Behaviour Research and Therapy 195 (2025) 104919

Contents lists available at ScienceDirect

Behaviour Research and Therapy

journal homepage: www.elsevier.com/locate/brat

Digital health interventions for occupational burnout in healthcare professionals: a multi-site randomised non-inferiority trial

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ARTICLE INFO

Keywords:
Digital health
Telehealth
Interventions
Burnout
Wellbeing

ABSTRACT

Background: Occupational burnout affects between 11 % and 30 % of healthcare professionals and is associated with staff sickness, job turnover, increased costs and poorer quality of care. This study aimed to compare the effects of two theoretically distinctive interventions for burnout in healthcare professionals.
Methods: This multi-site randomised non-inferiority trial recruited 465 healthcare professionals working across 20 National Health Service (NHS) providers in England. Recruitment took place between October 1, 2020 and June 30, 2021. Participants were randomly assigned to digital health interventions based on cognitive behavioural therapy (CBT; $n = 227$) or job crafting (JC; $n = 238$), each of which lasted 6-weeks and involved participation in weekly webinars (1hr) supplemented by online coping skills modules. The primary outcome (Oldenburg Burnout Inventory) was measured at baseline, after 6 weeks, and after 6 months. Between-group differences were compared using analysis of covariance adjusting for baseline measures, testing a non-inferiority hypothesis.
Results: At 6 weeks, the adjusted mean difference of 0.47 (95 % CI: –0.25 to 1.20; $p = .197$) in the OLBI favoured CBT. Although this difference was not statistically significant, the non-inferiority hypothesis was not supported based on a pre-specified minimum clinically important difference. At 6 months, the adjusted mean difference favoured CBT indicating superiority; 0.80 (95 % CI: 0.05 to 1.54; $p = .036$).
Conclusions: Brief digital health interventions can help to improve occupational burnout and well-being in healthcare professionals. CBT was more effective than JC.

1. Introduction

Occupational burnout, resulting from chronic workplace stress, is associated with exhaustion, disengagement and reduced professional efficacy according to the international classification of diseases (World Health Organization, 2020). Burnout is prevalent in healthcare professionals, affecting around 11 % of nurses (Woo et al., 2020) and 30 % of physicians worldwide (De Hert, 2020), with higher rates in critical

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https://doi.org/10.1016/j.brat.2025.104919
Received 10 October 2024; Received in revised form 14 October 2025; Accepted 10 November 2025
Available online 11 November 2025
0005-7967/

care and mental health professionals (Moss et al., 2016; O'Connor et al., 2018). Burnout is a known risk factor for several adverse health outcomes including cardiovascular disease and depression (Salvagioni et al., 2017). Moreover, burnout is one of the main reasons for staff shortages due to sickness and turnover in health services, which adversely impacts the quality of care and patient experience (Sizmur & Raleigh, 2018). Hence, it can be said that burnout has a multilevel economic and health impact on organisations, professionals and patients.

A number of interventions for burnout have been examined in clinical trials for health professionals; the most common involving job-specific training, relaxation, meditation, stress management and cognitive-behavioural interventions (Lee et al., 2016; Richardson & Rothstein, 2008; West et al., 2016). Of these, cognitive-behavioural interventions are the most well-established, showing larger effect sizes than others according to meta-analytic evidence (Richardson & Rothstein, 2008). A common criticism of such interventions is that they focus on the individual as the locus of change while ignoring the wider organisational context and job-specific challenges that maintain occupational stress. Evidence suggests that context-focused interventions such as reduced work hours and job-focused training have fairly limited effects on burnout (West et al., 2016), but these could be combined with individual-focused interventions. *Job crafting* is a novel approach that combines both individual and context-focused interventions (Tims & Bakker, 2010), and it has emerging empirical support from cross-sectional and longitudinal studies (Lichtenthaler & Fischbach, 2019). However, rigorous evidence from clinical trials involving healthcare professionals is scarce.

