Self-Guided Behavioral Activation Using an Online Single-Session Intervention: Content and Lexical Analyses of Activity Scheduling

Allison Peipert

Lauren A. Rutter

Indiana University Bloomington

Jacqueline Howard

TRAILS, A Project of Tides Center

Lorenzo Lorenzo-Luaces

Indiana University Bloomington

The Common Elements Toolbox (COMET) is a self-guided online single-session intervention (SSI) containing cognitive-behavioral elements, including behavioral activation (BA). Little is known about the process of activity scheduling in BA. Using data from an 8-week randomized controlled trial of COMET with 409 online workers with a history of psychopathology, two raters coded the types of activities individuals scheduled during the intervention. Additionally, we compared the activities to a BA dictionary developed from therapist-led psychotherapy. We explored baseline clinical and demographic variables that were predictive of the activity category scheduled and explored the scheduled activity category as a predictor of depression, anxiety, and well-being post-intervention. Results yielded 9 different activity types, most commonly sedentary hobbies (41%), physical activity (29%), and active hobbies (18%). We found a small overlap (17%) between the self-guided BA activities in our COMET sample and those in the existing BA dictionary. Demographic variables were predictive of activity category, but clinical variables were not. The type of activity scheduled was not predictive of post-intervention outcomes. In self-guided BA, individuals, particularly men, less educated participants, and racial-ethnic minorities, tend to pick sedentary activities. Findings underscore the need for adaptive and personalized interventions.

DEPRESSION is a common disorder and leading cause of disability worldwide (Liu et al., 2020; Whiteford et al., 2013), although it is heterogeneous in its presentation and prognosis (Buss, Watts, et al., 2023). Characteristic symptoms include low mood, anhedonia, and fatigue (American Psychiatric Association, 2013). There are multiple evidence-based interventions for symptoms of depression, including cognitive behavioral therapies (CBTs). Behavioral activation (BA) is a form of CBT with substantial evidence for its efficacy in the treatment of depression (Dimidjian et al., 2006; Dobson et al., 2008; Etherton & Farley, 2022). BA is based on behavioral theories of depression, namely that depression results in decreased levels of positive reinforcement and increased avoidance that is maintained through negative reinforcement (Martell et al., 2001). BA aims to teach patients the relationship between activity and mood and increase the presence of rewards in the environment. Common strategies of BA include activity monitoring, activity

scheduling, assessment of goals and values, and skills training (Kanter et al., 2010). Meta-analytic studies of BA support its effectiveness in treating depression (Ekers et al., 2014) and possibly other common mental disorders (Fernández-Rodríguez et al., 2023).

Despite the support for BA and other interventions as efficacious in the treatment of depression, these treatments have had little impact in reducing the public health burden of untreated mental illness (Kazdin & Blase, 2011). The prevailing unmet mental health needs may be due in part to the barriers related to receiving traditional psychotherapy or other forms of treatment, including limited time availability, lack of financial resources, lack of insurance coverage, stigma, and low provider availability (Andrade et al., 2014; Kazdin & Blase, 2011). Inaccessibility of evidence-based treatment for mental illness is particularly relevant in low-resource settings in the United States, such that communities that have larger representation of Black or Hispanic populations, as well as those in rural areas, have less access to mental health facilities (Cummings et al., 2013). Even when providers can be accessed, waiting times for treatment can be long and have increased recently (Peipert et al., 2022). These findings suggest that the current model of mental health care needs to change in order to accommodate the burden of common mental disorders, including depression and anxiety (Kazdin, 2017).

One proposed solution to this resource-need gap is the provision of low-intensity treatments (LITs). LITs, which may not require the use of a professional, have the potential to address the public health burden of mental disorders by serving as a more accessible tool for mental health care. These LITs can be self-guided (i.e., "unguided") or use professionals or paraprofessionals to guide the intervention (i.e., "guided"). Both guided and self-guided LITs have been proven to be effective relative to controls like waiting lists and care as usual (e.g, Cuijpers, 1997; Gregory et al., 2004). In general, guided LITs are more efficacious than self-guided LITs (Cuijpers et al., 2010), with guided LITs appearing to have similar efficacy to face-to-face therapy (Cuijpers et al., 2019). Moreover, providers are generally interested in the implementation potential for LITs in clinical settings (e.g., while patients are placed on a waiting list), despite their current use being rare (Peipert et al., 2023). Collectively, the results from these studies indicate that LITs provide a tenable and effective treatment alternative for people with common mental disorders, including depression and anxiety.

Single-session interventions (SSIs) are a type of LIT that can be delivered in one sitting. Face-to-face SSIs are effective for fear-based disorders (e.g., simple phobias), but still require the presence of a trained provider (Bertuzzi et al., 2021). Self-guided digital SSIs may scalable because internet access is relatively widespread. One recent meta-analysis demonstrates support for SSIs as an effective treatment for psychopathology in youth (Schleider & Weisz, 2017). In this work, efficacy of SSIs was not statistically different between therapist-guided ("guided") versus self-guided ("unguided") formats (Schleider & Weisz, 2017). The Common Elements Toolbox (COMET) is an SSI delivered online and self-guided. COMET contains CBT and positive psychology elements, including BA. In one study of the COMET intervention for graduate students, the participants found the intervention feasible and acceptable, and demonstrated improved perceived coping skills (Wasil et al., 2021). In a randomized controlled trial (RCT) of COMET with undergraduate students, participants demonstrated reduced depression symptoms (Wasil et al., 2021). However, in a second RCT of COMET with online workers, the outcomes did not demonstrate statistically or clinically significant (e.g., large) differences between the intervention and control groups (Lorenzo-Luaces & Howard, 2023. Thus, it is unclear how and for whom SSIs, like COMET, may be effective.

In sum, efficacy studies provide support for BA as a stand-alone treatment for depression and other common mental disorders. BA may have the potential to be delivered through more cost-effective formats, such as internet-delivery or LIT (Alber et al., 2023; Huguet et al., 2018). Nonetheless, BA is underutilized in routine care settings (Becker et al., 2013; Stewart & Chambless, 2007), and is not represented in many popular apps for mental well-being (Buss, Steinberg, et al., 2024). Furthermore, gaps remain in the literature to understand how BA is defined and assessed (Lorenzo-Luaces, 2023; Lorenzo-Luaces et al., 2016). Proposed mechanisms often include activation and increased environmental reward, but evidence of these constructs as mediators of outcomes in research trials is weak and often limited to self-report (Hoyer et al., 2020; Manos et al., 2010). Few researchers have addressed the nature of the BA activities themselves (Manos et al., 2010), specifically whether more "activating" activities (vs. sedentary ones) have greater benefit, or the benefit of social activities over solitary ones. It remains unclear whether activity type may influence clinical outcomes, as certain

activities may target depression symptoms and processes more directly than others. For instance, engaging in social activities may be more rewarding than activities that are solitary and may serve to increase avoidance of social interactions.

