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Days between sessions predict attrition in text-based internet intervention of Binge Eating Disorder

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ABSTRACT

Background: The number of days between treatment sessions is often overlooked as a predictor of attrition in psychotherapy. In text-based Internet interventions, days between sessions may be a simple yet powerful predictor of attrition.
Objective: We hypothesized that a larger number of days between sessions increased the likelihood of attrition among participants with Binge Eating Disorder (BED) in a 12-session Internet-based cognitive behavioral therapy (iCBT) program. Participants could work on the sessions whenever convenient for them and received written support from a psychologist.
Material and methods: We compared 201 adult participants with mild to moderate BED (85 non-completers and 116 completers) on the number of days between sessions to predict attrition rates.
Results: Mixed model binomial logistic regression showed that non-completers spent significantly more days between sessions across the first four treatment sessions (1–4) when controlling for age, gender, and intake measures of BMI, BED, overall health status (EQ VAS), and depression symptoms (MDI) (OR = 1.042, $p < .001$). Age (OR = 0.976, $p < .001$) and EQ VAS (OR = 0.984, $p < .001$) were also significant. The risk of attrition increased by 4.2 % for each additional day participants spent completing a session.
A receiver operating characteristic (ROC) curve analysis showed that classification accuracy increased across sessions from 61.1 % in session 1 and 65.7 % in session 2 to 68.8 % in session 3 and 73.2 % in session 4. The optimal cut-off point in session 4 was 17.5 days, which detected 60.4 % of non-completers (sensitivity) and 78.4 % of completers (specificity).
An exploratory repeated measures of ANOVA of days between sessions showed a significant within-subjects effect, where both non-completers and completers spent more days between sessions as they progressed from sessions 1 through 4 ($F = 20.54$, $df = 3$, $p < .001$). There was no interaction effect, suggesting that the increase in slope did not differ between non-completers and completers.
Conclusions: Participants spending more days between sessions are at increased risk of dropping out of treatment. This may have important implications for identifying measures to reduce attrition, e.g., intensifying interventions through automated reminders or therapist messages. Our findings may have important transdiagnostic implications for text-based Internet interventions. Further studies should investigate the predictive value of days between sessions in other diagnoses.

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1. Introduction

Binge Eating Disorder (BED) is an eating disorder characterized by recurring episodes of binge eating, lack of control over eating, and marked distress by the symptoms (American Psychiatric Association, 2013). BED is associated with at least three of the following five symptoms of binge eating: (1) eating faster than normal; (2) eating until uncomfortably full; (3) eating when not feeling hungry; (4) eating alone due to embarrassment; and (5) feeling disgusted, depressed or guilty afterward. The binge eating episodes must occur at least once per week for three months. Unlike bulimia nervosa, BED is not associated with compensatory behaviors like vomiting.

Internet-based interventions are effective in treating mental health disorders, including eating disorders (Bauer and Moessner, 2013; Fairburn and Murphy, 2015; Melioli et al., 2016). Text-based Internet cognitive behavioral therapy (iCBT) has proven effective in treating BED (Jensen et al., 2020; Wyssen et al., 2021). Although iCBT is effective, some studies using text-based Internet interventions report high attrition rates (Beintner et al., 2020; Puls et al., 2020). Therefore, it is essential to identify predictors of attrition to improve adherence. Some studies examine predictors of adherence and treatment effect in conventional treatment of eating disorders (Fassino et al., 2009; Vall and Wade, 2015), but little is currently known about such predictors in text-based Internet interventions.

Compared with conventional treatment, it is easy to collect objective data measurements in Internet-based treatment (Manwaring et al., 2008). Therefore, iCBT is advantageous in identifying objective predictors of attrition and treatment outcome, and some may have transdiagnostic properties (Linnet et al., 2022). Baseline measures (e.g., pretests) show poor or mixed performance in identifying adherence and treatment effects in iCBT (Bremer et al., 2018). Consequently, there is increasing interest in investigating process variables that describe how patients respond to therapy during treatment. Examples of predictive process measures in iCBT include symptom scores between sessions (Forsell et al., 2020; Forsell et al., 2019) and number of words and messages in the text-based intervention (Linnet et al., 2022; Van der Zanden et al., 2014; Wallert et al., 2018).

