates representing patient demographic characteristics were incorporated (Model 4). Models were estimated using version 1.1.23 of the lme4 library (Bates et al., 2015) in R 3.6.0. The lme4 library utilizes a full-information (restricted) maximum likelihood (FIML) estimator, which provides unbiased parameter estimates for any arbitrary pattern of missingness, under the conditional MAR assumption (R Core Team, 2013). Although the conditional MAR assumption cannot be inconclusively established, our inclusion of gender, race, and age as covariates accounts for several commonly observed predictors of missingness. In addition, the FIML estimator has been shown to perform well even when meaningful predictors of missingness are not included in the analytic model (i.e., conditional MAR is not strictly satisfied).

3. Results

Participant demographic and baseline characteristics for each of the analysis samples (PHQ-9 and GAD-7) are provided in Table 1. On average, participants were in early-middle adulthood, nearly two thirds

Table 1
Demographic information and engagement in treatment components.

	PHQ-9 sample[a] N = 761	GAD-7 sample[a] N = 1254
Age (mean (SD))	32.98 (8.37)	32.94 (7.79)
% female	63.86%	65.15%
Race/ethnicity		
% minority	53.22%	51.91%
% unknown	7.62%	8.53%
Baseline PHQ-9 (mean (SD))	14.14 (3.59)	10.29 (5.24)
Baseline GAD-7 (mean (SD))	12.52 (4.59)	12.69 (3.54)
# therapy sessions completed (mean (SD))	5.31 (3.46)	5.29 (3.38)
# digital lessons completed (mean (SD))	3.87 (3.05)	3.82 (2.89)
# digital exercises completed (mean (SD))	11.10 (15.73)	10.46 (14.31)
Duration of care (week) (mean (SD))	6.68 (6.26)	6.78 (6.36)

[a] The samples included for the analyses on depression symptoms and on anxiety symptoms are partially overlapping as participants with clinical levels of both depression (PHQ-9 $\geq$ 10) and anxiety (GAD-7 $\geq$ 8) were included in both analyses.

of each sample reported being female, and more than half identified with a minority ethnic or racial group. Participants in the PHQ-9 subsample completed on average 5.31 therapy sessions, 3.87 digital lessons and 11.10 exercises during an average length of care of 6.68 weeks. For the GAD-7 subsample, participants completed on average 5.29 therapy sessions, 3.82 digital lessons, and 10.46 digital exercises during an average length of care of 6.78 weeks.

Figs. 2 and 3 depict participants' engagement in the different treatment components therapy sessions, digital exercises and digital lessons for the analyses on depression and anxiety symptoms respectively. Engagement in all components of care declined over time in care.

Tables 2 and 3 report the number of active enrollment by week as well as the number and percentage of those who provided any assessment responses during each interval for the analyses on depression and anxiety symptoms respectively. On average, the weekly response rate was 65.21% for the PHQ-9 subsample and 63.40% for the GAD-7 subsample.

3.1. GAD-7

Parameter estimates for the GAD-7 subsample are provided in Table 4. Results from the unconditional analysis (Model 1) suggests that on average, participants exhibit a significant initial decline in GAD-7 during the first week (1–7 days after) of treatment (b = −1.22 [−1.28, −1.17], $P < .001$). Moreover, the presence of a significant quadratic coefficient (b = 0.06 [0.06, 0.07], $P < .001$) indicates that the rate of decline in GAD-7 scores diminishes (i.e., becomes more positive) over the course of treatment. More specifically, GAD-7 scores declined quickly over the first few weeks of treatment, though the average trajectory flattened gradually during the middle stages of treatment, and more rapidly during the later stages.

In Model 2, significant coefficients emerged for therapy sessions (b = −0.72 [−0.87, −0.56]) and digital lessons (b = −0.19 [−0.31, −0.08]), which suggests that engaging in a therapy session was associated with a 0.72 lower GAD-7 scores during the first week, and that engaging with each digital lesson was uniquely associated with an expected 0.19 decrease GAD-7 scores during the first week. However, completion of digital exercises was not associated with GAD-7 scores.

Model 3 incorporated the lagged engagement predictors, and significant coefficients emerged for therapy sessions (b = −0.58 [−0.75, −0.41]) and digital lessons (b = −0.25 [−0.38, −0.12]) completed during the second week (8–14 day period) prior to the GAD-7 report, but not for digital exercises. These effects suggest that engaging in each therapy session was associated with 0.58 lower GAD-7 scores in the second week (8–14 days after), and completion of each digital lesson was associated with 0.25 lower GAD-7 scores in the second week. Moreover, the coefficients associated with therapy sessions and digital lessons during the first week changed slightly from Model 2 (b = −0.81 [−0.97, −0.64] and − 0.19 [−0.31, −0.07] respectively). Finally, completion of digital exercises was not associated with GAD-7 scores during the first or second week.