In one of the few studies exploring processes of change related to BA, Burkhardt and colleagues (2021) used natural language processing of text-based counselling sessions from over 10,000 online patients. The patients completed 12 weeks of online counseling sessions via the Talkspace platform matched with providers, about 75% of whom endorsed a cognitive-behavioral theoretical orientation (Hull et al., 2020). Burkhardt and colleagues used the text-based data to compare the language indicators of participation in pleasurable activities to symptom outcomes. Using this methodology, they built a measure of BA as a dictionary of terms that were related to positive outcomes in BA. The results of this study showed that activation can be assessed through linguistic indicators, which can be applied to text-based therapy session data to differentiate outcomes in depression symptoms. Other studies have correlated self-reported frequency of activities based on different theoretical underpinnings (e.g., BA developed by Martell et al., 2001, and behavioral activation treatment for depression [BATD] developed by Lejuez et al., 2001) with symptom outcomes. While helpful, these studies do not delineate the theoretical nature of BA, including the types of activities to include in activity scheduling (Manos et al., 2010).

More process research on BA, particularly when it is delivered in more scalable forms, for example, as an LIT, could help improve the streamlining and dissemination of BA approaches. The purpose of the present study is to explore the nature of activities scheduled by participants in an RCT of COMET. We aim to assess the types of activities scheduled, the frequency of these activities, clinical and demographic predictors of activity type, and employ a natural language processing approach to compare the activity language used in COMET with the activity language used in BA conducted with a provider to quantitatively measure similarity in activities between SSI-delivered BA and BA psychotherapy. Using the categories generated from content analysis, we explored the relationship of activity categories to treatment outcomes in the COMET intervention.

Methods

We reanalyzed data from an 8-week preregistered RCT comparing the COMET-SSI with a waiting list control in online workers (Lorenzo-Luaces & Howard, 2023. The design and analysis of the study were both preregistered, although the current reanalysis was not. Institutional review board approval from Indiana University was obtained as part of this study and all participants provided informed consent. As we were interested in participants in the treatment condition, we only included data from the treatment arm and did not analyze participants in the control arm of the RCT. Participants randomized to the treatment condition completed a one-time self-guided four-module online intervention. For this study, we will only discuss the BA module. Participants then completed follow-up surveys at 2-weeks, 4-weeks, and 8-weeks postintervention. Where applicable, our analyses focus on the 2-week and 8-week follow-up periods.

COMET

COMET is a self-guided 4-module intervention based on core principles of CBT (i.e., cognitive restructuring and BA) and positive psychology (i.e., gratitude and self-compassion). COMET was designed to take approximately 30–40 minutes to complete. It presents individuals with psychoeducation in the form of texts and brief psychosocial exercises. For BA, participants were guided through an activity scheduling exercise via text and open response questions where they were asked to reflect on activities they find enjoyable and meaningful. Participants then were asked to list three examples of activities, emphasizing activities with an "active component" with examples provided (e.g., "cooking") over "passive" activities (e.g., watching television). Participants were then asked to select one of the three brainstormed activities to plan to engage in more frequently. Finally, participants completed an activity plan, where they identified when they will complete the activity, where it will take place, who else will be involved, and ways to tackle potential obstacles to completing their plan. Participants completed each section of the activity plan in separate open-response entries. Participants were encouraged to practice the skills regularly in order to get the most benefit from the program, though no formal reminders were included.

PARTICIPANTS

The original research team sampled online workers living in the United States using Prolific, an online research platform. Participants were eligible if they answered "yes" to the question "Do you have—or have you ever had—a diagnosed, ongoing mental health illness/condition?" No exclusion criteria were used. Participants were compensated

PEIPERT ET AL.

at a rate of $7.50 per hour. The total maximum compensation for all parts of the study was $11.25. Demographic and baseline clinical variables are reported in Table 1.

MEASURES

Patient Health Questionnaire-8 (PHQ-8)

Depression symptoms were assessed with the PHQ-8, a version of the PHQ-9 that excludes the question of death ideation and self-harm. A previous systematic review supports the use of the PHQ-8 in lieu of the 9-item questionnaire (Wu et al., 2020). PHQ-9 is a 9-item self-report measure that assesses the frequency of symptoms of major depressive disorder as outlined by the DSM-5. Response options range from 0 ("not at all") to 3 ("nearly every day"). Total scores on the PHQ-8 range from 0–24 with greater scores

Table 1
Demographic and Clinical Variables for 409 Participants With a History of Psychopathology Who Were Randomized to Complete the Common Elements Toolbox (COMET) Single-Session Intervention (SSI)

		N (%); Median (IQR)
Age		33 (26, 43)
Gender		
	Female	247 (60%)
	Male	132 (32%)
	Genderqueer/other	27 (7%)
Race/ethnicity		
	Non-Hispanic White	312 (77%)
	Non-Hispanic Black	21 (5%)
	Hispanic	27 (7%)
	Other	44 (11%)
Sexual orientation		
	Heterosexual/straight	260 (64%)
	LGBQ+	146 (36%)
Education		
	Less than high school	7 (2%)
	High school diploma/GED	50 (12%)
	Some college	126 (31%)
	Associate's degree	46 (11%)
	Bachelor's degree	123 (30%)
	Master's degree	48 (12%)
	Doctoral or professional degree	9 (2%)
Income		
	<$15,000	42 (10%)
	$15,000–$24,999	39 (10%)
	$25,000–$34,999	44 (11%)
	$35,000–$49,999	79 (19%)
	$50,000–$74,999	80 (20%)
	$75,000–$99,999	55 (13%)
	$100,000–$149,999	39 (10%)
	$150,000–$199,999	13 (3%)
	>$200,000	8 (2%)
Number of friends can count on		
	0–1	96 (24%)
	2–5	271 (66%)
	6+	41 (10%)
Perceived health		
	Excellent/Good	163 (40%)
	Average	163 (40%)
	Poor/Terrible	82 (20%)
Depression (PHQ-8)		11 (7, 17)
Anxiety (GAD-7)		8 (5, 13)
WHO-5		28 (16, 48)

Note. N = 409, GAD-7 = Generalized Anxiety Disorder Scale-7, GED = General Education Development, IQR = interquartile range, LGBQ + = lesbian, gay, bisexual, queer/questioning, PHQ-8 = Patient Health Questionnaire-8, WHO-5 = World Health Organization Well-being Index-5.

indicating greater frequency of depressive symptoms. A score greater than or equal to 10 on the PHQ-9 has been identified as a positive screen for major depression (Kroenke & Spitzer, 2002). As such, a score of 9 on the PHQ-8 was considered a positive screen for depression.