Generally, in treatment interventions attrition factors are often unexplored (Aardoom et al., 2013), and therefore important implications for research and clinical practice are missing, which could potentially help improve adherence. Some studies have investigated the relationship between compliance and adherence with regard to: The number of days a self-monitoring diary was completed (Carrard et al., 2011a; Carrard et al., 2011b); time spent on the therapy material (Manwaring et al., 2008; Puls et al., 2020); the number of days waiting for treatment (Linnet and Pedersen, 2014); personal contact before treatment and e-mail correspondence during treatment (Brauhardt et al., 2014). Most studies have focused on symptom severity, comorbidity, and demographic factors compared to the degree of completion (von Brachel et al., 2014; Wagner et al., 2015).

Little is currently known about the predictive properties of the number of days between sessions in iCBT. Days between sessions may be a promising predictor of attrition and adherence in text-based Internet interventions, where patients control when they login to treatment. This sharply contrasts with conventional treatment, where patients often depend on the therapists' availability for treatment access.

In sum, there is currently a gap in the literature on the predictive properties of days between sessions on treatment attrition. This study aimed to address this knowledge gap by utilizing a novel approach to predict attrition rates in text-based Internet intervention by investigating the number of days between sessions. To our knowledge, this is the first study of days between sessions in text-based Internet interventions. We hypothesized that participants spending more days between sessions had an increased risk of dropping out of treatment.

2. Materials and methods

2.1. Design and ethics

Participants were enrolled in a 12-session text-based iCBT program called "internet treatment of Binge Eating Disorder" (iBED). Several studies have been published on the iBED program (Holmberg et al., 2022; Jensen et al., 2020; Linnet et al., 2022; Runge et al., 2022). Participants received written support from a psychologist in a pragmatic cohort design. The program was designed with an aim for participants to complete sessions weekly; in practice, many participants took longer, while a few took shorter for completion. The program is hosted on a digital treatment platform (Minddistrict). iBED consists of written psychoeducation and therapeutic exercises on goal-setting, stable eating patterns, identification of binge eating triggers, problem-solving skills, new coping strategies, and relapse prevention. The participants complete exercises and receive written therapist support on each exercise before progressing to the next session. Participants could work on the sessions whenever it was convenient for them. Many participants emphasized this as a primary motivation for seeking online treatment because it enabled them to fit the treatment program into their work or family schedule.

Therapist provide asynchronous feedback to participants, i.e., therapists do not answer participants in real time. Therapists have up to seven days, to provide feedback, after participants complete sessions. Therapists send reminders to inactive participants. A clinical guideline for therapists is to send reminders to participants if they are inactive for >14 days.

Participants completed questionnaires prior to entering treatment (pre-test) before the first session (called "session 0"), and at the last session ("session 11", post-test). Session 0 was labeled "0" to indicate that it was an introductory welcoming session before starting the treatment exercises of the program. All participants gave digital written informed consent to participate in the treatment program. All procedures were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The Southern Region of Denmark IRB committee approved the study (20212000-57).

Participants were excluded from the study (not treatment) if they skipped sessions, as this prohibited sequentially calculating the time between sessions. Some participants had a reversed order of sessions, and these participants were sorted in the chronological order of session completion.

2.2. Participants

Two hundred one participants (116 completers and 85 noncompleters) were included in the program. The 116 completers finished all 12 sessions of the program, while non-completion was defined as completing anywhere from 0 to 11 sessions. Participants were recruited through open enrollment at a website hosted by the Centre for Digital Psychiatry in the Mental Health Services in the Region of Southern Denmark. Participants applied for treatment by completing questionnaires about eating disorder symptoms and were included if they met the DSM-5 diagnostic criteria for mild to moderate BED (American Psychiatric Association, 2013) and had no or mild cooccurring mental health disorders. The online program was part of a larger project group, where other psychiatric units treated participants with severe to extreme BED and moderate to severe comorbidity using face-to-face therapy. Cut-offs of the severity of BED were assessed using the Binge Eating Disorder Questionnaire (BED-Q). The screening and treatment did not include face-to-face, video, telephone, or chat contact but was solely based on the participants' written answers.