Digital health versions of these interventions may be a promising avenue to maximise the accessibility of burnout support for healthcare professionals, who often work in challenging settings (i.e., mobile units for ambulance staff) and schedules (i.e., shift patterns). Emerging evidence from clinical trials indicates that digital health interventions could be an effective way to improve mental health and occupational outcomes in healthcare professionals, although relatively few trials have examined burnout as a primary outcome (see review by Aye et al., 2024). The present study aimed to test the comparative effectiveness of two theoretically distinctive approaches, cognitive-behavioural therapy (CBT) and job crafting (JC), which were designed as digital health interventions tailored for a healthcare workforce during the acute phase of the COVID-19 pandemic.

2. Methods

2.1. Study design

This was a pragmatic, open-label, multi-site randomised non-inferiority trial involving healthcare professionals working across 20 National Health Service (NHS) Trusts and contracted NHS service providers in England. We hypothesised that both interventions would be associated with reduced burnout and improved well-being post-intervention, and that these improvements would be maintained at 6-months follow-up. We hypothesised that JC (a novel intervention) would be non-inferior to CBT (a well-established and effective intervention) after the acute intervention and after 6 months. As a pragmatic trial, the participants did not receive any incentives, to evaluate attendance and outcomes in routine healthcare conditions. The study was approved by an NHS research ethics committee and the Health Research Authority (REF: 20/EM/0236), after which it was preregistered in an international database (https://doi.org/10.1186/ISRCTN18197153).

2.2. Participants

To maximise external validity to the healthcare environment, the trial was open to all NHS professionals who (a) were employed full-time or part-time in participating healthcare organisations (including community providers) and (b) whose role involved direct patient contact either in a clinical or administrative capacity. Exclusion criteria were (a) not being in work at the time of recruitment (e.g., maternity leave, sickness leave); (b) working on temporary contracts shorter than the duration of the study; (c) having a role without direct patient contact; (d) consenting to take part but choosing not to complete baseline assessment questionnaires.

2.3. Recruitment, randomisation and masking

Participants were recruited in two waves, each lasting one month (October 2020; June 2021). Principal investigators at each NHS provider promoted the study via workforce-wide email communications, using a standard information sheet and a promotional video prompting them to complete an electronic consent form. Consenting participants were randomised to one of two digital health interventions using a computer-generated 1:1 randomisation schedule in blocks of ten, stratified by NHS organisation and role (clinical or administrative). The randomisation schedule was masked to the study team and allocation was managed by an independent researcher. The statistical analysis was conducted by an independent analyst who had no part in the design of the study, randomisation or data collection, using a dataset that masked group allocation.

2.4. Procedures

Consenting participants were invited to complete an online survey, after which they were able to register an account on the study website and to choose a convenient day and time to participate in a live webinar (a selection of options was available each week to maximise accessibility). Participants were then invited to attend a series of six webinars, each lasting 1 h, covering their allocated intervention (either CBT or JC) and delivered via video conference once per week. The webinars were psychoeducational and participatory in style, covering key concepts, coping skills and promoting discussion with participants. Webinars were facilitated by a team of psychological professionals including psychological wellbeing practitioners, counsellors, and trainee clinical psychologists. To support treatment fidelity, the facilitators were grouped in two teams, each exclusively delivering one of the two interventions, without access to materials or website content for the other intervention. Each session was delivered based on pre-defined and structured presentation materials, thus ensuring adherence to the content of the modules for each intervention. The webinars were not recorded or monitored, to guarantee participants' confidentiality, and hence fidelity was not rated by independent observers.

At the end of each weekly webinar, participants were encouraged to use the website to engage in an interactive *skills practice*, which involved implementing specific coping skills covered in that week's webinar. The website included content summaries for all weekly webinars and interactive skills practices to promote consolidation of learning, all of which was available to participants for six months after the end of the webinar series. Participants had access to a version of the website that was matched to their random allocation (e.g., those randomised to JC could only access JC-related content and were blinded to the CBT content). Participants were prompted by email to complete electronic surveys after six weeks (post-intervention), and also six months after the end of interventions.