Generalized Anxiety Disorder Scale-7 (GAD-7)

Anxiety symptoms were assessed with the GAD-7, a 7-item self-report measure that assesses the frequency of generalized anxiety symptoms. Responses range from 0 ("not at all") to 3 ("nearly every day"), yielding total scores that range from 0–21 with greater scores indicating greater frequency of generalized anxiety symptoms. A score greater than or equal to 10 on the GAD-7 has been identified as a positive screen for anxiety in primary care settings (Spitzer et al., 2006), while in clinical populations, both acute psychiatric samples (Beard & Björgvinsson, 2014) and outpatient samples (Rutter & Brown, 2017, the GAD-7 functions better as an indicator of GAD severity than a screening tool.

World Health Organization Well-Being Index-5 (WHO-5)

Well-being was assessed with the WHO-5, a 5-item self-report measure of subjective well-being. Items are rated on a 6-point Likert scale ranging from 0 ("at no time") to 5 ("all of the time"), yielding total raw scores that range from 0–25. Raw scores are multiplied by four to generate a score from 0–100 with greater scores indicating higher levels of subjective well-being. A score of <50 is considered the cutoff to screen for major depression in some studies (Topp et al., 2015), and a score of <28 is considered a positive screen for major depressive disorder (Lowe et al., 2004).

ANALYSIS PLAN

Content Analysis

Two authors (AP & LR) used qualitative content analysis to code activities generated by participants into established BA themes from a manual of BA for depression, Brief Behavioral Activation Treatment for Depression (Lejuez et al., 2001). Content analytic methods were chosen to use a deductive approach to sorting activities into categories and quantify their frequency (Downe-Wamboldt, 1992). Initial activity category codes included: family relationships, social relationships, intimate relationships, education/training, employment/career, hobbies/recreation, volunteer/charity work, physical/health, spirituality, and psychological/emotion (Lejuez et al., 2001). After reviewing the data, both coders established an initial codebook and definitions from these categories. After data were coded into initial activity categories, dis-

crepancies between raters were resolved through discussion. The initial codebook contained one code for "hobbies," which included a large degree of heterogeneity, in particular regarding how "active" the hobbies were. Given the intervention specifically instructed participants to generate "activating" activities, we coded hobbies into "active" vs. "passive" categories. Because of difficulty resolving discrepancies for this large category, we employed a "wisdom of the crowds" approach, crowdsourcing the rating of hobbies to 100 online workers from Prolific. The raters divided the "hobbies" theme into "active" vs. "sedentary" hobbies and the two raters (AP & LR) verified agreement with these ratings. Each category was coded as a dummy variable (i.e., "0" or "1") to allow for certain activities which may fall into multiple categories (e.g., playing a board game with friends). For each category, we report the frequencies and percentage of endorsement of activity categories.

Predictors of Activity Categories

We explored demographic and clinical predictors of the most commonly selected activity categories by conducting a series of logistic regressions. Specifically, we used binomial logistic regressions with the dependent variables of selecting a specific activity category (e.g., scheduling a physical activity vs. not scheduling a physical activity). Each model includes demographic information and baseline clinical variables: gender (male vs. female vs. genderqueer/other), age, race/ethnicity (Non-Hispanic White, Non-Hispanic Black, Hispanic, Other), education (as a numeric variable ranging from 1 to 6, including the following: less than high school or high school/GED, some college, associate's degree, bachelor's degree, master's degree, or doctorate), income (as a numeric variable ranging from 1 to 9 including <$15,000, $15,000–$24,999, $25,000–$34,999, $35,000–$49,999, $50,000–$74,999, $75,000–$99,999, $100,000–$149,999, $150,000–$199,999, and >$200,000), number of friends they can count on (e.g., perceived social support, as a numeric variable ranging from 1 to 3, including 0–1 friends, 2–5 friends, and 6 or greater friends), perceived health (as a numeric variable that ranged from 1 to 3 including terrible/poor, average, and good/excellent), and depression as a numeric variable measured by the PHQ-8 score (see Table 1 for details). Some participant data were missing, resulting in the inclusion of 357 participants in the regressions.

Natural Language Processing (NLP) Outcomes

To quantify the similarity of the self-generated BA content to those used in online text-based counseling sessions, we compared the self-generated activ-

ities in our data to a BA dictionary developed by (Burkhardt et al., 2021) using the Linguistic Inquiry and Word Count (LIWC) software (Boyd et al., 2022). This novel and exploratory approach allowed us to generate a quantitative analysis of the overlap in lexicon between the activities generated by SSI participants and those in online counseling. This analysis quantifies the words used by our subjects in their BA activity scheduling that overlap with the dictionary, to create a percentage of overlap for each subjects' response.

Predicting Primary Outcomes
We explored whether primary outcomes (i.e., PHQ-8, GAD-7, and WHO-5) were predicted by the activity category participants chose to schedule. We ran a series of linear regressions with 2- and 8-week follow-up scores on each outcome measure (i.e., PHQ-8, GAD-7, WHO-5) as the dependent variable predicted by baseline scores on that measure (i.e., PHQ-8, GAD-7, WHO-5), the activity category scheduled measured as a binary variable of active (i.e., active hobby or physical activity) or not active (i.e., sedentary hobby), and the baseline demographic variables included in the predictors of activity categories above (i.e., gender, age, race/ethnicity, education, income, perceived social support, and perceived health). All regressions were tested for multicollinearity using Variance Inflation Factors. Missing data resulted in the inclusion of 280–285 participants for the 2-week follow-up outcomes, and 273–275 participants for the 8-week follow-up outcomes reported. Missingness was impacted by study attrition but also whether or not participants selected an activity that fell into the category variables included in the regressions.