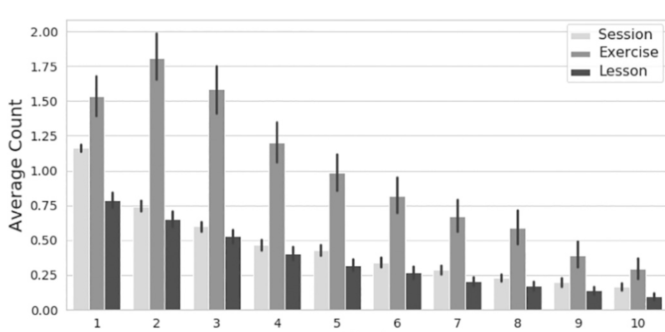

Fig. 2. Completion of therapy sessions, digital exercises and lessons during BC-CBT (depression symptoms analysis).

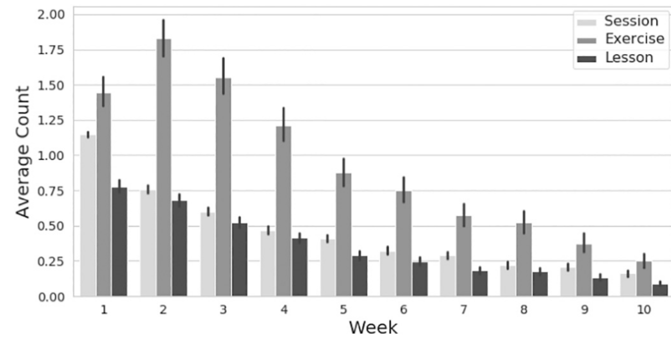

Fig. 3. Completion of therapy sessions, digital exercises and lessons during BC-CBT (anxiety symptoms analysis).

Table 2
Enrollment and summary statistics of assessments by week (depression symptoms analysis).

Week	Number of episodes enrolled	Number of episodes provided assessments (%)	PHQ-9 (mean (SD))	PHQ-9 (median)	GAD-7 (mean (SD))	GAD-7 (median)
−2 to −1	N/A	81 (N/A)	13.44 (3.23)	13.00	11.90 (4.67)	12.00
−1 to 0	N/A	606 (N/A)	14.21 (3.63)	13.00	12.59 (4.58)	13.00
0 to 1	761	490 (64.39%)	10.46 (5.15)	10.00	10.13 (5.00)	10.00
1 to 2	709	510 (71.93%)	9.24 (4.76)	9.00	8.66 (4.47)	8.00
2 to 3	638	417 (65.36%)	8.08 (4.79)	7.00	8.22 (4.51)	7.00
3 to 4	576	366 (63.54%)	7.39 (4.51)	7.00	7.47 (4.26)	7.00
4 to 5	536	323 (60.26%)	7.30 (4.81)	7.00	7.04 (4.36)	7.00
5 to 6	489	286 (58.49%)	6.62 (4.56)	6.00	6.61 (4.12)	6.00
6 to 7	440	263 (59.77%)	6.44 (4.52)	6.00	6.62 (4.41)	6.00
7 to 8	391	238 (60.87%)	6.42 (4.51)	6.00	6.64 (4.37)	6.00
8 to 9	330	177 (53.64%)	6.35 (4.49)	6.00	6.02 (3.89)	6.00
9 to 10	294	161 (54.76%)	5.79 (4.36)	5.00	6.04 (4.24)	6.00
10 to 11	244	150 (61.48%)	6.34 (4.33)	5.50	6.62 (4.27)	6.00
11 to 12	188	102 (54.26%)	6.56 (4.32)	6.00	6.35 (3.71)	6.00
12 to 13	158	96 (60.76%)	6.26 (3.70)	6.00	5.91 (3.38)	6.00
13 to 14	117	79 (67.52%)	6.53 (4.72)	5.00	6.18 (4.19)	6.00
14 to 15	73	63 (86.30%)	6.15 (4.72)	5.00	5.78 (4.53)	6.00
15 to 16	12	12 (100.00%)	6.38 (4.73)	5.50	7.03 (4.08)	7.50

Demographic covariates were incorporated in the final step (Model 4), and significant effects emerged for the effect-coded vectors representing ethnicity suggesting that clients who identified as an ethnic minority reported lower GAD-7 scores at baseline (b = −0.43 [−0.69, −0.16]), whereas clients who declined to provide ethnicity information reported higher scores at baseline (b = 0.42 [0.02, 0.82]). Additionally, the aforementioned linear and quadratic coefficients for Week, as well as the coefficients for the engagement predictors remained unchanged from Model 3.