2.5. Interventions

Cognitive-behavioural therapy. Drawing from cognitive behavioural therapy (Hollon & Beck, 2004) and the social-cognitive theory of stress (Lazarus & Folkman, 1984), this intervention assumes that occupational stress is activated by work demands and maintained by the person's appraisal of and behavioural responses to these demands. As such, the locus of change is in the individual's way of thinking and action strategies to deal with work challenges and to optimise work-life balance. The sessions cover coping skills featured in prior controlled trials that have empirical support from meta-analyses (Lee et al., 2016) including: five-areas formulation, cognitive restructuring, problem solving, relaxation skills and behaviour change techniques. These coping skills are organised in modules focusing on managing physiological reactions, managing stressful thoughts, managing personal expectations and rules, and adopting helpful habits and routines.

Job crafting. The job demands-resources model (Demerouti et al., 2001) and the effort-reward imbalance model (Siegrist, 1996) propose that occupational stress occurs when work demands outweigh available resources and rewards. Furthermore, individual differences in variables such as overcommitment, self-efficacy and autonomy may exacerbate this imbalance (Davis, 2020). Informed by this literature, this intervention draws on the job crafting model (Tims & Bakker, 2010) as a framework to make changes intended to reduce the imbalance between demands-resources-rewards. The intervention is organised in modules focusing on managing job tasks (task crafting); managing relationships with colleagues and patients (relational crafting); amplifying rewards (cognitive crafting); and enhancing one's work context (environment crafting) and skills (development crafting).

Detailed explanations of the modules across both interventions, theoretical targets for change (i.e., maintaining factors) and examples of change methods are available in the Supplemental Materials.

2.6. Outcomes

Primary outcome. The Oldenburg Burnout Inventory (OLBI) is a 16-item questionnaire designed to assess two interrelated facets of burnout, *emotional exhaustion* and *disengagement* (Demerouti et al., 2001). Items are scored between 1 (strongly agree) and 4 (strongly disagree). For both dimensions, four items are phrased positively, and four items are phrased negatively (reverse scored). Examples of positively and negatively phrased items are: "I can tolerate the pressure of my work very well"; "During my work, I often feel emotionally drained". After reverse-scoring, higher sum scores are indicative of more severe burnout. The measure has been found to have high internal consistency (α = .74 to 0.76 for each subscale) as well as robust convergent, and discriminant validity in samples including various professional groups (Halbesleben & Demerouti, 2005). High reliability indices were observed in the present sample in the full OLBI scale (α = .85) and subscales (α = .78, α = .76) measured at baseline. The primary (pre-registered) outcome was burnout severity on the full OLBI scale, which was measured at 6-weeks (post-intervention) and 6 months follow-up.

Secondary data sources. All participants reported their demographic and occupational characteristics at baseline assessment. They also reported their number of sick days off work in the last month, measured at baseline and at the end of the 6-week intervention. To minimise response burden, participants completed the Warwick-Edinburgh Mental Well-being Scale (WEMWBS; Tennant et al., 2007) only at two time-points; baseline and 6 months follow-up. This is a 14-item questionnaire covering different aspects of mental well-being, with Likert scale items scored on a 1–5 scale. The sum score ranges from 14 to 70, with higher scores indicating greater psychological well-being. The scale has good internal consistency (α = .89 to 0.91) and test-retest reliability (0.81) in adult respondents (Tennant et al., 2007). Reliability in the present sample was α = .92.

2.7. Statistical analysis

Sample size calculation. Informed by data reported in a previous clinical trial that used the OLBI measure (Laker et al., 2023), we calculated a minimum clinically important difference (MCID) of 0.15 and a standard deviation of change of 0.27. We estimated that 140 participants (70 in each arm) were required to detect a difference in means of 0.15 with a 5 % (two-sided) significance level and 90 % power. This target was increased to 240 (120 in each arm) for the trial to be robust to 40 % attrition. The power calculation was only based on the primary outcome, so analyses for secondary outcomes are considered exploratory and not aligned to a non-inferiority approach.

Primary analysis. Mean OLBI scores (dependent variable) were compared between groups using analysis of covariance (ANCOVA), adjusting for baseline severity and entering the intervention group as an independent variable. ANCOVA models were produced for the 6-week and 6-month follow-up time-points.

