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The use of coaching in smartphone app-based cognitive behavioral therapy for body dysmorphic disorder

Emily E. Bernstein [a,b,*,1], Jennifer L. Greenberg [a,b,1], Hilary Weingarden [a,b], Ivar Snorrason [a,b], Berta Summers [a], Jasmine Williams [a], Rachel Quist [a], Joshua Curtiss [a,c], Oliver Harrison [d], Sabine Wilhelm [a,b]

[a] Massachusetts General Hospital, United States of America
[b] Harvard Medical School, United Kingdom
[c] Northeastern University, United States of America
[d] Koa Health, United States of America

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ABSTRACT

Background: Body dysmorphic disorder (BDD) is severe and undertreated. Digital mental health could be key to expanding access to evidence-based treatments, such as cognitive behavioral therapy for BDD (CBT-BDD). Coach guidance is posited to be essential for effective uptake of digital interventions. However, little is known about how different patients may use coaching, what patterns correspond to meaningful outcomes, and how to match coaching to patient needs.

Methods: Participants were 77 adults who received a 12-week guided smartphone CBT-BDD. Bachelor's-level coaches were available via asynchronous messaging. We analyzed the 400 messages sent by users to coaches during treatment. Message content was coded using the efficiency model of support (i.e., usability, engagement, fit, knowledge, and implementation). We aimed to clarify when and for what purposes patients with BDD used coaching, and if we can meaningfully classify patients by these patterns. We then assessed potential baseline predictors of coach usage, and whether distinct patterns relate to clinical outcomes.

Results: Users on average sent 5.88 messages (SD = 4.51, range 1–20) and received 9.84 (SD = 5.74, range 2–30). Regarding frequency of sending messages, latent profile analysis revealed three profiles, characterized by: (1) peak mid-treatment (16.88 %), (2) bimodal/more communication early and late in treatment (10.39 %), and (3) consistent low/no communication (72.73 %). Regarding content, four profiles emerged, characterized by mostly (1) engagement (51.95 %), (2) fit (15.58 %), (3) knowledge (15.58 %), and (4) miscellaneous/no messages (16.88 %). There was a significant relationship between frequency profile and age, such that the early/late peak group was older than the low communication group, and frequency profile and adherence, driven by the mid-treatment peak group completing more modules than the low contact group. Regarding content, the engagement and knowledge groups began treatment with more severe baseline symptoms than the fit group. Content profile was associated with dropout, suggesting higher dropout rates in the miscellaneous/no contact group and reduced rates in the engagement group. There was no relationship between profile membership and other outcomes.

Discussion: The majority of participants initiated little contact with their coach and the most common function of communications was to increase engagement. Results suggest that older individuals may prefer or require more support than younger counterparts early in treatment. Additionally, whereas individuals using coaching primarily for engagement may be at lower risk of dropping out, those who do not engage at all may be at elevated risk. Findings can support more personalized, data-driven coaching protocols and more efficient allocation of coaching resources.

* Corresponding author at: 185 Cambridge Street, Suite 2000, Boston, MA 02114, United States of America.
E-mail address: eebernstein@mgh.harvard.edu (E.E. Bernstein).

[1] Co-first authors.

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1. Introduction

Body dysmorphic disorder (BDD), characterized by often debilitating fixation on perceived appearance flaws, is chronic, severe, and undertreated (Association AP, 2013; Phillips et al., 2013). Although cognitive behavioral therapy tailored for BDD (CBT-BDD) is effective for many patients (Harrison et al., 2016; Wilhelm et al., 2019), few people can access therapists who are familiar with BDD let alone trained to deliver this evidence-based, specialized treatment (Marques et al., 2011). New, more accessible, and scalable support is needed. Digital mental health—particularly smartphone and mobile-based delivery of this intervention—could be part of the solution (Linardon et al., 2019; Wilhelm et al., 2020a). These technologies allow standardized, evidence-based tools to be available continuously and in digestible, interactive formats. To date, multiple internet-based CBT-BDD interventions (Enander et al., 2016; Gentile et al., 2019; Enander et al., 2014; Schoenenberg et al., 2023; Rautio et al., 2023; Hartmann et al., 2021) and one smartphone app-based CBT-BDD (Perspectives) have been developed (Wilhelm et al., 2020b; Wilhelm et al., n.d.). Early studies show that digital CBT content can be delivered safely and effectively for BDD. Although retention rates vary widely (55 % - 95 %), consistent with the broader digital mental health literature, individuals who provide outcomes data tend to assign digital CBT-BDD high acceptability and satisfaction ratings (Enander et al., 2016; Schoenenberg et al., 2023; Rautio et al., 2023; Wilhelm et al., 2022).

However, these treatments are all guided; they include concurrent support from clinicians or trained coaches. Indeed, experts in digital mental health regularly assert that human support (e.g., messaging or calls with a coach or therapist) is critical to maximizing treatment engagement and efficacy (Mohr et al., 2011; Torous et al., 2018), particularly for individuals with severe psychopathology such as BDD and obsessive-compulsive disorder (OCD) (Mohr et al., 2011; Torous et al., 2018). The efficiency model of support examines benefits gained from an intervention relative to the resources allocated (Mohr et al., 2019). Integrating human support into digital interventions can address gaps in usability (e.g., navigating the technology), engagement (e.g., via encouragement and accountability), fit (e.g., tailoring standard strategies to an individual), knowledge (e.g., clarifying or delivering content), and implementation (e.g., problem-solving barriers to translating skills to patient's daily life) (Mohr et al., 2019). This model has since been used to guide the development of coaching protocols for digital mental health interventions (Chow et al., 2020; Mohr et al., 2017).

Yet, presently little empirical guidance exists for implementing human support. In fact, little is known about what coaching actually looks like in practice (e.g., frequency, content) let alone what it *should* look like to optimize outcomes or resources (Bernstein et al., n.d.). Although it is known that coaches typically send significantly more messages than users (Mohr et al., 2017; Carolan et al., 2017; Chen et al., 2019; Goldin et al., 2019; Graham et al., 2020; Newman et al., 2020), it remains unclear whether the overall number of exchanges with, or messages sent to, a coach relate to treatment response (Bernstein et al., n.d.). Similarly, only a few studies have examined the content or function of user messages, but not how these qualitative features relate to patient presentations or experiences in treatment (Carolan et al., 2017). Consequently, we remain unable to predict the type of support a user may need, to steer users or coaches towards more optimal patterns of communication, or to identify communication patterns that may indicate risk of dropout or poor response. Using theory-driven taxonomies, like the efficiency model, to parse real-world data could improve our understanding and allocation of human support in digital mental health (Muñoz, 2017).