Results

SAMPLE CHARACTERISTICS
The participants in the COMET-SSI sample were on average in their mid-30's, mostly non-Hispanic White, and over half female-identifying. Over a third identified as lesbian, gay, bisexual, or queer/questioning. Additional demographic and baseline clinical information is reported in Table 1.

ACTIVITY CATEGORIES
Nine different activity types were identified through content analysis of scheduled positive activities (see Table 2 for examples). The nine categories included: sedentary hobbies (41%), physical activities (29%), active hobbies (18%), social activities (6%), task-oriented activities (3%), psychological/emotional activities (1%), spiritual activities (0.6%), volunteering (0.2%), and academic activities (0.1%).

PREDICTORS OF ACTIVITY CATEGORIES
We explored demographic and clinical predictors of selecting a specific activity category using three binomial logistic regressions for each of the most common activities generated by participants: sedentary hobbies, physical activities, and active hobbies (see Table 3). Thus, these were the binomial dependent variables for each model (i.e., whether participants chose to select or not select this type of activity). To explore predictors of selecting each activity type, we included baseline clinical and demographic variables of gender, age, race/ethnicity, level of education, income, perceived social support, perceived physical health, and baseline PHQ-8 score. We tested each regression for multicollinearity and Variance Inflation Factors all fell within acceptable range (i.e., <5).

The regressions suggest participants who identified as female, who had more formal education, and who had greater perceived social support were less likely to select BA activities that fell under the category of sedentary hobbies. In contrast, participants who were non-Hispanic Black or Hispanic were more likely to schedule sedentary hobbies. The regression predicting active hobbies found no statistically significant predictors of scheduling an active hobby in the BA module.

Table 2
Activity Categories and Example Scheduled Activities Generated by 409 Participants in the COMET Trial

Activity category	Definition	Examples
Sedentary hobbies	Hobbies with little or no physical movement	Listening to music
Physical activities	Forms of exercise or sports	Hiking
Active hobbies	Hobbies that require movement	Traveling
Social activities	Activities that mention other people	Going out with friends
Task-oriented activities	Chores, household maintenance	Cleaning
Psychological/emotional activities	Meditation	Meditation
Spiritual activities	Related to religious practice	Praying
Volunteering	Charity or volunteer work	Volunteering
Academic activities	Mention school, learning	Studying a subject that interests me

Table 3
Logistic Regression Analyses Predicting Participants' Likeli-hood to Select Activity Categories From Demographic and Clinical Predictors ($N = 357$)

Sedentary Hobbies

Predictor	OR	95% CI	p
Gender			
Male	1.00	—	
Female	0.46**	0.28, 0.75	0.002
Genderqueer/other	1.02	0.40, 2.59	>0.9
Age	1.00	0.97, 1.02	0.60
Race/Ethnicity			
Non-Hispanic White	1.00	—	
Non-Hispanic Black	4.40**	1.57, 13.7	0.007
Hispanic	4.50**	1.63, 14.5	0.006
Other	1.41	0.67, 2.98	0.40
Education	0.80*	0.67, 0.95	0.01
Income	1.01	0.89, 1.14	>0.90
Social support	0.58*	0.37, 0.91	0.02
Physical health	1.12	0.80, 1.57	0.50
PHQ-8	1.02	0.98, 1.07	0.30

Active Hobbies

Predictor	OR	95% CI	p
Gender			
Male	—	—	
Female	1.30	0.66, 2.69	0.50
Genderqueer/other	0.57	0.08, 2.31	0.50
Age	0.99	0.96, 1.02	0.50
Race/ethnicity			
Non-Hispanic White	1.00	—	
Non-Hispanic Black	0.28	0.01, 1.45	0.20
Hispanic	0.26	0.01, 1.34	0.20
Other	0.50	0.12, 1.52	0.30
Education	1.00	0.79, 1.26	>0.90
Income	0.90	0.75, 1.07	0.20
Social support	1.48	0.78, 2.86	0.20
Physical health	1.12	0.70, 1.79	0.60
PHQ-8	0.97	0.92, 1.03	0.40

Physical Activities

Predictor	OR	95%CI	p
Gender			
Male	1.00	—	
Female	1.70*	1.03, 2.85	0.04
Genderqueer/other	1.13	0.41, 2.95	0.80
Age	1.00	0.98, 1.02	0.90
Race/Ethnicity			
Non-Hispanic White	1.00	—	
Non-Hispanic Black	0.31	0.08, 0.93	0.053
Hispanic	0.17*	0.03, 0.61	0.02
Other	0.90	0.42, 1.90	0.80
Education	1.30**	1.09, 1.54	0.003
Income	1.10	0.97, 1.25	0.13
Social support	1.20	0.76, 1.88	0.40
Physical health	0.93	0.66, 1.30	0.70
PHQ-8	1.00	0.96, 1.05	>0.90

CI = Confidence Interval, OR = Odds Ratio, PHQ-8 = Patient Health Questionnaire-8
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$

Outcomes of the regression predicting physical activities were similar to the outcomes on seden-tary activities, such that participants who identi-fied as female and who had more formal education were more likely to select this activity category. Additionally, participants who were His-panic were less likely to schedule physical activities.

nlp outcomes

LIWC analysis found an average lexicon overlap of 17% between the self-guided BA activities gen-erated by COMET participants and those in the BA dictionary generated from text-based counsel-ing sessions. When restricted to the BA activities COMET participants chose to schedule as part of the module, this average overlap increased to 19%. Example items that were noted to have com-plete overlap with the BA dictionary included "ex-ercising," "piano," and "painting."

predicting primary outcomes

We explored the predictive value of activity scheduling categories on primary outcome mea-sures, PHQ-8, GAD-7, and WHO-5, at 2-weeks and 8-weeks postintervention using a series of lin-ear regressions. Table 4 reports 8-week results across primary outcomes. Each regression used the primary outcome measure (e.g., PHQ-8 at 2 weeks) as the dependent variable and included a dichotomous variable for the scheduled activity that may have been active (i.e., physical activities, active hobbies) or not active (i.e., sedentary hobby). The regressions also included the same demographic characteristics included to predict activity categories at baseline (i.e., gender, age, race/ethnicity, education, income, perceived social support, and perceived health).