Secondary analyses. Between-group comparisons on OLBI subscales and WEMWBS were performed using the ANCOVA method described above, at both time-points. Standardized mean differences with 95 % confidence intervals and effect sizes (Cohen's *d*) were calculated for all comparisons. Within-group changes in outcome measures over time were examined using paired-sample *t*-tests and pre-post intervention effect sizes. The cumulative number of sick days for the full sample was calculated before and after the intervention period, to assess the extent to which COVID-19 infections may have affected participation.

The primary analysis followed intention-to-treat principles, including all randomised cases and applying multiple imputation of missing data (expectation-maximisation method with baseline data as predictors) to minimise bias due to attrition. A sensitivity analysis examined the primary outcome in a complete-case analysis. A per protocol analysis was also carried out, only including data from participants who attended at least one intervention webinar.

3. Results

3.1. Sample characteristics and engagement with interventions

As shown in the CONSORT diagram (Fig. 1), 571 healthcare professionals consented to participate between October 1, 2020 and June 30, 2021, of whom 465 (81 %) completed baseline measures and were included in the trial. Most participants were white British (83.0 %) females (88.6 %) with a mean age of 42 years (SD = 10.77), the majority of whom were nursing and allied health professionals (65.2 %). Baseline measures and detailed sample characteristics are presented in Table 1. Approximately 63.9 % of participants actually attended at least one intervention webinar. The mean number of webinars attended was 2.62 (SD = 2.42; range = 0 to 6) and the mean number of skills completed in the website was 1.98 (SD = 2.42; range = 0 to 6). Participants who engaged with the interventions (attended $\geq$ 1 webinar) attended a mean of 4.07 sessions (SD = 1.79; range = 1–6) and completed an average of 3.04 skills practices (SD = 2.44; range = 0–6), with only 30 % of them attending all 6 sessions. There were no statistically significant differences in the mean number of attended sessions between groups, comparing CBT versus JC. There were no statistically significant differences in baseline characteristics between groups, comparing those who attended versus those that did not.

As shown in the CONSORT diagram (Fig. 1), there was substantial loss to follow-up (~55 %), consistent with the number of participants who did not attend any webinars. There were no statistically significant differences in baseline characteristics between participants who were lost to follow-up and those who were not.

3.2. Primary outcome

All ANCOVA results are displayed in Table 2. At 6 weeks follow-up, the mean OLBI score in the JC group was 39.48 (SD = 0.26) compared with 39.00 (SD = 0.26) in the CBT group. The adjusted mean difference was not statistically significant; 0.47 (95 % CI: –0.25 to 1.20; p = .197). However, the upper bound of the confidence interval exceeded the pre-specified MCID margin of 0.15, therefore the non-inferiority hypothesis was not supported. At 6 months follow-up, the corresponding mean OLBI scores were 39.80 (SD = 0.27) versus 39.00 (SD = 0.27). The adjusted mean difference was statistically significant; 0.80 (95 % CI:

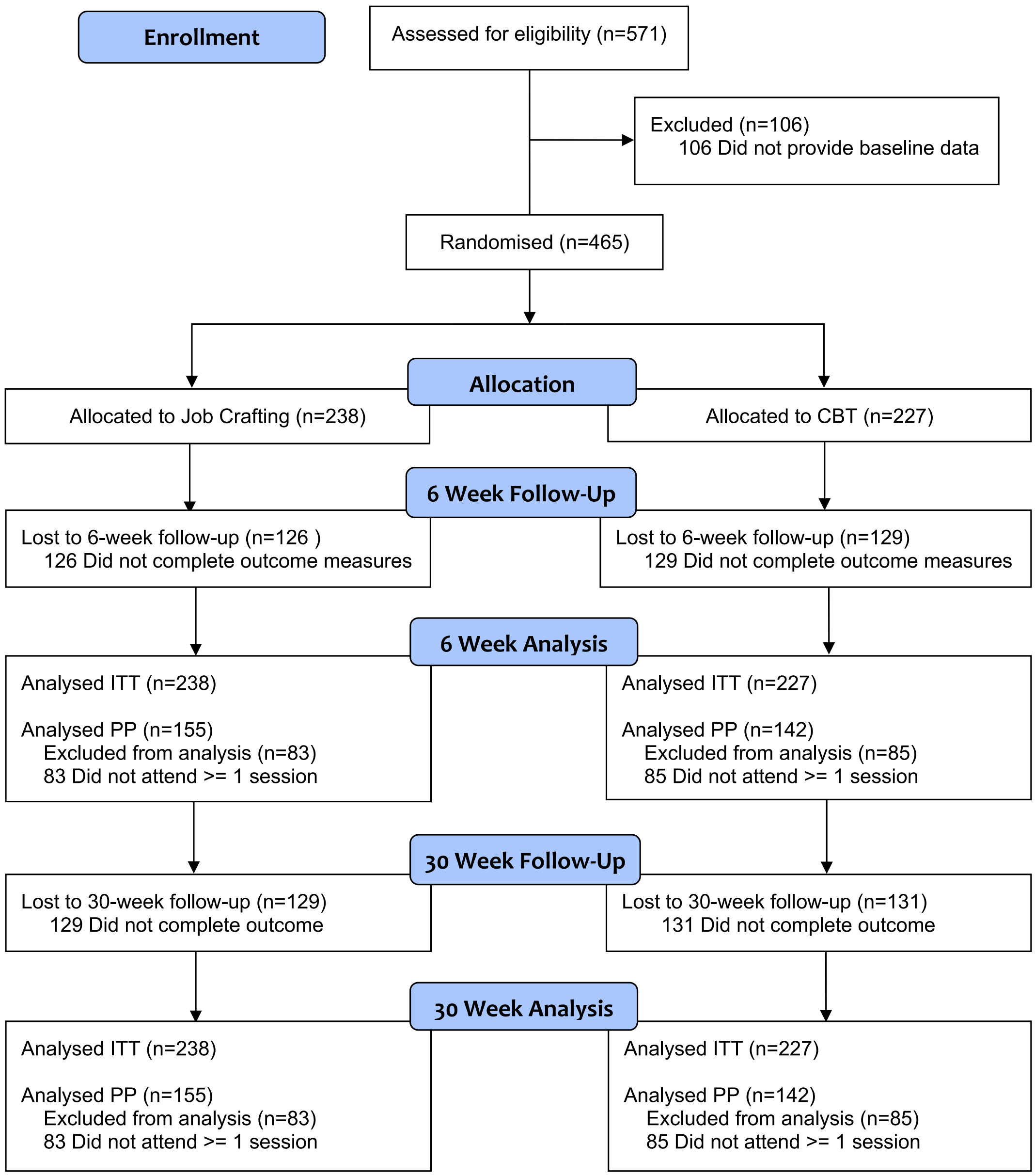

Fig. 1. CONSORT diagram.

0.05 to 1.54; $p = .036$). The point estimate exceeds the MCID, and the confidence interval excludes zero, indicating a clinically and statistically significant superiority of CBT at this time-point. Effect sizes for these comparisons ($d = 0.03$ to 0.09), shown in Fig. 2, favoured CBT. Sensitivity analyses confirmed that these results remained stable using intention-to-treat and complete-case analysis.

3.3. *Secondary outcomes*

No statistically significant differences between groups were found in OLBI subscales at any measurement time-point, except for the disengagement subscale which indicated significant differences at 6-months follow-up favouring CBT (0.46 [0.09 to 0.84], $d = 0.11$, $p = .015$). Statistically significant mean differences in WEMWBS at 6-months follow-up favoured CBT (−1.73 [−2.83 to −0.64], $d = -0.26$, $p = .002$). Within-group improvement over time in OLBI was statistically significant for CBT and JC at 6-weeks ($d = 0.48$ and 0.43, respectively) and 6-months follow-up ($d = 0.49$ and 0.38). Within-group improvement in WEMWBS was also statistically significant for CBT and JC at 6-months follow-up ($d = -0.54$ and -0.40). The number of sessions attended was correlated with within-group improvements in OLBI at week 6 ($r = 0.14$, $p = .002$), OLBI at 6-months follow-up ($r = 0.12$, $p = .008$), and WEMWBS at 6-months follow-up ($r = -0.10$, $p = .029$). The number of online skills practices completed was correlated with within-group improvements in OLBI at week 6 ($r = 0.10$, $p = .038$), in WEMWBS at 6-months follow-up ($r = -0.11$, $p = .015$), but not with OLBI at 6-months follow-up ($r = 0.07$, $p = .111$). The sample-wide cumulative number of sick days was 349 in the month before starting interventions and 778 in the last month of the intervention period.