2.3. Materials

2.3.1. Binge-Eating Disorder Questionnaire (BED-Q)

(Holmberg et al., 2022; Jensen et al., 2020; Lichtenstein et al., 2021; Linnet et al., 2022; Runge et al., 2022) is a 9-item questionnaire. Item 1–7 make up the sum score (0–35). These items match the DSM diagnostic criteria: (1) eating larger amount of food within a short time (two hours); (2) losing control over ones eating; (3) eating faster than normal; (4) eating until uncomfortably full; (5) eating without being hungry; (6) eating alone; and (7) experiencing negative feelings after overeating.

Items 1–7 is rated as follows: 0 = no (none/week); 1 ≤ 1/week; 2 = 1–3/week; 3 = 4–7/week; 4 = 8–13/week; 5 ≥ 13/week. The sum score is interpreted as: 0 = no symptoms; 1–9 = subclinical symptoms of BED; 10–14 = mild BED; 15–21 = moderate BED; 22–28 = severe BED; 29–35 = extremely severe BED. The present sample included participants with mild to moderate BED symptoms, corresponding to a score between 10 and 21. Item 8 controls for compensatory behaviors such as self-induced vomiting, while item 9 assesses whether binges are experienced as distressing. The BED-Q is currently under validation; we expect the psychometric properties of the BED-Q to be satisfactory.

2.3.2. The Major Depression Inventory (MDI)

(Bech et al., 2001; Cuijpers et al., 2007) was used to screen for depressive symptoms. The MDI has ten items rated on a 6-point Likert scale from 0 to 5. The total score ranges from 0 to 50, with higher scores reflecting more symptoms of depression. Recommended cut-off points are 21 for mild depression, 26 for moderate depression, and 31 for severe depression. The MDI has a Crohnbach's alpha of 0.89, and satisfactory external validity (Cuijpers et al., 2007).

2.3.3. EuroQol Five-dimensions Visual Analogue Scale (EQ VAS)

The VAS scale from the EQ-5D-5L was used to assess global subjective functioning among participants. The EQ VAS is built as a thermometer that measures current subjective health-related quality of life (HRQoL) on a measure from 0 to 100, where 0 is the worst imaginable health state/death and 100 is the best possible health state. It is designed to measure health in large-scale groups (EuroQol–a new facility for the measurement of health-related quality of life, 1990). The EuroQoL (EQ-5D) has been extensively validated, and show sufficient internal and external validity (see, e.g., Kontodimopoulos et al., 2008).

2.4. Statistics

Data were analyzed using Statistical Package for the Social Sciences (SPSS) version 28 (IBM Corp, 2021). We used independent sample *t*-tests to test for group differences between completers and non-completers on age and intake scores of BED-Q, BMI, MDI, and EQ VAS. We used Chi-squares to test for group differences in gender, educational level, source of income, children, and marital status.

To ensure sufficient sample size, we were only able to analyze the time between sessions of the first four sessions (0–1, 1–2, 2–3 and 3–4). Thirty seven participants (18,4 %) dropped out before session 4, reducing the sample size from 201 to 164.

We used two approaches to analyze the predictive value of days between sessions: First, we analyzed days between sessions for each session (1, 2, 3, and 4) using binary logistic regression; second, we analyzed days between sessions across the first four treatment sessions (1–4) using a mixed effects logistic regression model with robust standard errors. The rationale for using both binary logistic regression and mixed effects analyses was that the binary logistic regression analysis allowed us to compare days between sessions in each of the treatment sessions (1, 2, 3, and 4), while the mixed effects model allowed us to compare days between sessions across all sessions (1–4).