This question is especially nuanced in BDD. On the one hand, contact with a clinician could be essential for navigating low BDD-related insight and experiences of shame, both common and treatment-interfering presentations (Eisen et al., 2004; Weingarden et al., 2018), or for understanding and approaching non-intuitive or challenging therapeutic activities (e.g., mirror retraining, exposures) (Wilhelm et al., 2013). On the other hand, clinician contact could also be uniquely triggering or counterproductive in BDD, as patients can exhibit compulsive interpersonal behaviors, like reassurance seeking and comparison, or interpret coach interactions as oversight or commentary on their performance. Some patients may be more amenable to or even benefit more from self-directed exercises. We therefore need more information about how different patients with BDD use human support when it is made available, what patterns correspond to clinically meaningful outcomes, and how we can better recognize patient needs and adapt coaching protocols accordingly. This is a critical knowledge gap in the effort to optimize app-based treatment for BDD and close the treatment gap. Whereas disseminating an app or online program may be inexpensive and swift, expanding coaching is more complicated and resource-demanding; dissemination is constrained by the cost, availability, and training of coaches and clinicians as well as state-by-state licensing laws. Thus, personalizing and optimizing coaching for BDD are questions with direct implications for real-world feasibility, scalability, and effectiveness.

In this study, we qualitatively and quantitatively analyzed text communications between individuals with moderate to severe BDD and their coaches during a 12-week course of app-based CBT-BDD (Wilhelm et al., 2022). The app led users through seven treatment modules or sections, each of which provided users with one of the core component skills comprising CBT-BDD (e.g., cognitive restructuring, exposures with ritual prevention, mirror retraining). The goal is to clarify when patients with BDD utilize coaching and for what purpose; and then, critically, whether variability or patterns therein relate to baseline characteristics or outcomes. Results would set us up to use human resources more efficiently and effectively in technology-driven support of individuals with BDD.

Specifically, our first aim was to identify distinct patterns of communication between users and coaches. First, using *frequency* of messages by week in treatment as indicators, one cluster might comprise individuals who engage frequently with their coach during the introductory treatment modules (psychoeducation; understanding BDD symptoms) and rarely thereafter; a second cluster might comprise individuals who engage frequently and consistently; and so on. Second, using the *content* of messages sent by users as indicators, one cluster might comprise individuals who largely request help personalizing exercises; a second cluster might comprise individuals who most often use messaging maladaptively, to seek reassurance; a third cluster might comprise individuals whose use of messages span a broader range of purposes such as clarifying concepts, goal setting, and troubleshooting barriers to treatment.

Our second aim was to explore clinical predictors and implications of such communication patterns. Without knowledge of which clusters would emerge, we did not have specific hypotheses regarding the demographic or baseline clinical characteristics most associated with the different clusters. We also did not have specific hypotheses regarding which cluster(s) would be associated with better or worse outcomes. However, we expected that clusters with consistently and significantly above or below average communications (i.e., participants at the extremes) would have the poorest outcomes, potentially reflecting high distress, difficulty engaging with skills, or low motivation for change. Sustained use of reassurance seeking could also be an early indicator of non-response. In contrast, a drop in communication by the end of treatment could reflect acquired independence or confidence in skills gained.

2. Methods

This project drew data from a recently completed randomized controlled trial (RCT) for adults with primary BDD (Wilhelm et al., 2022). Institutional Review Board approval and informed consent were obtained prior to the initiation of any study procedures. Participants in the sample ($N = 77$) were those who were offered 12-weeks of app-based cognitive behavioral therapy with coach support (immediately ($n = 40$) or after a 12-week waitlist condition ($n = 37$)). Eligible participants were at least 18 years old, living in the United States, and presenting with a primary DSM-5 diagnosis of BDD. Exclusion criteria included prior receipt of CBT-BDD, concurrent psychotherapy, recent (within the past 2 months) psychotropic medication changes, severe substance use, severe depression, or acute suicidal ideation, and lifetime mania or psychosis. Symptom severity in this sample was moderate to severe and comparable to in-person clinical trials. The most common body areas of concern reported were skin ($n = 55$), hair ($n = 44$), body build ($n = 43$), nose (n = 43), and face size ($n = 39$); 17 participants endorsed dissatisfaction with a lack of muscularity. A majority of participants ($n = 63$) met criteria for comorbid psychiatric diagnoses, the most common of which were major depressive disorder ($n = 51$), social anxiety disorder ($n = 23$), and generalized anxiety disorder ($n = 18$). A majority of participants ($n = 68$) endorsed past psychotherapy, 17 of whom reported individual CBT (most commonly for anxiety and/or depression; $n = 12$). Demographic and clinical characteristics of the sample are in Table 1. Standardized assessments were conducted virtually at baseline, mid-treatment (week 6), and post-treatment (week 12).

Table 1
Demographic and clinical characteristics of the sample.

Variable	M (SD)
Demographics	
Age	27.0 (9.81)
	N (%)
Gender identity	
Women	64 (83.1 %)
Men	12 (15.6 %)
Genderqueer or non-binary	1 (1.3 %)
Hispanic or Latino	9 (11.7 %)
Sexual Minority	30 (39.0 %)
Race	
White	56 (72.7 %)
Asian	11 (14.3 %)
Black/African American	1 (1.3 %)
More than one race	8 (10.4 %)
Other	1 (1.3 %)
Education	
≤High school graduate	14 (18.2 %)
Technical school/some college	22 (28.6 %)
College graduate	20 (26.0 %)
Graduate or professional school	21 (27.3 %)
Employment	
Full-time (≥ 35 h/week)	31 (40.3 %)
Part-time (<35 h/week)	6 (7.8 %)
Student	34 (44.2 %)
Unemployed	2 (2.6 %)
Homemaker	4 (5.2 %)
Clinical characteristics	M (SD)
BDD Duration	13.4 (10.8)
Comorbidity	
None	26 (33.8 %)
1	27 (35.1 %)
2	16 (20.8 %)
3+	8 (10.4 %)
BDD-YBOCS	28.3 (5.4)
BABS	14.2 (4.20)
QIDS-SR	10.7 (4.27)
Credibility	18.3 (4.27)
Expectancy	14.4 (4.71)
Past Therapy	
None	13 (16.9 %)
BDD therapy	11 (14.3 %)
CBT for a non-BDD problem or disorder	13 (16.9 %)
Other	40 (51.9 %)

Note. BDD-YBOCS=Yale-Brown Obsessive Compulsive Scale Modified for BDD; BABS=Brown Assessment of Beliefs Scale; QIDS-SR = Quick Inventory of Depressive Symptomatology-Self Report.