Table 3
Enrollment and summary statistics of assessments by week (anxiety symptoms analysis).

Week	Number of episodes enrolled	Number of episodes provided assessments (%)	PHQ-9 (mean (SD))	PHQ-9 (median)	GAD-7 (mean (SD))	GAD-7 (median)
−2 to −1	N/A	151 (N/A)	9.41 (4.76)	9.00	12.32 (3.42)	12.00
−1 to 0	N/A	995 (N/A)	10.31 (5.30)	10.00	12.75 (3.55)	12.00
0 to 1	1254	780 (62.20%)	8.31 (5.26)	7.00	9.93 (4.68)	9.00
1 to 2	1184	817 (69.00%)	7.23 (4.76)	6.00	8.40 (4.21)	7.00
2 to 3	1076	706 (65.61%)	6.30 (4.54)	5.50	7.64 (4.21)	7.00
3 to 4	982	587 (59.78%)	5.93 (4.23)	5.00	7.20 (4.01)	7.00
4 to 5	900	532 (59.11%)	5.76 (4.41)	5.00	6.77 (4.12)	6.00
5 to 6	807	463 (57.37%)	5.41 (4.33)	4.00	6.33 (3.97)	6.00
6 to 7	733	433 (59.07%)	5.20 (4.12)	4.50	6.35 (4.04)	6.00
7 to 8	647	378 (58.42%)	5.37 (4.45)	5.00	6.26 (4.18)	6.00
8 to 9	546	291 (53.30%)	5.35 (4.33)	4.00	6.18 (4.14)	6.00
9 to 10	482	262 (54.36%)	5.15 (4.16)	5.00	6.09 (4.26)	5.00
10 to 11	404	234 (57.92%)	5.15 (4.17)	4.00	6.17 (4.04)	6.00
11 to 12	322	170 (52.80%)	5.48 (3.91)	5.00	6.37 (4.05)	6.00
12 to 13	271	166 (61.25%)	5.11 (3.78)	4.00	5.79 (3.51)	5.25
13 to 14	199	128 (64.32%)	5.29 (4.32)	4.00	6.08 (4.00)	5.50
14 to 15	119	95 (79.83%)	5.37 (4.30)	5.00	5.80 (4.12)	5.00
15 to 16	32	32 (100.00%)	5.44 (3.69)	5.00	6.32 (3.58)	6.00

3.2. PHQ-9

Parameter estimates for the PHQ-9 subsample are provided in Table 5. Results from the unconditional analysis (Model 1) revealed a steep initial decline in depression scores during the first week of treatment (b = −1.46 [−1.53, −1.38], $P < .001$), and the significant quadratic coefficient (b = 0.08 [0.07, 0.08], $P < .001$) indicates that the rate of decline in PHQ-9 scores becomes more positive as treatment progresses. As seen in the anxiety analysis, depression scores declined rapidly over the first few weeks of treatment, but the average trajectory became flatter during the later stages.

In Model 2, significant coefficients emerged for therapy sessions (b = −0.92 [−1.13, −0.71]) and digital lessons (b = −0.18 [−0.33, −0.02]), indicating that engaging in each therapy session was associated with a 0.92 lower PHQ-9 score during the first week, and each completed digital lessons was associated with 0.18 lower PHQ-9 scores. However, completion of digital exercises was not uniquely associated with depression scores reported in the first week.

Model 3 incorporated the lagged engagement predictors, and significant coefficients emerged for therapy sessions (b = −0.58 [−0.81, −0.34]) and digital lessons (b = −0.27 [−0.45, −0.10]) completed 8 to 14 days prior to the PHQ-9 report, but not for digital exercises. These effects suggest that each therapy session delivered was associated with 0.58 lower PHQ-9 scores in the second week (8–14 days after), and completion of each digital lesson was associated with 0.27 lower depression scores during the second week. As before, the first week coefficients for therapy sessions and digital lessons changed slightly from Model 2 (−1.01 [−1.23, −0.79] and −0.18 [−0.34, −0.02] respectively), and completion of digital exercises was not associated with PHQ-9 scores during the first or second week.