In the mixed effects logistic regression model with robust standard errors, we used the number of days participants spent between sessions as the independent variable and group (non-completers vs. completers) as the dependent variable. We defined completers as having completed all sessions in the program. The analysis was controlled for potential confounders of: gender, age, BED-Q, EQ VAS, BMI, and MDI. The outcome was reported as raw odds ratios (OR) that only included days between sessions in the analysis, and as adjusted odds ratios with confidence intervals (Adj. OR) that included days between sessions and the confounding variables.

In the binary logistic regression analyses, we also used days between sessions as the independent variable and group (non-completers vs. completers) as the dependent variable, only this time, we performed separate analyses for sessions 1, 2, 3, and 4. We controlled for confounders of: gender, age, BED-Q, EQ VAS, BMI, and MDI. The outcome was reported as raw odds ratios (OR) that only included days between sessions, and as adjusted odds ratios with confidence intervals (Adj. OR) that included days between sessions and the confounding variables.

To ascertain the clinical value of days between sessions as a predictor of attrition, we investigated the optimal cut-off point in the number of days between sessions that would predict the risk of attrition among participants. We used a receiver operating characteristic (ROC) curve analysis to determine the classification accuracy of completers vs. non-completers, i.e., the number of participants accurately predicted as completers and non-completers. We used a Kolmogorov-Smirnov analysis to estimate the optimal cut-off in the number of days between sessions for differentiating completers and non-completers. We also used the Kolmogorov-Smirnov analysis to calculate the sensitivity and specificity of the cut-off.

Finally, we explored whether there was a change in days spent between sessions as participants progressed through the program, and whether non-completers and completers differed in changes of days between sessions. We used a repeated measures ANOVA to investigate the change in days between sessions within each group and to test for potential group differences (interaction effect) in days between sessions across sessions the four sessions (1–4).

3. Results

Non-completers and completers did not differ significantly at intake on measures of gender, BMI, BED, EQ VAS and MD, see Table 1. However, non-completers were significantly younger than completers ($t = -1.67$, $p < .01$).

The binary logistic regression analyses showed that days between sessions significantly predicted attrition in each session (1, 2, 3, and 4), see Table 2. The highest significance levels were found in session 1 (OR = 1.069, $p < .001$) and 2 (OR = 1.071, $p < .001$), while lower significance levels were found in session 3 (OR = 1.036, $p < .01$) and 4 (OR = 1.028, $p < .01$). EQ VAS was the only confounder, which reached significance level in session 1 (OR = 0.981, $p < .05$).

The mixed effects model analysis showed that non-completers spent significantly more days between sessions across the four treatment sessions (1–4), OR = 1.047, $p < .001$. The results remained significant when controlling for age, gender, and intake measures of BMI, BED, EQ VAS, and MDI (OR = 1.042, $p < .001$). The risk of attrition increased by 4.2 % for each additional day participants spent completing a session. Age (OR = 0.976, $p < .001$) and EQ VAS (OR = 0.984, $p < .001$) also significantly predicted attrition. Being one year younger increased the risk of dropout by 3.4 %, while one point lower on the EQ VAS scale increased the risk of dropout by 1.6 %.

The ROC curve analysis showed an increasing classification accuracy for detecting non-completers from sessions 1 through 4. Classification accuracy increased from 61.1 % in session 1 and 65.7 % in session 2 to 68.8 % in session 3 and 73.2 % in session 4. The classification accuracy in session 4 detected 60.4 % of non-completers (sensitivity) and 78.4 % of completers (specificity). The optimal cut-off point for classifying non-completers and completers was 9.5 days in session 1, 14.5 days in session 2, 15.5 days in session 3, and 17.5 days in session 4.

The repeated measures of ANOVA showed a significant within-

Table 1
Descriptive Statistics of completers and non-completers at enrollment.