We did not find that scheduled activity category (i.e., active vs. not active) was predictive of any of the primary outcomes at week 2 or week 8. In this intervention, activity level did not significantly influence depression, anxiety, and subjective well-being outcomes. Rather, outcomes were largely predicted by baseline scores and demographic vari-ables, such as education, income, and perceived health status.

Discussion

Behavioral activation is an efficacious and widely studied treatment for depression. Despite this, sur-prisingly little is known about its processes overall, or as a low-intensity treatment without the guid-

Table 4
Linear Regression Analyses Predicting Participants' Primary Outcomes (PHQ-8, GAD-7, WHO-5) at 8 Weeks Postintervention From Demographic, Clinical, and Behavioral Activation Scheduled Activity Level Predictors

PHQ-8 at 8 weeks post-intervention (N = 275)

Coefficient	Estimate	Standard Error	t-value	p
Intercept	0.87	1.56	0.56	0.58
Baseline PHQ-8	0.70[***]	0.04	15.85	<0.001
Scheduled activity- active (vs. sedentary)	0.08	0.48	0.17	0.86
Gender				
Male	—			
Female	−0.35	0.50	−0.69	0.49
Genderqueer/other	1.16	1.00	1.16	0.25
Age	−0.01	0.02	−0.59	0.55
Race/ethnicity				
Non-Hispanic White	—			
Non-Hispanic Black	0.77	1.03	0.75	0.46
Hispanic	−1.35	1.04	−1.30	0.20
Other	−0.48	0.74	−0.65	0.52
Education	−0.10	0.17	−0.62	0.54
Income	−0.28[*]	0.13	−2.21	0.03
Social support	0.70	0.43	1.62	0.11
Physical health	1.00[**]	0.34	2.95	0.003

GAD-7 at 8-weeks post-intervention (N = 273)

Coefficient	Estimate	Standard Error	t-value	p
Intercept	−0.18	1.41	−0.13	0.90
Baseline PHQ-8	0.64[***]	0.04	15.29	<0.001
Scheduled activity- active (vs. sedentary)	0.74	0.43	1.72	0.09
Gender				
Male	—			
Female	−0.29	0.45	−0.65	0.52
Genderqueer/other	0.35	0.89	0.39	0.70
Age	−0.02	0.02	−1.06	0.29
Race/ethnicity				
Non-Hispanic White	—			
Non-Hispanic Black	0.31	0.92	0.33	0.74
Hispanic	−0.90	0.93	−0.97	0.33
Other	−0.40	0.66	−0.60	0.55
Education	0.05	0.15	0.32	0.75
Income	−0.23[*]	0.11	−2.02	0.04
Social support	0.63	0.38	1.65	0.10
Physical health	1.28[***]	0.29	4.39	<0.001

WHO-5 at 8-weeks post-intervention (N = 275)

Coefficient	Estimate	Standard Error	t-value	p
Intercept	16.19[*]	6.50	2.49	0.01
Baseline PHQ-8	2.73[***]	0.22	12.57	<0.001
Scheduled activity- active (vs. sedentary)	−1.58	2.07	−0.76	0.45
Gender				
Male	—			
Female	−2.12	2.18	−0.97	0.33
Genderqueer/other	−2.72	4.34	−0.63	0.53
Age	0.06	0.09	0.74	0.46
Race/ethnicity	—			
Non-Hispanic White	−3.43	4.40	−0.78	0.44
Non-Hispanic Black	1.41	4.47	0.32	0.75
Hispanic	3.88	3.18	1.22	0.22
Other	1.54[*]	0.72	2.14	0.03

Education	0.69	0.54	1.28	0.20
Income	−2.08	1.83	−1.14	0.26
Social support	−3.57*	1.48	−2.42	0.02
Physical health	−3.43	4.40	−0.78	0.44

Note. N = 409, GAD-7 = Generalized Anxiety Disorder Scale-7, PHQ-8 = Patient Health Questionnaire-8, WHO-5 = World Health Organization Well-being Index-5.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

ance and accountability of a therapist. Using a self-guided online treatment, the Common Elements Toolbox (COMET; Wasil et al., 2021), this study examined how individuals engage in BA, and specifically how the types of activities they generate match with existing values-based positive events scheduling. An interesting pattern emerged in our results, such that individuals did not generate as many "active" activities as the prompt recommended, leading to an exploration of potential differences in active vs sedentary activities by demographics and clinical variables. Overall, our results showed that female-identifying participants, those with more education, and those with more perceived social support were generally more likely to schedule "active" activities, and less likely to schedule sedentary hobbies. Additionally, non-Hispanic Black and Hispanic participants were more likely to select sedentary hobbies to schedule. These results suggest opportunities for personalizing the delivery of BA (DeRubeis et al., 2014; Lorenzo-Luaces et al., 2021), especially when delivered as an LIT, for instance, to add more structure and feedback with participant responses, or including just-in-time adaptive components to the intervention (Nahum-Shani et al., 2018).

We also explored whether the category of activity scheduled predicted primary outcomes, depression symptoms, anxiety symptoms, and subjective well-being, at 2-weeks and 8-weeks postintervention. Theoretically, it would make sense that activities traditionally considered to be more "activating" would have a greater efficacy on mood outcomes than less "activating" activities. However, our study did not find the category of activity scheduled to be predictive of outcomes at either follow-up point, despite our study being powered to detect relatively small correlations, $r = 0.14$. Though we cannot conclude why this is the case, a few theories may be possible. First, it might be that that activity type does not affect clinical outcomes. There may be no difference in the benefits between, for instance, adding a sedentary vs. active activity in their effect on mood. It may instead be that there are differential functions attributed to different activities that produced the benefit of BA, and that might not be reflected in activity type specifically. For example, some individuals may read to distract themselves, others to relax, and others to find intellectual stimulation. Alternatively, the original hypothesis that activity type does affect clinical outcomes may be correct, and rather there are other explanations for the null finding, including that participants may not have completed the activity they planned, or used the skills as described or that we need more fine-grained measurement of activities. Future work could provide greater nuance in understanding how activities relate to outcomes by measuring value or other functional-contextual variables that may moderate the effects of activity scheduling on mood.