Demographic covariates were incorporated in the final step (Model 4), and significant effects emerged for the effect-coded vectors representing gender suggesting that clients who identified female reported lower PHQ-9 scores at baseline (b = −0.30 [−0.55, −0.05]), though no other covariates emerged as significant. Finally, the aforementioned linear and quadratic coefficients for Week, as well as the coefficients for the engagement predictors remained significant in the expected direction.

3.3. Sensitivity analysis

Simultaneously entering therapy sessions, exercises, and digital

Table 4
GAD-7 results.

	Model 1		Model 2		Model 3		Model 4	
	Est. [95% CI]	t_{obs}	Est. [95% CI]	t_{obs}	Est. [95% CI]	t_{obs}	Est. [95% CI]	t_{obs}
Intercept	10.95 [10.74, 11.17]	–	11.34 [11.11, 11.56]	–	11.51 [11.28, 11.74]	–	11.69 [11.41, 11.97]	–
Week	−1.22 [−1.28, −1.17]	44.43**	−1.16 [−1.22, −1.11]	41.02**	−1.04 [−1.10, −0.98]	32.89**	−1.04 [−1.10, −0.98]	32.89**
Week^2	0.06 [0.06, 0.07]	27.02**	0.06 [0.05, 0.06]	23.04**	0.05 [0.04, 0.05]	17.39**	0.05 [0.04, 0.05]	17.39**
Therapy sessions last 7 days	–	–	−0.72 [−0.87, −0.56]	8.89**	−0.81 [−0.97, −0.64]	9.75**	−0.81 [−0.97, −0.64]	9.74**
Digital exercises last 7 days	–	–	0.01 [−0.03, 0.06]	0.58	0.04 [0.00, 0.09]	1.86†	0.04 [0.00, 0.09]	1.87†
Digital lessons last 7 days	–	–	−0.19 [−0.31, −0.08]	3.28**	−0.19 [−0.31, −0.07]	3.12**	−0.19 [−0.31, −0.07]	3.12**
Therapy sessions 8–14 days	–	–	–	–	−0.58 [−0.75, −0.41]	6.68**	−0.58 [−0.75, −0.41]	6.68**
Digital exercises 8–14 days	–	–	–	–	0.02 [−0.03, 0.07]	0.83	0.02 [−0.03, 0.07]	0.83
Digital lessons 8–14 days	–	–	–	–	−0.25 [−0.38, −0.12]	3.69**	−0.25 [−0.38, −0.12]	3.71**
Age	–	–	–	–	–	–	0.01 [−0.01, 0.03]	0.65
Gender	–	–	–	–	–	–	−0.01 [−0.18, 0.17]	0.08
Minority ethnicity	–	–	–	–	–	–	−0.43 [−0.69, −0.16]	3.18**
No ethnicity disc.	–	–	–	–	–	–	0.42 [0.02, 0.82]	2.04*
Deviance (−2LL)	41,707.2		41,584.1		41,499.0		41,487.5	
AIC	41,723.2		41,606.1		41,527.0		41,523.5	
BIC	41,778.9		41,682.6		41,624.3		41,648.7	

Note. N = 1254.
** $P < .01$.
* $P < .05$.
† $P < .10$.

Table 5
PHQ-9 results.