2.1. Treatment

The app includes seven treatment modules, covering the core components of CBT-BDD: psychoeducation, cognitive restructuring, exposure, ritual prevention, mindfulness and attention retraining, enhancing self-esteem and compassion through modifying core beliefs and pursuing values-based activities, and relapse prevention (Wilhelm et al., 2013; Wilhelm et al., 2011). The app format allowed participants to review content and complete accompanying exercises at their own pace and convenience; it also supported personalization, for example exercise suggestions based on participants' selected goals.

2.2. Coach support

Coaches were Bachelor's-level staff members ($n = 9$, 100 % identified as women), who completed standardized, pre-trial training on BDD (MGH Psychiatry Academy BDD webinar and knowledge test) and CBT (MGH Psychiatry Academy training course and knowledge test). Coaches received a coaching manual detailing core tenets of the supportive accountability model: coaches are ideally viewed as trustworthy, knowledgeable, helpful, and collaborative and try to increase salience and perceived utility or personal relevance of new target behaviors (Mohr et al., 2011). To ensure ongoing high-quality support, all coaches participated in weekly supervision with a licensed clinician with expertise in CBT-BDD. Bachelor's-level coaches were available during the 12-weeks of treatment primarily via asynchronous in-app secure messaging to promote engagement and answer questions. They also completed a brief baseline and brief mid-treatment phone call (< 30 min) using semi-structured scripts as guides to orient patients to treatment and update treatment goals, respectively. Participants were assigned a coach at baseline and were in contact with the same coach for the duration of treatment. Coaching was presented as a standard component of treatment available to all participants for answering questions, assisting with challenges, or offering general support and encouragement; participants were encouraged to use the messaging function to whatever extent they wished. Coaches were directed to support, but not provide, active treatment. Example functions include enhancing motivation, helping patients to adapt exercises to their specific symptoms or situation, recommending modules to try or review based on progress, clarifying concepts or skills, navigating the app, and providing accountability. There were no set guidelines for the frequency of communication between users and coaches; however, coaches were encouraged to reach out to participants who had not accessed in the app in a given week. Expectations were set for participants and coaches that coaches would respond to messages within one business day. See Supplementary Table S1 for the Checklist for Recommended Reporting of Human Support in Digital Mental Health Treatment (Bernstein et al., n.d.).

2.3. Measures

At baseline, doctoral-level independent evaluators completed the Mini International Neuropsychiatric Interview (MINI 7.02) (Sheehan et al., 1998) and the Columbia-Suicide Severity Rating Scale (C-SSRS) (Posner et al., 2008) to establish inclusion/exclusion criteria and characterize the sample. The primary outcome was BDD symptom severity measured with the 12-item semi-structured clinician-rated Yale-Brown Obsessive Compulsive Scale Modified for BDD (BDD-YBOCS) (Phillips et al., 1997). Scores can range from 0 to 48; higher scores reflect more severe past week BDD symptoms. Secondary outcomes included BDD-related insight (Brown Assessment of Beliefs Scale; BABS (Eisen et al., 1998)) and depression symptom severity (Quick Inventory of Depressive Symptomatology—Self Report; QIDS-SR (Rush et al., 2003)). Higher scores denote worse insight and more severe depression, respectively, over the past week. Independent evaluators were blind to condition. Participants also rated their treatment expectancy at baseline

(Credibility & Expectancy Questionnaire (Devilly and Borkovec, 2000)) and treatment satisfaction at mid-treatment and post-treatment (Client Satisfaction Questionnaire; CSQ (Larsen et al., 1979; Attkisson and Zwick, 1982)). Higher scores reflect greater credibility, expectancy, and satisfaction.

2.4. Data analysis

Raw text data (smartphone app messages) were reviewed and coded by two independent raters (JW, RQ). Disagreements were resolved by review from a third rater (EB). Raters were trained and completed their ratings using a codebook based on the efficiency model of support and knowledge of BDD (e.g., reassurance-seeking and comparison rituals). The codebook included definitions and examples of simulated messages for each possible label (outlined in Supplementary Table S2). Categories were usability, engagement, fit, knowledge, implementation (efficiency model), ritualizing (specific to BDD), and miscellaneous (to capture messages unrelated to treatment, e.g., rescheduling an assessment). Raters were instructed to label the primary content theme of a given message. However, raters were allowed to denote instances where they felt two or more labels were needed. Ultimately, only 3 messages were determined to have co-primary labels and were thus included in analyses as 2 separate entries (e.g., usability and fit).

2.4.1. Aim 1: communication patterns

The frequency of messages sent by users were tabulated across treatment and by week. We then used exploratory latent profile analyses (LPA) to test for the existence of distinct profiles of frequency of coach communications by module (R package *tidyLPA*). Variances were constrained to be equal across classes, and covariances were fixed to 0. We used the following criteria to select the number of resulting profiles: (a) Bayesian Information Criterion (BIC; model fit), (b) Integrated Completed Likelihood (ICL) criterion (includes penalty for entropy; measure of precision of classification), (c) Bootstrapped k – 1 likelihood ratio test (LRT; improvement of model fit, i.e., compares model with current number (k) of profiles to one with one fewer (k − 1) profile to determine if precision is improved by the addition of an extra profile). On balance, the optimal number of profiles would have the lowest BIC value, smallest criterion value, and significant LRT as well as meaningful and interpretable.

We then tabulated the relative proportions of each message type sent overall and by each user. We repeated the above LPA procedure using user-level data to test for the existence of distinct profiles of *why* participants engage coach support. Note that proportions were used rather than raw numbers to not bias results by how frequently participants communicated in general.