LIMITATIONS AND STRENGTHS

Several limitations of the study are worth considering. First, the COMET intervention did not include an adherence check to verify whether COMET participants followed through on their plans to complete their scheduled BA activity. Thus, it is not known the extent to which participants successfully engaged in BA as we would expect it to be effective. As we know from the RCT results (Lorenzo-Luaces & Howard, 2023), COMET was not an effective intervention in this group, despite prior work supporting its efficacy in other settings. Provided BA is an evidence-based intervention, it was even more important to consider what might explain variability in outcomes within this setting. While variability in the selected intervention could have accounted for individual differences in the efficacy of the intervention, our results do not support this hypothesis. Another limitation of the original dataset was that participants were not screened for an interest in treatment, they were recruited through the Prolific platform for participation. A third limitation is the interpretation of the lexicon analysis. We compared the terms used by our participants with the dictionary developed by Burkhardt and colleagues. It is possible that using more complex natural language processing algorithms would have yielded a

greater overlap in activities selected. It is possible that the low overlap between the two lexicons is due to the different contexts in which the data were collected, although this would not explain the abundance of passive activities in our data. Finally, we employed the PHQ-8 in lieu of the PHQ-9, which limits our ability to study suicidality and thoughts of death with a low-intensity intervention. Though previous work supports the use of the PHQ-8 as an alternative to the PHQ-9 (Wu et al., 2020), suicidality and death ideation with LITs for depression is understudied and would be a particularly important area for future study given the self-guided nature of many LITs.

The strengths in this study include the large sample size within a depressed sample, suggesting the intention to recruit participants who may benefit from a CBT-based SSI was successful. Additionally, online workers are a notably difficult to treat sample with other recent research demonstrating null findings on interventions in online worker samples when similar interventions have shown efficacy with other samples (Mullarkey et al., 2022). We also triangulated self-report and text-based data to understand the process of change in BA across multiple units of analysis. Finally, we measured internalizing symptoms along with transdiagnostic outcomes like well-being to obtain a better picture of how activity scheduling may relate to outcomes.

IMPLICATIONS

Low-intensity treatment interventions, specifically SSIs, present an opportunity for individuals to gain access to evidence-based skills without committing to a course of therapy. There is ample evidence that self-guided SSIs work well in targeting common mental disorders in youth (Schleider & Weisz, 2017), but there is still much to be learned about how individuals engage with them. Our study showed that women and individuals with a higher level of education were more likely to generate active hobbies when prompted to list BA activities. This pattern of results is similar to findings that there are demographic differences in treatment engagement (Ekers et al., 2014). However, our results may also suggest that there may be considerable differences between self-guided BA compared to guided BA. Specifically, users of the self-guided SSI may schedule more sedentary activities, and ones that involve less social support compared to BA in traditional psychotherapy settings. Implications of this work include providing more psychoeducation and specificity in what constitutes BA. Alternatively, language models could

be leveraged to give participants real-time feedback on their activity selection.

Our initial idea that BA should be "active," as the name suggests, is based on the literature that physical activity is effective in preventing depression (Schuch et al., 2017; Wolf et al., 2021) along with the theory that underlies BA. However, many value-based activities may be sedentary, but nonetheless reinforcing, and still provide good benefits in managing depression. For example, engaging in creative arts can enhance mental health and well-being in children (Wright et al., 2022). While BA is an effective treatment for depression, and we can make inferences about its mechanisms from basic research in reward-learning, more research is needed on the specific components of BA that make it effective (Hoyer et al., 2020; Lorenzo-Luaces et al., 2016; Manos et al., 2010). Notably, some minoritized groups in our sample (i.e., those with lower education, racial-ethnic minorities) also had an increased likelihood of selecting sedentary activities. This is also consistent with our work showing that adolescents with higher levels of depression, anxiety, and loneliness use more social media (a commonly sedentary activity) and exercise less (Rutter et al., 2021). More work is needed to understand how to further personalize treatments of depression within an SSI, including to minoritized groups. Additional structure, psychoeducation, and personalization may have potential to improve participant activation, and thus improve outcomes in a LIT (Lorenzo-Luaces et al., 2021). Future adaptations may focus on just-in-time adaptations, such as including a check for perceived likelihood of following through on the participants' action plan, or a check if participants rate anticipated pleasure of the activity as low.

The simplicity and comprehensible nature of BA makes this evidence-based treatment particularly well-suited for its translation into an LIT or SSI. Future work should investigate ways to increase participation in more seemingly rewarding and activating behaviors with little to no guidance from a professional, and how activity type and frequency may influence gains through LIT-delivered BA.

References

Alber, C. S., Krämer, L. V., Rosar, S. M., & Mueller-Weinitschke, C. (2023). Internet-based behavioral activation for depression: systematic review and meta-analysis. *Journal of Medical Internet Research, 25,* e41643.

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596.

Andrade, L. H., Alonso, J., Mneimneh, Z., Wells, J. E., Al-Hamzawi, A., Borges, G., Bromet, E., Bruffaerts, R., de Girolamo, G., de Graaf, R., Florescu, S., Gureje, O., Hinkov, H. R., Hu, C., Huang, Y., Hwang, I., Jin, R., Karam, E. G., Kovess-Masfety, V., ... Kessler, R. C. (2014). Barriers to mental health treatment: results from the WHO World Mental Health surveys. *Psychological Medicine, 44*(6), 1303–1317. https://doi.org/10.1017/S0033291713001943.

Beard, C., & Björgvinsson, T. (2014). Beyond generalized anxiety disorder: psychometric properties of the GAD-7 in a heterogeneous psychiatric sample. *Journal of anxiety disorders, 28*(6), 547–552.

Becker, E. M., Smith, A. M., & Jensen-Doss, A. (2013). Who's using treatment manuals? A national survey of practicing therapists. *Behaviour Research and Therapy, 51*(10), 706–710.

Bertuzzi, V., Fratini, G., Tarquinio, C., Cannistrà, F., Granese, V., Giusti, E. M., Castelnuovo, G., & Pietrabissa, G. (2021). Single-session therapy by appointment for the treatment of anxiety disorders in youth and adults: a systematic review of the literature. *Frontiers in Psychology, 12*, 721382.

Boyd, R. L., Ashokkumar, A., Seraj, S., & Pennebaker, J. W. (2022). *The development and psychometric properties of LIWC-22*. University of Texas at Austin. https://www.liwc.app.