	Model 1		Model 2		Model 3		Model 4	
	Est. [95% CI]	tobs	Est. [95% CI]	tobs	Est. [95% CI]	tobs	Est. [95% CI]	tobs
Intercept	12.04 [11.77, 12.31]	–	12.52 [12.23, 12.82]	–	12.70 [12.40, 13.00]	–	13.00 [12.61, 13.40]	–
Week	−1.46 [−1.53, −1.38]	38.38**	−1.38 [−1.45, −1.30]	35.17**	−1.26 [−1.34, −1.17]	28.69**	−1.26 [−1.34, −1.17]	28.66**
Week2	0.08 [0.07, 0.08]	23.95**	0.07 [0.06, 0.07]	20.16**	0.06 [0.05, 0.07]	15.75**	0.06 [0.05, 0.07]	15.70**
Therapy sessions last 7 days	–	–	−0.92 [−1.13, −0.71]	8.47**	−1.01 [−1.23, −0.79]	9.00**	−1.01 [−1.23, −0.79]	9.04**
Digital exercises last 7 days	–	–	−0.005 [−0.06, 0.05]	0.16	0.02 [−0.03, 0.08]	0.80	0.02 [−0.03, 0.08]	0.80
Digital lessons last 7 days	–	–	−0.18 [−0.33, −0.02]	2.19*	−0.18 [−0.34, −0.02]	2.19*	−0.18 [−0.34, −0.02]	2.19*
Therapy sessions 8–14 days	–	–	–	–	−0.58 [−0.81, −0.34]	4.88**	−0.58 [−0.81, −0.35]	4.92**
Digital exercises 8–14 days	–	–	–	–	0.04 [−0.02, 0.09]	1.18	0.03 [−0.02, 0.09]	1.15
Digital lessons 8–14 days	–	–	–	–	−0.27 [−0.45, −0.10]	3.01**	−0.27 [−0.45, −0.09]	3.00**
Age	–	–	–	–	–	–	0.02 [−0.01, 0.04]	1.01
Gender	–	–	–	–	–	–	−0.30 [−0.55, −0.05]	2.32*
Minority ethnicity	–	–	–	–	–	–	−0.28 [−0.67, 0.12]	1.38
No ethnicity disc.	–	–	–	–	–	–	0.56 [−0.07, 1.18]	1.77†
Deviance (−2LL)	26,313.9		26,210.5		26,162.1		26,152.6	
AIC	26,329.9		26,232.5		26,190.1		26,188.6	
BIC	26,381.7		26,303.6		26,280.6		26,305.0	

Note. N = 761.
** $P < .01$.
* $P < .05$.
† $P < .10$.

lessons completed during the first and during the second weeks provides a strong test of the unique association between each element of the blended care model, while accounting for the predictive utility of the other elements. Although this approach affords greater precision, it may also obscure smaller effects that might emerge if each predictor was considered by itself. In an effort to better understand the predictive utility of each BCT element in insolation, a series of sensitivity analyses based on Model 4 were conducted, in which the first week (1–7 days prior) and the second week (8–14 days prior) of each element (i.e., therapy sessions, digital exercises, digital lessons) was entered in isolation.

For GAD-7, the model incorporating therapy sessions produced coefficients for the first week (b = −0.89 [−1.03, −0.74], t(6625) = 11.90, $P < .001$), and second week (b = −0.69 [−0.84, −0.53], t(6546) = 8.72, $P < .001$) that were comparable to those obtained in Model 4. A similar pattern emerged for the coefficients associated with digital lessons during the first week (b = −0.40 [−0.51, −0.30], t(6751) = 7.43, $P < .001$) and second week (b = −0.43 [−0.55, −0.32], t(6541) = 7.23, $P < .001$). Although the coefficients associated with digital exercises failed to reach significance in Model 4, a relationship did emerge when the effect of this predictor was considered in isolation. Specifically, completion of digital exercises during the first week was associated with lower GAD-7 (b = −0.06 [−0.10, −0.02], t(6752) = 2.85, $P = .004$) scores, but not during the second week (b = −0.04 [−0.08, 0.00], t (6523) = 1.76, $P = .08$).

Turning to the models for PHQ-9, the sensitivity analysis incorporating therapy sessions produced coefficients for the first week (b = −1.11 [−1.31, −0.91], t(4043) = 11.06, $P < .001$), and second week (b = −0.69 [−0.90, −0.49], t(4006) = 6.56, $P < .001$) that were comparable to those obtained in Model 4. A similar pattern emerged for digital lessons for the first week (b = −0.46 [−0.61, −0.32], t(4133) = 6.28, $P < .001$), and second week (b = −0.48 [−0.64, −0.32], t(4010) = 5.92, $P < .001$). As previously observed, the effects associated with digital exercises emerged when the effect of this predictor was considered in isolation. Specifically, completion of digital exercises during the first week was associated with lower PHQ-9 (b = −0.09 [−0.15, −0.04], t (4159) = 3.22, $P < .001$), but this effect did not emerge for the second week (b = −0.02 [−0.07, 0.04], t(4021) = 0.61, $P = .54$). Overall, the findings of the sensitivity analyses were consistent with the primary results (Model 4), but they also illustrate that the association between completion of digital exercises and PHQ-9 or GAD-7 scores is outweighed by digital lessons and therapy sessions.

4. Discussion

The BC-CBT program described here was provider focused, that is, the provider was expected to produce the majority of therapeutic change. The program also featured a seamless integration of provider and digital care components that were overlapping and complementary throughout the duration of care. Specifically, providers assigned personalized digital lessons and exercises to clients who were expected to complete them between live video therapy sessions. Separate analyses were conducted to investigate changes in depression and anxiety symptoms, including in each analysis only participants who scored in the clinical range of symptoms, with some participants being included in both depression and anxiety analyses.