2.4.2. Aim 2. Clinical associations

We used ANOVAs and chi-square tests to examine whether profiles differ in baseline characteristics (age, gender identity, race, ethnicity, education, employment status, treatment credibility and expectancy, past experience with face-to-face therapy, BDD symptom severity (BDD-YBOCS), and BDD-related insight (BABS)). We then used a series of mixed effects models to test whether profiles differ in treatment outcomes as a function of time (baseline, week 6, week 12). Outcomes data include BDD symptom severity (BDD-YBOCS), BDD-related insight (BABS), depression symptom severity (QIDS-SR), and treatment satisfaction (CSQ). Chi-square tests were used to assess the relationship between profile membership and dropout during treatment and ANOVAs to assess the relationship between profile membership and adherence. Dropout was defined as not completing the trial (i.e., completing the 12 weeks of treatment and post-treatment assessment). Adherence was defined as percentage of compulsory modules completed.

3. Results

3.1. Aim 1: communication patterns

A total of 1158 messages were sent over the course of the study (758 by coaches; 400 by users). App users on average sent 5.88 messages (SD = 4.51, median = 4, range 1–20) and received 9.84 messages from their coach (SD = 5.74, median = 9, range 2–30). See Fig. 1 for weekly breakdown.

3.1.1. Frequency

The average number of messages sent was similar across weeks of treatment (Fig. 1; Supplementary Table S3). LPA revealed no number of profiles with both the lowest BIC and ICL criterion values. A three-profile solution was selected to balance the two and provide meaningful, interpretable results (e.g., no profile comprised <10 % of the sample). The three profiles were characterized by: (1) peak in communication mid-treatment (n = 13; 16.88 % of participants), (2) bimodal pattern, or more frequent communication early and late in treatment (n = 8; 10.39 % of participants), and (3) consistent low (or no) communication (n = 56; 72.73 % of participants) (see Table 2 for fit statistics; Fig. 2 for profiles; Fig. 3 for individual plots).

3.1.2. Content

Regarding labels of message content, inter-rater reliability was moderate to high (Cronbach's Kappa = 0.55). In descending order, 54.84 % of user messages were classified as engagement, 14.39 % as fit, 12.90 % as miscellaneous, 7.94 % as usability, 7.20 % as knowledge, 1.99 % as implementation, and 0.74 % as ritualizing (Fig. 4; see Supplementary Table S2 for content terminology codebook). LPA revealed no number of profiles with both the lowest BIC and ICL criterion values. A four-profile solution was selected to balance the two and provide meaningful, interpretable results (e.g., no profile comprised <10 % of the sample). LPA revealed four profiles, characterized by mostly (1) engagement (n = 40; 51.95 % of participants), (2) fit (n = 12; 15.58 % of participants), (3) knowledge (n = 12; 15.58 % of participants), and (4) miscellaneous or no messages sent n = 13; (16.88 % of participants) (see Table 2 for fit statistics; Fig. 2 for profiles; Fig. 3 for individual plots). Chi-square test revealed no association between profile membership for frequency of messages and content of messages, $\chi^2 = 8.94$, $p = .18$.

3.2. Aim 2: clinical associations

3.2.1. Baseline predictors

Analyses revealed that for both frequency and content, profiles did not differ in terms of assigned treatment group (immediate treatment versus waitlist), gender, race, ethnicity, sexual minority status, education, employment status, treatment credibility, treatment expectancy, duration of BDD illness, past experience with therapy, or BDD-related insight (BABS), $ps > .05$. There was a significant effect for age and frequency profiles, $F(2,74) = 3.06$, $p = .05$, but not content profiles, $p > .05$; follow-up tests showed that the frequency effect was driven by participants in the early/late peak group ($M_{age} = 34.8$, SD = 18.5) being significantly older than participants in the consistently low communication group ($M_{age} = 25.8$, SD = 8.18). There was also a significant effect for BDD symptom severity (BDD-YBOCS) and content profiles, $F(3,73) = 3.41$, $p = .02$, but not frequency profiles, $p > .05$; follow-up tests showed that the content effect was driven by the engagement group (M = 29.2, SD = 5.18) and the knowledge group (M = 29.6, SD = 4.01) both having more severe baseline symptoms than the fit group (M = 24.0, SD = 5.86). See Table 3 for all results.

3.2.2. Clinical outcomes

Analyses revealed no significant profile by time effects in relation to BDD-YBOCS, BABS, QIDS-SR, or CSQ scores, $ps > .05$ (Table 3). There was a significant effect for content profiles differing in terms of dropout,