	Completers (n = 116)		Non-completers (n = 85)		X^2/t Sig. level
	Mean/n	St.D/%	Mean/n	St.D/%	
Gender					0.015
Male	13	11.2 %	10	11.8 %	
Female	103	88.8 %	75	88.2 %	
Age	40.43	12.02	37.8	9.53	$t = -1.67$ 0.008
Marital status					0.531
Relationship, married, other	72	62.1 %	57	67.1 %	
Single, divorced, widower	44	37.9 %	28	32.9 %	
Education					0.89
Lower education	26	22.4 %	24	28.2 %	
Higher education	90	77.6 %	61	71.8 %	
Primary income					0.126
Job/Salary	75	64.7 %	57	67.1 %	
Other	41	35.3 %	28	32.9 %	
Binge Eating Disorder – Q (BED-Q)	3.81	0.74	3.7	0.79	0.771
Body Mass Index (BMI)	36.47	9.41	38.48	9.0	0.820
Major Depression Inventory (MDI)	21.98	8.09	24.15	8.39	0.841
EQ VAS[c]	62.11	18.86	53.92	19.76	0.197
Days Per Session 1	7.48	5.46	11.54	11.29	<0.001
Days Per Session 2	9.03	7.07	14.46[a]	11.14	<0.001
Days Per Session 3	10.51	8.84	15.53[b]	14.26	0.001
Days Per Session 4	14.76	14.91	25.42[c]	24.50	0.005

[a] n = 71 noncompleters.
[b] n = 60 noncompleters.
[c] n = 48 noncompleters.

subjects effect, where both non-completers and completers spent more days between sessions as they progressed from sessions 1 through 4 ($F = 20{,}54$, $df = 3$, $p < ,001$), see Fig. 1. However, there was no significant interaction effect, suggesting that the increase in slope did not differ between non-completers and completers.

4. Discussion

In this study, we hypothesized that BED participants spending more days between sessions had an increased risk of dropping out of text-based iCBT.

We found that days between sessions significantly predicted attrition in each of the four sessions (1, 2, 3, 4). Furthermore, days between sessions significantly predicted attrition across all four sessions. Hence, days between sessions appear to be a reliable predictor of attrition.

Both completers and non-completers showed an increase in the number of days between sessions as they progressed from sessions 1 and 2 to sessions 3 and 4 (see Table 1). However, the increase was larger in non-completers than in completers. The increase might reflect decreased motivation and/or reinforcement of the program as participants progressed through treatment. For instance, Pedersen et al. (2019) found that two weeks of inactivity predicted treatment dropout, and program engagement significantly decreased leading up to dropout. Non-completers could also be more affected by negative factors such as technical difficulties, illness, divorce, or finals. For instance, Moshe et al. (2022) found that lower age, medium (vs. high) social support and a higher number of days to module completion predicted a higher risk of dropout. Lack of social support—or negative social support—might therefore increase the risk of program disengagement and attrition.

In our sample, other factors such as sampling bias could also affect the results. Participants who dropped out of treatment could not be re-entered into the sample. Therefore, the number of participants is lower in sessions 2–4, which could affect the distributions and *p*-values across sessions. In sum, several factors could contribute to the increase in the number of days between sessions, and we currently know very little about which factors contribute to this increase.

The odds ratios declined from sessions 1 and 2 to sessions 3 and 4. This means that each additional day between sessions had a lower prediction of the odds of attrition as the sessions progressed. This could be a problem of linearity. The binomial logistic regression analysis used in this study assumes a linear relation between days between sessions and the odds ratio of attrition. However, days between sessions may be a concave function of attrition. This is consistent with the Prospect theory in behavioral economics that the utility of a gain (here a motivational gain) is a concave function (Kahneman and Tversky, 1979). According to the prospect theory, the motivational gain would be greater if participants completed a session in 6 rather than 7 days compared with 16 rather than 17 days, even though the difference of one day is the same. Thus, the motivational gain of completing sessions is less if participants spend more days completing sessions compared with spending fewer days completing sessions. Lower motivational gain could lead to demotivation, which could increase the risk of attrition. Further studies should examine the functional relation between days per session and attrition.