Results revealed that clients exhibited a notable initial decline in anxiety and depression symptoms, and symptoms continued to improve over time at a lower rate. Engaging in therapy sessions or digital lessons predicted improvement in anxiety and depression symptoms during the following week (1–7 days), and the beneficial effects of engagement appeared to extend through the following week as well. Specifically, engaging with a therapy session or digital lesson predicted lower GAD-7 and PHQ-9 scores during the second week (8 to 14 days later). Prior research showed that the BC-CBT program as a whole was clinically effective in decreasing symptoms of depression and anxiety when delivered to clients on a large scale. Specifically, in a sample of 385 clients with clinical range depression and/or anxiety symptoms at baseline these symptoms significantly declined with time with both a linear effect (b = −0.49, $P < .001$ for depression and b = −0.64, $P < .001$ for anxiety), and a quadratic effect (b = 0.04, $P < .001$ for both depression and anxiety) emerging. Approximately 73% (n = 283) of clients demonstrated reliable improvement and 83% (n = 319) recovered on either the PHQ-9 or GAD-7 (Lungu et al., 2020). The findings presented in the current study take our understanding of the BCT-CBT intervention one step further in demonstrating that the provider and digital elements of the program, specifically the digital sessions, had independent contributions to the effectiveness of the program. This suggests that removing either the provider (which would reduce the program to unguided iCBT) or the digital components (which would reduce the program to traditional psychotherapy) from the BC-CBT program is likely to decrease its effectiveness overall.

The BC-CBT program evaluated was designed with a significant emphasis on live sessions with a provider. The largest proportion of a client's time is spent in session, which corresponds with the relative magnitude of symptom improvement observed in our results. Although digital materials were designed to have a supporting role, the digital lessons appeared to carry considerable clinical potency themselves. Prior research found the number of modules completed in self-help digital interventions for depression and anxiety to correlate with clinical outcomes (Donkin et al., 2011), and our finding extends these observations to blended care models. Thus, the expected decline in symptoms associated with engaging in therapy sessions during the past week (1–7 days prior) and the week before (8 to 14 days prior) was -1.39 ($-0.81 + -0.58$) points on GAD-7 and -1.59 ($-1.01 + -0.58$) points on PHQ-9. The combined effects of completing digital lessons in the past week and the week before was -0.44 ($-0.19 + -0.25$) points on GAD-7 and -0.45 ($-0.18 + -0.27$) points on PHQ-9. It appears, then, that the added effect of the digital lessons during the past week and the week before represented 32% and 28% of the magnitude of the effect of the therapy sessions on GAD-7 and PHQ-9 respectively. It should be noted that the length of a digital lesson is approximately 20% of that of a therapy session (the average duration of a digital lesson was ~10 min and of therapy sessions ~50 min). Future research should examine whether the clinical potency of and client engagement in the digital lessons will change if their length increases significantly. It is also important to note that our results in terms of the potency of the digital lessons for enacting clinical change were demonstrated in a blended model of care where the provider played a key role in personalizing the digital content to clients' presenting problem and in motivating the client to complete the content. Prior research found lower levels of efficacy for digital interventions not supported by a provider (Wright et al., 2019). Thus it is possible that the potency of the digital content would be diminished if the provider were not part of care, as is the case in unguided iCBT interventions.

The digital exercises did not appear to produce significant clinical contribution when analyzed jointly with therapy sessions and digital lessons. This does not necessarily mean that these exercises are not useful and should not be included in future blended care interventions. First, sensitivity analyses suggested that when examined in isolation (without the contributions of therapy sessions and digital lessons), exercises do indeed contribute to clinical improvements in both depression and anxiety scores, suggesting that while they do have clinical utility, it is being overshadowed by the likely superior clinical potency of therapy sessions and digital lessons. Furthermore, digital exercises may play an important role in facilitating clinical change offered by therapy sessions and digital lessons, by promoting between-session engagement, contributing to client's sense of self-efficacy in managing symptoms of depression or anxiety, and providing continuity of treatment (Shalom et al., 2015). It is also important to note that the digital exercises included in the BC-CBT intervention were designed to take little time to complete (from less than one to a few minutes) to maximize client engagement. Future work can investigate expanding digital exercises to increase their clinical potency and explore trade-offs between the complexity, length of exercises and client engagement.