Burkhardt, H. A., Alexopoulos, G. S., Pullmann, M. D., Hull, T. D., Areán, P. A., & Cohen, T. (2021). Behavioral activation and depression symptomatology: longitudinal assessment of linguistic indicators in text-based therapy sessions. *Journal of Medical Internet Research, 23*(7), e28244.

Buss, J. F., Steinberg, J. S., Banks, G., Horani, D., Rutter, L. A., Wasil, A. R., Ramirez, I., & Lorenzo-Luaces, L. (2024). Availability of internet-based cognitive-behavioral therapies for Depression: a systematic review. *Behavior Therapy, 55*(1), 201–211. https://doi.org/10.1016/j.beth.2023.06.003.

Buss, J. F., Watts, A. L., & Lorenzo-Luaces, L. (2023). Methods for quantifying the heterogeneity of psychopathology. *BMC Psychiatry, 23*(1), 897.

Cuijpers, P. (1997). Bibliotherapy in unipolar depression: a meta-analysis. *Journal of Behavior Therapy and Experimental Psychiatry, 28*(2), 139–147.

Cuijpers, P., Donker, T., van Straten, A., Li, J., & Andersson, G. (2010). Is guided self-help as effective as face-to-face psychotherapy for depression and anxiety disorders? A systematic review and meta-analysis of comparative outcome studies. *Psychological Medicine, 40*(12), 1943–1957. https://doi.org/10.1017/s0033291710000772.

Cuijpers, P., Noma, H., Karyotaki, E., Cipriani, A., & Furukawa, T. A. (2019). Effectiveness and acceptability of cognitive behavior therapy delivery formats in adults with depression: a network meta-analysis. *JAMA Psychiatry, 76* (7), 700–707. https://doi.org/10.1001/jamapsychiatry.2019.0268.

Cummings, J. R., Wen, H., Ko, M., & Druss, B. G. (2013). Geography and the Medicaid mental health care infrastructure: implications for health care reform. *JAMA Psychiatry, 70*(10), 1084–1090.

DeRubeis, R. J., Cohen, Z. D., Forand, N. R., Fournier, J. C., Gelfand, L. A., & Lorenzo-Luaces, L. (2014). The Personalized Advantage Index: translating research on prediction into individualized treatment recommendations. A demonstration. *PloS ONE, 9*(1), e83875. https://doi.org/10.1371/journal.pone.0083875.

Dimidjian, S., Hollon, S. D., Dobson, K. S., Schmaling, K. B., Kohlenberg, R. J., Addis, M. E., Gallop, R., McGlinchey, J. B., Markley, D. K., & Gollan, J. K. (2006). Randomized trial of behavioral activation, cognitive therapy, and antidepressant medication in the acute treatment of adults with major depression. *Journal of Consulting and Clinical Psychology, 74*(4), 658.

Dobson, K. S., Hollon, S. D., Dimidjian, S., Schmaling, K. B., Kohlenberg, R. J., Gallop, R. J., Rizvi, S. L., Gollan, J. K., Dunner, D. L., & Jacobson, N. S. (2008). Randomized trial of behavioral activation, cognitive therapy, and antidepressant medication in the prevention of relapse and recurrence in major depression. *Journal of Consulting and Clinical Psychology, 76*(3), 468.

Downe-Wamboldt, B. (1992). Content analysis: method, applications, and issues. *Health Care for Women International, 13*(3), 313–321. https://doi.org/10.1080/07399339209516006.

Ekers, D., Webster, L., Van Straten, A., Cuijpers, P., Richards, D., & Gilbody, S. (2014). Behavioural activation for depression; an update of meta-analysis of effectiveness and sub group analysis. *PLoS ONE, 9*(6), e100100.

Etherton, J. L., & Farley, R. (2022). Behavioral activation for PTSD: a meta-analysis. *Psychological Trauma: Theory, Research, Practice, and Policy, 14*(5), 894.

Fernández-Rodríguez, C., Coto-Lesmes, R., Martínez-Loredo, V., González-Fernández, S., & Cuesta, M. (2023). Is activation the active ingredient of transdiagnostic therapies? A randomized clinical trial of behavioral activation, acceptance and commitment therapy, and transdiagnostic cognitive-behavioral therapy for emotional disorders. *Behavior Modification, 47*(1), 3–45.

Gregory, R. J., Schwer Canning, S., Lee, T. W., & Wise, J. C. (2004). Cognitive bibliotherapy for depression: a meta-analysis. *Professional Psychology: Research and Practice, 35* (3), 275–280. https://doi.org/10.1037/0735-7028.35.3.275.

Hoyer, J., Hoefler, M., & Wuellhorst, V. (2020). Activity and subsequent depression levels: a causal analysis of behavioural activation group treatment with weekly assessments over 8 weeks. *Clinical Psychology & Psychotherapy, 27*(3), 330–336.

Huguet, A., Miller, A., Kisely, S., Rao, S., Saadat, N., & McGrath, P. J. (2018). A systematic review and meta-analysis on the efficacy of Internet-delivered behavioral activation. *Journal of Affective Disorders, 235*, 27–38.

Hull, T. D., Malgaroli, M., Connolly, P. S., Feuerstein, S., & Simon, N. M. (2020). Two-way messaging therapy for depression and anxiety: longitudinal response trajectories. *BMC Psychiatry, 20*, 1–12.

Kanter, J. W., Manos, R. C., Bowe, W. M., Baruch, D. E., Busch, A. M., & Rusch, L. C. (2010). What is behavioral activation?: A review of the empirical literature. *Clinical Psychology Review, 30*(6), 608–620.

Kazdin, A. E. (2017). Addressing the treatment gap: a key challenge for extending evidence-based psychosocial interventions. *Behaviour Research and Therapy, 88*, 7–18. https://doi.org/10.1016/j.brat.2016.06.004.

Kazdin, A. E., & Blase, S. L. (2011). Rebooting psychotherapy research and practice to reduce the burden of mental illness. *Perspectives Psychological Science, 6*(1), 21–37. https://doi.org/10.1177/1745691610393527.

Kroenke, K., & Spitzer, R. L. (2002). *The PHQ-9: a new depression diagnostic and severity measure, Vol. 32*, 509–515.

Lejuez, C. W., Hopko, D. R., & Hopko, S. D. (2001). A brief behavioral activation treatment for depression: treatment manual. *Behavior Modification, 25*(2), 255–286.