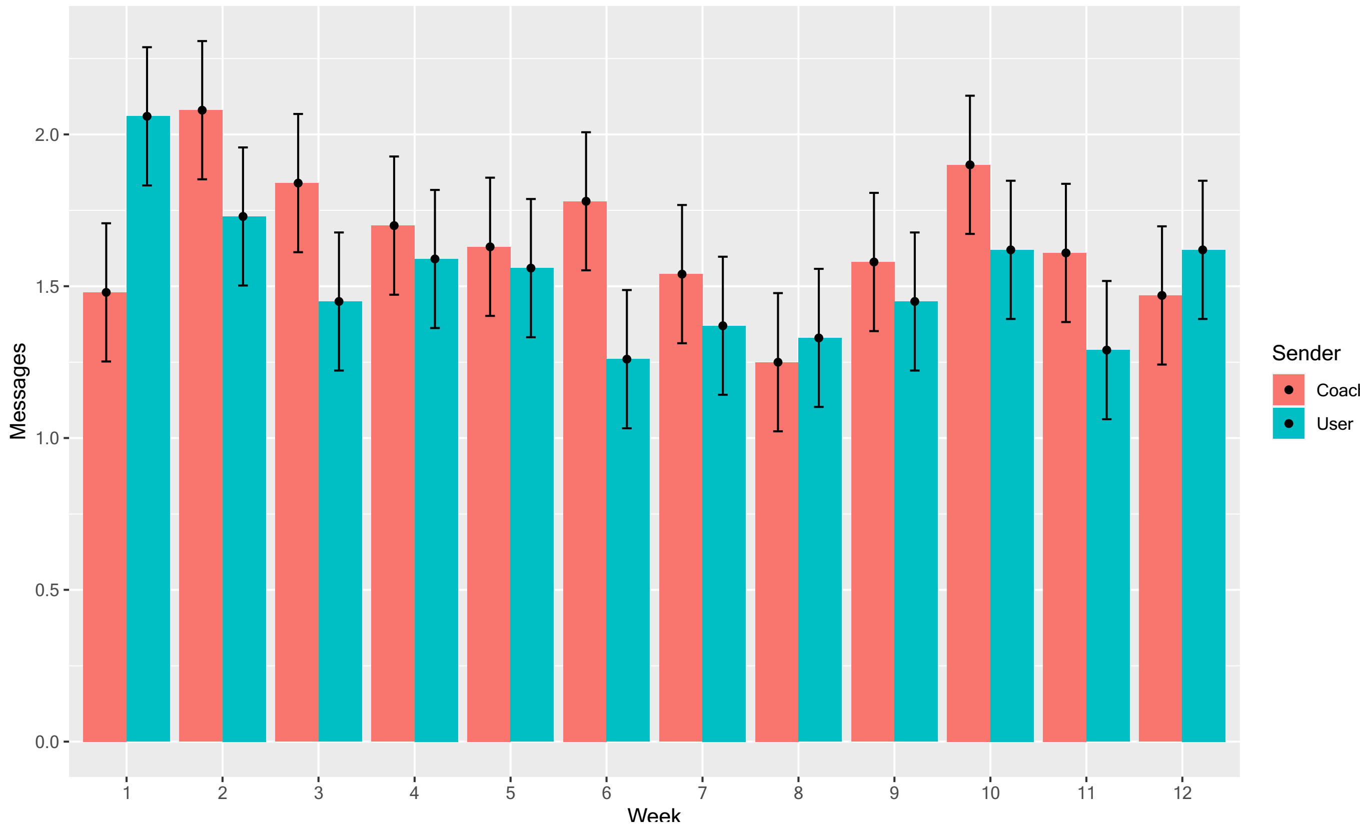

Fig. 1. Average number of messages sent per participant.

Table 2
Latent profile analysis fit statistics.

	Number of Profiles	BIC	ICL	LRT
Frequency	2	2329.73	−2330.54	105.55, p = .01
	3	2328.33	−2332.09	57.87, p = .01
	4	2315.42	−2316.5	69.38, p = .01
	5	2295.41	−2295.77	76.47, p = .01
	6	2360.69	−2392.61	−8.81, p = 1.00
Content	2	−611.88	604.08	43.60, p = .01
	3	−623.91	617.26	46.78, p = .01
	4	−669.91	665.69	80.75, p = .01
	5	−709.60	705.90	74.45, p = .01
	6	−730.95	724.92	56.09, p = .01

Note. BIC=Bayesian Information Criterion; ICL = Integrated Completed Likelikood; LRT = Bootstrapped k – 1 likelihood ratio test.

$\chi^2 = 10.51, p = .01$ (overall dropout: 22.08 %; $n = 17$), suggesting higher rates of dropout among participants in the miscellaneous/low contact group (p = .02; 46.15 %; n = 6) and reduced rates in the engagement group (p = .035; 12.50 %; n = 5). There was also a significant effect for frequency profiles differing in terms of adherence, F(2,74) = 3.46, p = .04; follow-up tests showed this to be driven by participants in the mid-treatment peak group (M = 61.5 %, SD = 25.8 %) completing more modules than the low contact group (M = 45.8 %, SD = 19.4 %).

4. Discussion

In this project, we implemented a theory-driven framework, based on the efficiency model of support (Mohr et al., 2019), to examine the frequency and function of messages sent from app users to their coaches in a 12-week smartphone app-based CBT-BDD (Muñoz, 2017). Overall, the majority of participants had infrequent contact with their coach across the 12-week treatment and, consistent with limited prior work, the most common function of messaging with a coach was for engagement (e.g., accountability, encouragement, acknowledging coach's contact or support) (Carolan et al., 2017; Sadeh-Sharvit et al., 2022).

Across the sample and course of treatment, the average number of user messages sent was relatively constant, approximately 1–2 per week. However, a closer look at individuals' data showed that participants fell into one of three patterns in terms of frequency of communication: above average communication at the beginning and/or end of treatment, above average communication in the middle of treatment, and consistently low communication across treatment. Interestingly, the only baseline factor associated with pattern of communication frequency was age; older participants were more likely to be in the first group (i.e., messaged coach more at the beginning and/or end of treatment). This is consistent with past literature suggesting that older users prefer—and may therefore benefit from— more human contact in digital therapies (Orr et al., 2020; Wildenbos et al., 2019). Notably, we did not find that this was driven by technology or usability concerns. Notably, older adults were not represented in this sample (age range: 18–62; median = 24), thus findings require replication and extension in more heterogeneous and representative samples. We also found that that although participants who rarely communicated with their coaches were less adherent (i.e., completed fewer treatment modules) than those who messaged frequently (particularly mid-treatment), frequency of messaging did not differentially relate to clinical outcomes. Past studies examining this relationship linearly similarly found that better outcomes were associated neither with users responding to more coach messages or sending more messages overall (Graham et al., 2020; Newman et al., 2020). Additionally, although more frequent contact may track with more app use, this does not necessarily translate to more *effective* skills use (Bernstein et al., 2022). This does not mean that coaching is unhelpful. Instead, it is possible that those who sought more coaching needed more coaching to have the same outcomes and that some participants simply needed a lower dose of treatment (both coach