The classification accuracy increased from sessions 1 and 2 to sessions 3 and 4. This suggests that clinicians can use the number of days between sessions to predict attrition with increased accuracy as participants progress through treatment. The increase in classification accuracy could be associated with the larger mean differences between completers and non-completers in sessions 3 and 4 compared to sessions 1 and 2 (see Table 1). However, the results might also be affected by differences in sample size across sessions 1–4.

Participants could access the program anytime to complete sessions,

Table 2
Binomial logistic regression analyses.

	Session 1, (N = 201)		Session 2, (n = 187)		Session 3, (n = 176)		Session 4, (n = 164)	
	OR	Adj. OR[a] (95 %-CI)	OR	Adj. OR[a] (95 %-CI)	OR	Adj. OR[a] (95 %-CI)	OR	Adj. OR[a] (95 %-CI)
Days	1.069**	1.065** (1.018 - 1.113)	1.074***	1.071*** (1.029 - 1.115)	1.042**	1.036* (1.004 - 1.069)	1.036**	1.028* (1.006 - 1.051)
Age		0.973 (0.945–1.001)		0.981 (0.951–1.011)		0.975(0.946–1.006)		0.973 (0.941–1.005)
Gender		1.221 (0.466–3.200)		0.736 (0.277–1.956)		0.917 (0.327–2.568)		1.236 (0.370–4.126)
MDI		1.009 (0.969–1.051)		1.005 (0.962–1.050)		1.007 (0.962–1.055)		0.992 (0.944–1.043)
EQ VAS		0.981 (0.964 -0.998)*		0.982 (0.964–1.001)		0.986 (0.967–1.005)		0.988 (0.967–1.009)
BED-Q		1.026 (0.924–1.140)		1.060 (0.948–1.186)		1.034 (0.920–1.163)		1.077 (0.950–1.220)
BMI		1.013 (0.979–1048)		1.013 (0.978–1.049)		1.018 (0.982–1.055)		1.002 (0.963–1.042)

[a] Adjusted for gender, age, EQ VAS, and intake measures of BMI, BED, and depression symptoms.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