Limitations: This study should be considered in the context of several limitations. PHQ-9 and GAD-7 were used for measures of clinical effectiveness of therapy sessions and digital lessons, which are self-report measures. Though they are exceedingly common both in treatment outcome studies and in the clinical community, interviewer-administered measures may have offered more sensitivity. Engagement in therapy sessions and digital lessons and exercises varied between clients and providers, which may have affected clinical outcomes. Given that this study was not a RCT, we cannot be certain that the results we observed were not due to other uncontrolled factors, thus our results should be interpreted with caution. Though a control group could not have been utilized considering that data came from routine mental health care offered as part of a provider-offered healthcare plan, the overall outcomes may have been more understandable with the inclusion of the control group. Additionally, because data came from clients who were employed, whether these results would generalize to individuals who are not gainfully employed (and may therefore be less socioeconomically advantaged) is not certain.

Digital interventions allow us to optimize treatments to a greater degree than interventions delivered solely by providers. Data from large scale blended care psychotherapy studies can help us better understand client's preferences in engaging with the different components of interventions (Kemmeren et al., 2019) and potentially inform unique methods of tailoring treatment to individual clients (Friedl et al., 2020). Component analyses of blended care interventions allow for a fine-grained understanding of how intervention elements contribute to clinical outcomes of interest that can guide future care personalization and optimization. For instance, cluster analyses of large patient populations participating in blended care psychotherapy could offer data about the optimal proportion of therapist-led sessions to digital lessons for a particular type of client (for instance, based on symptom profile, client's history, or other similar factors), as well as data regarding synergistic effects of specific digital lessons and specific session content. Such research has been proposed to compare, via a non-inferiority design, two different implementations of blended psychotherapy to traditional CBT (Baumeister et al., 2021). There is an abundance of evidence, both from in-person and digital interventions, that attrition from treatment is a significant concern (Webb et al., 2017), and optimization of treatment delivery based on patient profiles and dynamic allocation of treatment components may offer patients both the type of treatment that they will find more appealing as well as a speedier recovery (Friedl et al., 2020). Considering that in blended care interventions, therapeutic success is not solely the product of the provider's skills but also of the digital lesson content, as was evident in this study, a provider who can successfully motivate and reinforce digital lesson participation may attain better outcomes than a similarly skillful provider who fails to do so. Data from large scale studies could therefore offer guidance about the approaches and attributes of providers who are both most successful overall, as well as those who are most successful for specific types of clients, further optimizing treatment delivery and outcomes. There is a dearth of research in the field of digital and blended interventions on comparisons between guided iCBT interventions where providers offer support asynchronously via email, phone, messaging, etc. and blended care interventions where providers engage in synchronous real time sessions with clients on a regular basis. Future research exploring such comparisons could provide insights into the differential impact provider engagement can have depending on the modality and extent of engagement with clients.

Finally, blended care interventions should be explored for a variety of other disorders, subtypes of disorders, and comorbidities, to offer individuals more convenient, flexible, and effective treatment options.

Data availability statement

The datasets generated during and/or analyzed during the current study are not publicly available due to the fact that the data is related to the delivery of health care and subject to the Health Information Portability and Accountability Act of 1996.

Declaration of competing interest

AL and SYC are employed by Lyra Health, receive income from Lyra Health, and have been granted equity in Lyra Health. JJ and CC are employed by Lyra Health and Lyra Clinical Associates, receive income from Lyra Health and Lyra Clinical Associates, and have been granted equity in Lyra Health. RW is a paid consultant for Lyra Health. YL has nothing to disclose.

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fulfilling, productive lives.

Appendix A

The final model for generic outcome Y_{kjt} describing the observed PHQ9 or GAD7 score at time *t* for patient *j* who received treatment from provider *k* can be described by the following equations:

$$Y_{kjt} = \pi_{0jk} + \pi_{1j}*Week_{jt} + \pi_2*Week^2_{jt} + \pi_3*TherapySessions_{Last7Days} + \pi_4*DigitalExercises_{Last7Days} + \pi_5*DigitalLessons_{Last7Days} + \pi_6*TherapySessions_{Last8to14Days} + \pi_7*DigitalExercises_{Last8to14Days} + \pi_8*DigitalLessons_{Last8to14Days} + r_{Y\,kjt} \quad (1)$$