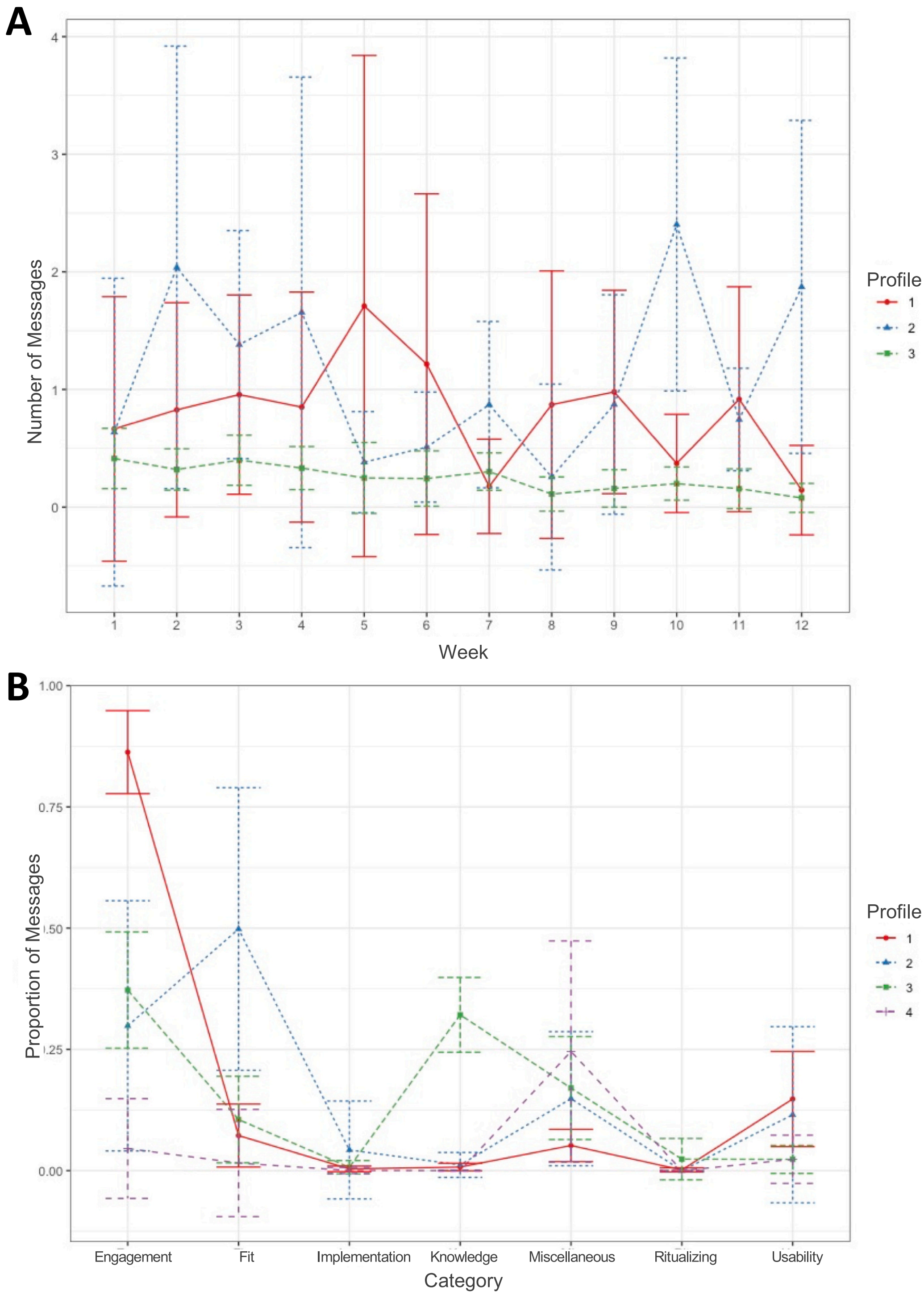

Fig. 2. Frequency and content of user-sent messages.
Note. (A) Frequency: Profile 1 = communication peaks mid-treatment; Profile 2 = communication peaks beginning and end of treatment; Profile 3 = consistent low communication. (B) Content: Profile 1 = engagement, Profile 2 = fit; Profile 3 = knowledge; Profile 4 = miscellaneous/no contact.

contact and app content). Indeed, low engagement may not always be problematic. Randomized trials directly comparing various prescribed levels of coaching as well as patient-selected levels would be necessary to better understand this. Taken together, pressing for regular contact with all users may be a suboptimal use of human resources.

In terms of the primary content or function of messages, profiles were defined by members using a particular category much more than members of other profiles did. Clusters included: engagement (i.e., utilizing coaches for accountability and motivation), fit (i.e., requesting assistance in tailoring exercises to align better with specific needs or situations), knowledge (i.e., seeking to better understand treatment concepts), and non-support-related communication (e.g., messages unrelated to treatment or no contact). Interestingly, few patients used messaging to engage in reassurance-seeking. We found that individuals starting treatment with more severe BDD symptoms were more likely to use their coaches for support with engagement and knowledge and those with less severe symptoms were more likely to engage coaches for support with fit. The former could reflect that more severe symptoms