Liu, Q., He, H., Yang, J., Feng, X., Zhao, F., & Lyu, J. (2020). Changes in the global burden of depression from 1990 to 2017: findings from the Global Burden of Disease study. *Journal of Psychiatric Research, 126*, 134–140. https://doi.org/10.1016/j.jpsychires.2019.08.002.

Lorenzo-Luaces, L. (2023). Identifying active ingredients in cognitive-behavioral therapies: what if we didn't? *Behaviour Research and Therapy, 168*, 104365.

Lorenzo-Luaces, L., & Howard, J. (2023). Efficacy of an unguided, digital single-session intervention for internalizing symptoms in web-based workers: randomized controlled trial. *Journal of Medical Internet Research, 25*, e45411.

Lorenzo-Luaces, L., Keefe, J. R., & DeRubeis, R. J. (2016). Cognitive-behavioral therapy: nature and relation to non-cognitive behavioral therapy. *Behavior Therapy, 47*(6), 785–803.

Lorenzo-Luaces, L., Peipert, A., De Jesus Romero, R., Rutter, L. A., & Rodriguez-Quintana, N. (2021). Personalized medicine and cognitive behavioral therapies for depression: small effects, big problems, and bigger data. *International Journal of Cognitive Therapy, 14*, 59–85.

Lowe, B., Spitzer, R. L., Grafe, K., Kroenke, K., Quenter, A., Zipfel, S., Buchholz, C., Witte, S., & Herzog, W. (2004). Comparative validity of three screening questionnaires for DSM-IV depressive disorders and physicians' diagnoses. *Journal of Affective Disorders, 2*(78), 131–140.

Manos, R. C., Kanter, J. W., & Busch, A. M. (2010). A critical review of assessment strategies to measure the behavioral activation model of depression. *Clinical Psychology Review, 30*(5), 547–561.

Martell, C. R., Addis, M. E., & Jacobson, N. S. (2001). *Depression in context: strategies for guided action*. WW Norton & Co..

Mullarkey, M., Dobias, M., Sung, J., Ahuvia, I., Shumake, J., Beevers, C., & Schleider, J. (2022). Web-based single session intervention for perceived control over anxiety during COVID-19: randomized controlled trial. *JMIR Mental Health, 9*(4), e33473.

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine*, 1–17.

Peipert, A., Adams, S., & Lorenzo-Luaces, L. (2023). "I would not want the mechanic to direct me to an engine repair manual": a qualitative analysis of provider perspectives on low-intensity treatments for patients on waiting lists. *BMC Psychiatry, 23*(1), 600. https://doi.org/10.1186/s12888-023-05055-6.

Peipert, A., Krendl, A. C., & Lorenzo-Luaces, L. (2022). Waiting lists for psychotherapy and provider attitudes toward low-intensity treatments as potential interventions: survey study. *JMIR Formative Research, 6*(9), e39787.

Rutter, L. A., & Brown, T. A. (2017). Psychometric properties of the generalized anxiety disorder scale-7 (GAD-7) in outpatients with anxiety and mood disorders. *Journal of psychopathology and Behavioral Assessment, 39*, 140–146.

Rutter, L. A., Thompson, H. M., Howard, J., Riley, T. N., De Jesús-Romero, R., & Lorenzo-Luaces, L. (2021). Social media use, physical activity, and internalizing symptoms in adolescence: cross-sectional analysis. *JMIR mental health, 8*(9), e26134.

Schleider, J. L., & Weisz, J. R. (2017). Little treatments, promising effects? Meta-analysis of single-session interventions for youth psychiatric problems. *Journal of the American Academy of Child and Adolescent Psychiatry, 56*(2), 107–115. https://doi.org/10.1016/j.jaac.2016.11.007.

Schuch, F. B., Morres, I. D., Ekkekakis, P., Rosenbaum, S., & Stubbs, B. (2017). A critical review of exercise as a treatment for clinically depressed adults: time to get pragmatic. *Acta Neuropsychiatrica, 29*(2), 65–71. https://doi.org/10.1017/neu.2016.21.

Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: the GAD-7. *Archives of Internal Medicine, 166*(10), 1092–1097.

Stewart, R. E., & Chambless, D. L. (2007). Does psychotherapy research inform treatment decisions in private practice? *Journal of Clinical Psychology, 63*(3), 267–281.

Topp, C. W., Østergaard, S. D., Søndergaard, S., & Bech, P. (2015). The WHO-5 well-being index: a systematic review of the literature. *Psychotherapy and Psychosomatics, 84*(3), 167–176. https://doi.org/10.1159/000376585.

Wasil, A. R., Taylor, M. E., Franzen, R. E., Steinberg, J. S., & DeRubeis, R. J. (2021). Promoting graduate student mental health during COVID-19: acceptability, feasibility, and perceived utility of an online single-session intervention. *Frontiers in Psychology, 12*, 569785. https://doi.org/10.3389/fpsyg.2021.569785.

Whiteford, H. A., Degenhardt, L., Rehm, J., Baxter, A. J., Ferrari, A. J., Erskine, H. E., Charlson, F. J., Norman, R. E., Flaxman, A. D., Johns, N., Burstein, R., Murray, C. J. L., & Vos, T. (2013). Global burden of disease attributable to mental and substance use disorders: findings from the Global Burden of Disease Study 2010. *The Lancet, 382*(9904), 1575–1586. https://doi.org/10.1016/S0140-6736(13)61611-6.

Wolf, S., Seiffer, B., Zeibig, J. M., Welkerling, J., Brokmeier, L., Atrott, B., Ehring, T., & Schuch, F. B. (2021). Is physical activity associated with less depression and anxiety during the COVID-19 pandemic? A rapid systematic review. *Sports Medicine*, 1–13. https://doi.org/10.1007/s40279-021-01468-z.

Wright, P., Down, B., & Davies, C. (2022). Learning, making and flourishing in non-formal spaces: participatory arts and social justice. *Education, Citizenship and Social Justice, 17*(1), 54–68.

Wu, Y., Levis, B., Riehm, K. E., Saadat, N., Levis, A. W., Azar, M., Rice, D. B., Boruff, J., Cuijpers, P., & Gilbody, S. (2020). Equivalency of the diagnostic accuracy of the PHQ-8 and PHQ-9: a systematic review and individual participant data meta-analysis. *Psychological Medicine, 50*(8), 1368–1380.