Eq. (1) indicates that outcome response for patient *j* who is receiving treatment from provider *k* at measurement occasion (e.g., Week) *t* can be expressed as a function of regression intercept π_{0jk}, which varies across patients (*j*) and providers (*k*). The π_{1j} term is a regression coefficient describing the linear component of the growth function that varies randomly across patients, whereas the π_2 describes the quadratic component that contains no additional random effects. $\pi_3 - \pi_8$ describes the effect of therapy sessions, digital exercises, and digital lessons completed during the past 7 or 8-to-14 days. Finally, the residual term, r_{Ykjt}, describes the response level errors in prediction (i.e., deviation between patients' observed and predicted outcome score at each measurement occasion). Each of the coefficients in Eq. (1) can be decomposed into upper-level equations to illustrate their fixed and random components. We combine levels 2 (patient) and 3 (provider) without loss of generality:

$$\pi_{0j} = \gamma_{000} + \gamma_{010}*Age_j + \gamma_{020}*Gender_j + \gamma_{030}*Minority1_j + \gamma_{040}*Minority2_j + u_{00j} + u_{00k} \quad (2)$$

where γ_{000} is the fixed intercept, which represents the average outcome score at Week 0 for a participant who completed 0 therapy sessions, digital lessons, and digital exercises. $\gamma_{010} - \gamma_{040}$ describe the association between patient-level control variables, Age (grand mean centered), Gender (effect-coded, male = −1, female = +1), and Ethno-racial Minority (effect coded with Non-Hispanic White as reference: Minority1 [Ethno-racial minority] = +1, Minority2 [Minority Status Unknown] = +1). In contrast, the u_{00j} term represents the patient-specific deviation from the average PHQ-9 score (i.e., patients start off with higher/lower initial outcome score) and u_{00k} represents the provider-specific deviation (i.e., providers start off with patients who have higher/lower initial outcome score) at Week 0, conditional on all covariates and other level 1 predictors (i.e., therapy sessions, digital exercises, digital lessons). Turning to the level 1 coefficients associated with Week:

$$\pi_{1jk} = \gamma_{100} + u_{11j} \quad (3)$$

$$\pi_{2jk} = \gamma_{200} \quad (4)$$

γ_{100} is the fixed linear slope, which represents the initial average change in outcome score for each week in treatment, whereas u_{11j} represents the patient-specific deviation (i.e., patients show faster/sloper initial decline in outcome) the average initial linear slope. γ_{200} is the fixed quadratic component of the time slope, which describes how the instantaneous linear slope changes over time. It is important to note that the $\pi_2 - \pi_8$ terms do not contain patient or provider-specific subscripts, which indicates that they do not vary randomly across these upper-level units. Therefore, the remaining upper level equations for $\pi_3 - \pi_8$ have the same structure and contain only a single fixed effect each:

$$\pi_3 \textit{ through } \pi_{12} = \gamma_{300} \textit{ through } \gamma_{1200} \quad (5\text{–}14)$$

These coefficients describe the unique predictive utility of therapy sessions, digital lessons, and digital exercises completed within the last 7 days (π_3–π_5) or 8 to 14 days (π_6–π_8) in predicting an outcome score, independent of treatment week. The absence of 'u' terms in these equations indicates that this model assumes the values of these coefficients to be constant across all participants (unlike our intercept and linear component of the growth trajectories).

The aforementioned fixed effects for the intercept (γ_{000}), week (γ_{100}), and week_squared (γ_{200}) terms describe the average trajectory of outcome scores over the course of treatment. However, the model also contained patient-specific (u_{00j}, u_{11j}) and provider-specific (u_{00k}) deviations from these fixed values, which account for differences in these coefficients across these upper-level subjects. Finally, we have a level 1 (response) deviation (r_{kjt}) reflecting the discrepancy between the patients expected response at a specific value of Week given their standing on sessions, exercises, and lessons ($\hat{Y}$) and their observed Y_{kjt}. These deviation terms are *random effects* that must be expressed as distributions, and we must acknowledge that the upper-level (provider, patient) terms are likely to be correlated, that is, patients with higher intercept deviations (i.e., positive u_{00k}) may be more likely to show a steeper initial decline in outcome scores (i.e., negative u_{11k}). As a result, we describe the degree of cross-patient and cross-provider variability in random effects using subject-specific (i.e., patient, provider) variance-covariance matrices. The provider-level matrix contains a single element, representing the variance in outcome scores at Week 0 that can be attributed to cross-provider differences. In contrast, the patient-level matrix contains 3 non-redundant elements representing cross-patient variability in model parameters: 1) τ^2_{00j}, representing intercept variance in outcome scores, 2) τ^2_{11j}, representing variance in the linear component of the growth trajectories, and 3) τ_{01j}, representing the covariance between intercept and linear slope. Estimates for these parameters are available upon request.

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