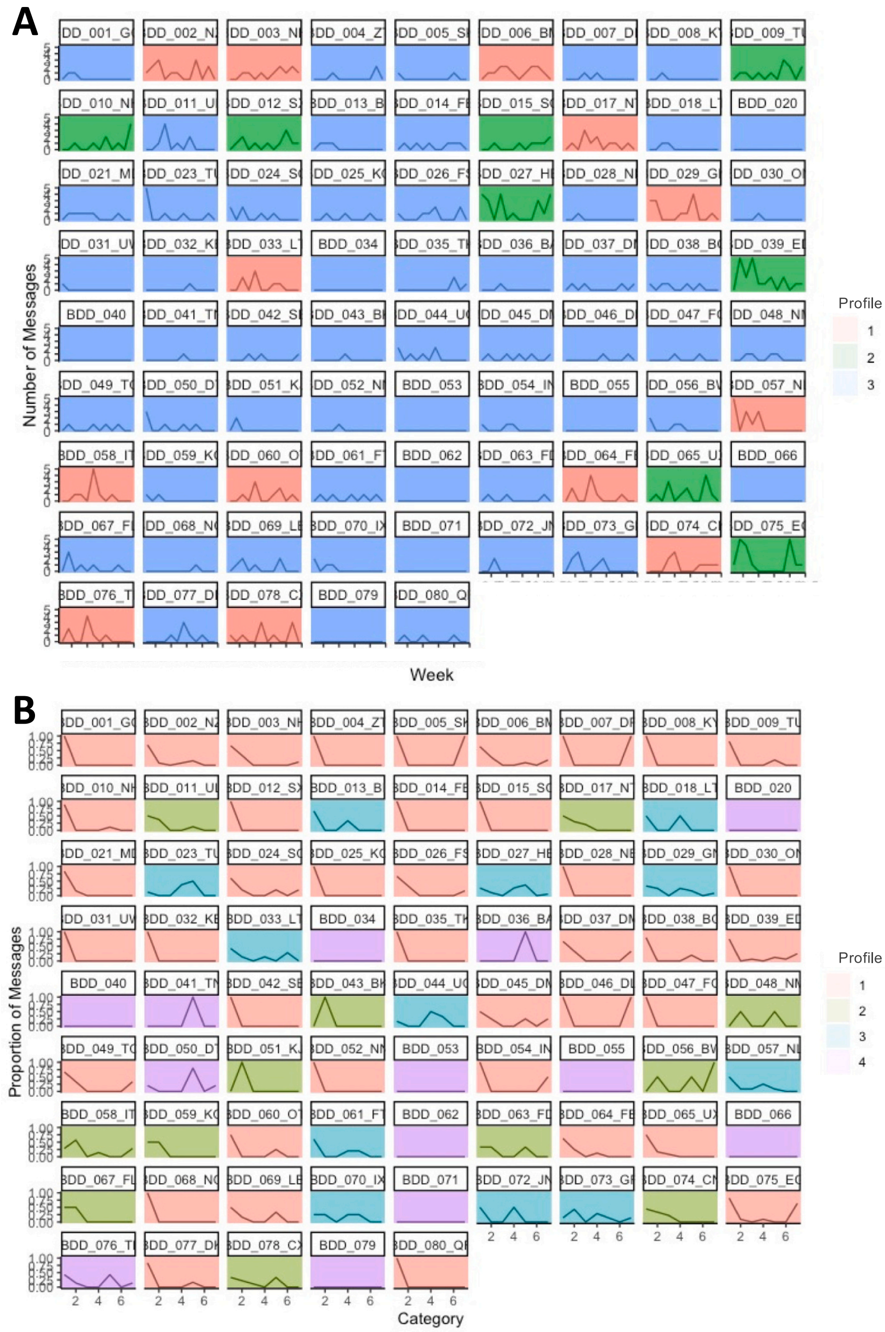

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Fig. 3. Individual plots grouped by profile.
Note. (A) Frequency: (Red) Profile 1 = communication peaks mid-treatment; (Green) Profile 2 = communication peaks beginning and end of treatment; (Blue) Profile 3 = consistent low communication. (B) Content: (Red) Profile 1 = engagement, (Green) Profile 2 = fit; (Blue) Profile 3 = knowledge; (Purple) Profile 4 = miscellaneous/no contact.

make treatment appear more challenging or confusing (e.g., exposures may feel more distressing, energy or concentration may be lower). The latter could reflect that for those with more mild symptoms, example exercises presented in the app can be perceived as too elementary (e.g., they may be ready for more challenging exposures sooner) or because their symptoms may be narrower (e.g., interference in just one domain), odds that the example exercises match their specific situation are lower. These insights could help future coaches better anticipate patient needs or even proactively tailor the types of messages they send.

Results also suggest that *how* participants use available coaching may be a better indicator of sustained engagement than the frequency of interactions. Notably, participants who primarily relied on their coaches for support with accountability and motivation (i.e., those falling into the “engagement” category) showed a higher likelihood of completing the treatment. It is conceivable that this group represents participants for whom an app-based treatment approach aligns well with their needs, abilities, or preferences. In contrast, participants who did not message their coach or whose messages were more often unrelated to treatment dropped out of treatment at disproportionately higher rates. This could reflect differences in motivation, self-efficacy, or ability to connect with an app-based approach and could suggest that face-to-face treatment may be warranted, which should be measured in future studies. Finding alternative ways to engage such patients early on could enhance retention rates.

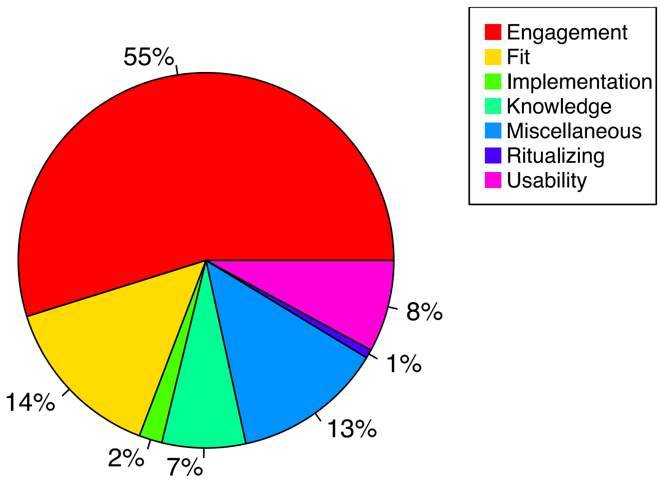

Fig. 4. Message categories.

Table 3
Comparison of profiles.

Baseline Factor	Difference among profiles	
	Frequency	Content
Treatment group	$\chi^2 = 2.03, p = .36$	$\chi^2 = 4.32, p = .23$
Age	$F(2,74) = 3.06, p = .05$*	$F(3,73) = 0.98, p = .41$
Gender (Woman)	$\chi^2 = 3.23, p = .20$	$\chi^2 = 1.22, p = .75$
Race (White)	$\chi^2 = 3.79, p = .15$	$\chi^2 = 2.51, p = .47$
Ethnicity (Hispanic/Latino)	$\chi^2 = 3.82, p = .15$	$\chi^2 = 2.50, p = .47$
Sexual Minority	$\chi^2 = 2.80, p = .25$	$\chi^2 = 3.19, p = .36$
Education (High School)	$\chi^2 = 1.73, p = .42$	$\chi^2 = 1.5, p = .68$
Employment	$\chi^2 = 2.35, p = .97$	$\chi^2 = 10.55, p = .57$
BDD Duration	$F(2,72) = 2.97, p = .06$	$F(3,71) = 1.18, p = .33$
Comorbidity	$\chi^2 = 8.49, p = .20$	$\chi^2 = 2.99, p = .96$
Treatment Credibility	$F(2,72) = 0.80, p = .45$	$F(3,71) = 0.08, p = .97$
Treatment Expectancy	$F(2,72) = 0.33, p = .72$	$F(3,71) = 0.23, p = .87$
Past therapy	$\chi^2 = 7.49, p = .28$	$\chi^2 = 9.52, p = .39$
BDD-YBOCS	$F(2,74) = 2.80, p = .07$	$F(3,73) = 3.41, p = .02$*
BABS	$F(2,74) = 0.47, p = .63$	$F(3,73) = 1.83, p = .14$