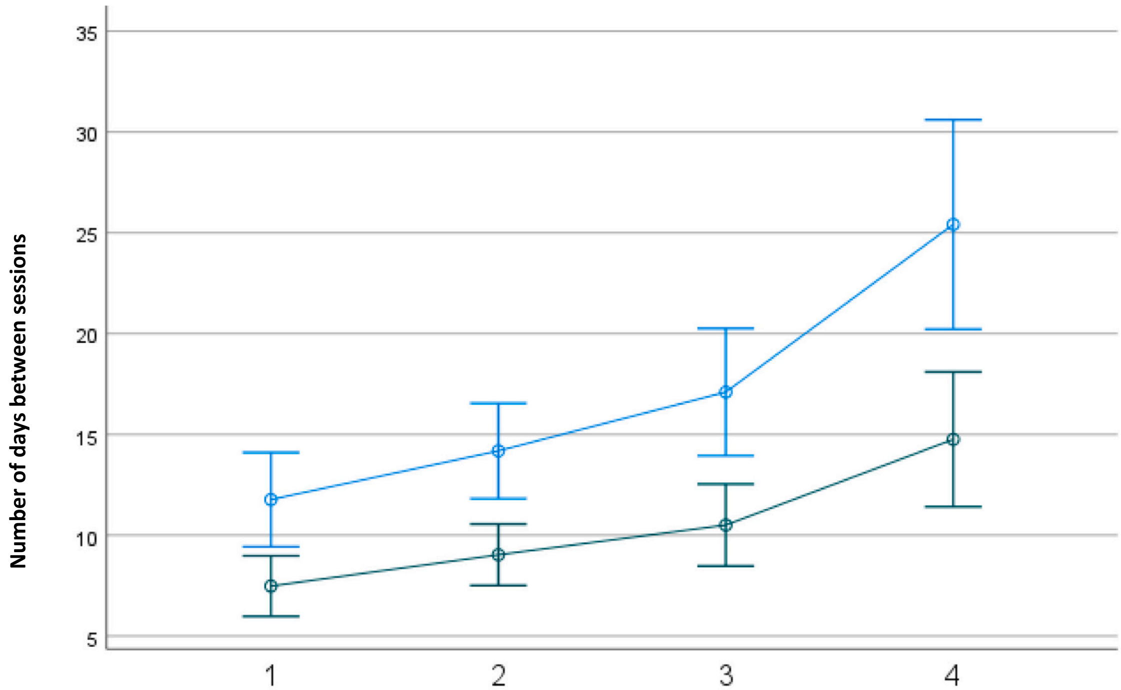

Fig. 1. Repeated measures ANOVA
Note. Blue line = non-completers; green line = completers. X-axis shows session numbers (1–4); y-axis shows the estimated marginal means of the number of days between sessions. Error bars show confidence intervals (CI).

and no sessions were scheduled with the therapist. In this open structure format, days between sessions may be a stronger predictor of attrition than in scheduled session treatment formats. For instance, days between sessions might be a poorer predictor of attrition in conventional treatment formats, where participants schedule appointments with therapists ahead of time. Often, it is the therapist's availability which determines the structure of sessions. However, as Internet interventions increasingly move toward a more flexible and open structure format, days between sessions may become a more prominent predictor of attrition in treatment. Therefore, it may be relevant to test days between sessions in other treatment formats, such as blended care and stepped care formats.

The optimal cut-off point for identifying non-completers on sessions 2–4 was around 15 days. A clinical guideline for therapists in the program was to write reminders to participants if they had not been active in the program for >14 days. It is possible that this practice influenced the results, so some participants responded to reminders early in the program and ended up completing the program or dropping out at a later point. Intensifying reminders to inactive participants through, e.g., weekly automated reminders or therapist messages might help improve adherence rates among some participants at risk for dropping out of treatment. For instance, early detection of reduced treatment response can help adjust treatment interventions, resulting in a better treatment outcome (Forsell et al., 2020; Forsell et al., 2019). Therefore, sending a reminder to participants spending more days between sessions might reduce attrition rates and improve the treatment effect. Future studies should investigate interventions that can reduce the risk of attrition among participants spending more days between sessions.

This study has several limitations that point to future studies. First, our sample size was limited, and we could only test the differences between completers and non-completers across the first four sessions. Our findings should be replicated in larger sample sizes that allow comparing completers and non-completers across more sessions. Second, our findings are limited to open format text-based Internet interventions, where participants themselves decide when to log in to the program. Our findings should be replicated in blended care or stepped care formats, where participants, e.g., schedule video consultations or face-to-face appointments with therapists in addition to the open format structure. Third, our findings should be reproduced in other patient populations. Days between sessions may be a transdiagnostic predictor of attrition, which can be found across many different disorders. However, the predictive properties of days between sessions may be stronger in some diagnostic groups (e.g., depressed patients) than others (e.g., anxiety disorder patients). Also, our population consisted of patients with mild to moderate BED and comorbidity, and this may represent a bias compared with other patient populations. Currently, we know very little about the predictive properties of days between sessions in other diagnostic populations, and future studies should therefore investigate the role of days between sessions across the diagnostic spectrum.

5. Conclusion

Our findings suggest that participants who spend more days between sessions are at increased risk for dropping out of treatment and that the number of days between sessions increases as participants progress through treatment. This may have real-life implications for clinicians in identifying participants at risk for dropping out of treatment and implementing measures to reduce attrition, e.g., intensifying interventions through automated reminders or therapist messages. The findings may have important transdiagnostic implications for text-based Internet interventions. Further studies should investigate the predictive value of days between sessions in other diagnoses.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The data supporting the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy and/or ethical restrictions.

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