Clinical Outcome	Profile × Time Interaction	
	Frequency	Content
BDD-YBOCS	$F(4, 127.33) = 1.97, p = .10$	$F(6, 130.32) = 1.21, p = .31$
BABS	$F(4,125.31) = 0.23, p = .92$	$F(6,126.08) = 1.91, p = .08$
QIDS-SR	$F(4,117.22) = 0.20, p = .94$	$F(6,122.73) = 0.61, p = .72$
CSQ	$F(2, 50.75) = 1.22, p = .30$	$F(3,54.19) = 0.16, p = .92$
Dropout	$\chi^2 = 5.20, p = .07$	$\chi^2 = 10.51, p = .01$*
Adherence	$F(2,74) = 3.46, p = .04$*	$F(3,73) = 0.95, p = .42$

Note. BDD-YBOCS=Yale-Brown Obsessive Compulsive Scale Modified for BDD; BABS=Brown Assessment of Beliefs Scale; QIDS-SR = Quick Inventory of Depressive Symptomatology-Self Report; CSQ = Client Satisfaction Questionnaire; CSQ.

* $p <= .05$

Surprisingly, however, groups otherwise did not differ in clinical outcomes. For example, those with more difficulties with fit did not respond less to treatment than those with fewer symptoms. Thus, screening the content of messages may help identify users who could benefit from more proactive engagement from a coach to reduce dropout. But in general, coaches may be able to follow users' preferences for the content of communications. Indeed, in this population in particular, it was encouraging to find such low levels of reassurance seeking and other ritualizing or maladaptive behaviors in coach interactions. Allowing participants agency in the degree of coach contact may itself be beneficial, contributing to a sense of personalization and encouraging participants to take ownership of their treatment and progress. Again, replication with other digital interventions as well as directly comparing prescribed coach contact to user-selected frequency are important next steps.

Combined with evidence from this and past studies showing that coaches typically send significantly more messages than users (Mohr et al., 2017; Carolan et al., 2017; Chen et al., 2019; Goldin et al., 2019; Graham et al., 2020; Newman et al., 2020), results suggest that even with low touch, non-professional coaching, human support could be used even more efficiently. For example, more than half of messages related to engagement, the majority of which were general check-ins and encouragement (e.g., patient responds that treatment is going well and they appreciate the message). Such outreach and supportive messages could likely be automated and patient responses screened for messages requiring further or not pre-written or templated responses. That requests for technical assistance, support generalizing skills to daily life, and ritualizing—three domains that could require more specialized support— were low further support the continued, more cost-effective use of non-professional coaches for many cases. In fact, reviews of internet-based interventions show that coaches' qualifications (i.e., professional versus non-professional) are poor predictors of outcomes (Baumeister et al., 2014; Johnston et al., 2021). Future research could examine more detailed onboarding procedures to show users how to get the most of coaching (e.g., example hurdles and corresponding messages they could send).

Simultaneously, future work should delve deeper into identifying individuals who may benefit from more support, but are not seeking it themselves. For example, coaching may be particularly helpful in cases of low insight; yet, low insight may reduce a person's perception of need or desire to engage. Similarly, shame is a common challenge and treatment barrier in BDD (Weingarden et al., 2018; Weingarden and Renshaw, 2015). The relative anonymity of digital interventions like Perspectives can reduce this obstacle in pursuit of treatment. Yet, individuals struggling with shame may also struggle to converse openly with a coach—even through asynchronous messaging. Alternative strategies for identifying and reaching these types of individuals are likely required to further enhance outcomes.

4.1. Limitations

Given the relatively small sample, this work requires replication and extension to realize its full clinical implications. For example, there is hope that digital health will reduce inequities in mental health treatment access and response, such as between White and racial and ethnic minority patients (Ramos and Chavira, 2022). Some have suggested that coaches will be essential to this mission to address user preferences, bolster the credibility and usability of digital tools, and actively work with individuals to adapt content to better match unique stressors or contexts (Rozbroj et al., 2014). With the present sample, we were underpowered to rigorously address these questions. We were also unable to test whether certain types of messages were more common or messages overall were more frequent following particular pages or exercises in the app. Additionally, coaches in this trial initiated much of the contact with users and complete onboarding (and frequently mid-point) phone calls; it is unclear how profiles or effects would differ if all communication was initiated by users or occurred exclusively by messaging. We were also unable to consider whether effects differ if messages are further split into those initiated by a user versus in response to a coach, or if the content of coach-initiated messages varies. It is also unknown whether findings would generalize to other apps or clinical populations.

5. Conclusions

There is a shortage of mental healthcare providers across the country, a gap that only widens for those needing care for BDD (Marques et al., 2011). There is great excitement that digital mental health could rapidly expand access. Yet, the field is still very young and evidence-based options limited. This study provides insight into a common, arguably critical, and yet rarely examined feature of these promising tools: human support. By looking at communication content and patterns across time, we hope to improve coaching protocols, decision trees, and recommendations for others, be able to eventually predict who will need what level and kind of support earlier on, and nudge patients towards patterns of communication that are more likely to promote positive outcomes for them.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Dr. Bernstein has received research support from Koa Health Digital Solutions LLC. Dr. Bernstein is a presenter for the Massachusetts General Hospital Psychiatry Academy in educational programs supported through independent medical education grants from pharmaceutical companies. Dr. Bernstein has a consulting agreement with Otsuka Pharmaceutical Development & Commercialization, Inc. and is on the Scientific Advisory Board for AugMend Health Inc.

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Dr. Summers has no potential conflicts to report.

Ms. Williams has no potential conflicts to report.

Ms. Quist has no potential conflicts to report.

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Dr. Harrison is Founder/CEO of Koa Health, a digital mental health company that collaborated with Dr. Wilhelm and her team at MGH to build Perspectives. Dr. Harrison also serves on the WHO Roster of Experts for Digital Health, sits on the Board of EMPOWER (a non-profit organization promoting the training of community health workers to provide mental healthcare), and is a member of the Expert Panel for implementing the Wellcome Trust's mental health strategy. Dr. Harrison is a Royal Society Entrepreneur in Residence in healthcare AI at Oxford University.

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Appendix A. Supplementary data

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