3.4. *Per protocol analysis*

No statistically significant differences between groups were found in OLBI or its subscales at any measurement time-point (see supplemental materials). Statistically significant mean differences in WEMWBS at 6-months follow-up favoured CBT -1.92 [−3.29 to −0.54], $d = -0.27$, $p = .006$).

Table 1
Sample characteristics.

	Total sample ($n = 465$)	Job crafting group ($n = 238$)	CBT group ($n = 227$)
Demographic characteristics			
Mean age (SD)	41.80 (10.77)	42.11 (10.89)	41.48 (10.65)
Gender n (%)			
Female	412 (88.6)	212 (89.1)	200 (88.1)
Male	47 (10.1)	23 (9.7)	24 (10.6)
Other	1 (0.2)	0 (0)	1 (0.4)
Ethnicity n (%)			
White British	386 (83.0)	199 (83.6)	187 (82.4)
Ethnic minority	79 (17.0)	39 (16.4)	40 (17.6)
Employment features			
Working hours (SD)	35.58 (7.61)	35.89 (7.31)	35.25 (7.92)
Job role n (%)			
Administrative	12 (2.6)	7 (2.9)	5 (2.2)
Medical professionals	24 (5.2)	14 (5.9)	10 (4.4)
Dentists	2 (0.4)	0 (0.0)	2 (0.9)
Pharmacists	4 (0.9)	1 (0.4)	3 (1.3)
Mental health professionals	120 (25.8)	63 (26.5)	57 (25.1)
Nursing and allied health professionals	303 (65.2)	153 (64.3)	149 (66.1)
Participating NHS trusts n (range of participants)	20 (1–58)	20 (1–31)	19 (2–27)
Baseline characteristics			
OLBI total mean (SD)	42.11 (6.23)	41.87 (5.87)	42.35 (6.59)
OLBI disengagement subscale mean (SD)	19.23 (3.66)	19.15 (3.43)	19.32 (3.90)
OLBI exhaustion subscale mean (SD)	22.87 (3.52)	22.73 (3.40)	23.03 (3.64)
WEMWBS mean (SD)	42.84 (8.11)	42.90 (7.38)	42.78 (8.83)
Engagement			
Mean sessions attended (SD) [a]	2.62 (2.42)	2.68 (2.41)	2.56 (2.44)
Attendance ≥ 1 session n (%)	297 (63.9)	155 (65.1)	142 (62.6)
Mean skills completed (SD)	1.98 (2.42)	2.06 (2.47)	1.89 (2.38)

SD; standard deviation; NHS; National Health Service; OLBI; Oldenburg Burnout Inventory; WEMWBS; Warwick-Edinburgh Mental Wellbeing Scale.
[a] Mean sessions attended based on whole sample including participants who attended 0 sessions.

4. Discussion

This clinical trial offered digital health interventions to 465 healthcare professionals across 20 NHS organisations. Using a "blended care" approach, participants could engage in facilitated webinars as well as self-directed practice using a website available to them throughout the study period. Despite their scalability and ease of access, only 64 % of eligible participants actually attended at least one webinar, which represents a lower participation rate than the average (M = 70 %, range = 20 %–100 %) reported by other burnout-focused studies (Ahola et al., 2017). Hence, it cannot be concluded that digital health interventions maximise accessibility in this context. The cumulative number of monthly sick days doubled during the intervention period, indicating that COVID-19 infections and illness were highly likely to have hampered participation. Notwithstanding this, we observed statistically significant improvements over time in both intervention groups, indicating that participants' occupational wellbeing indicators improved after the intervention period and stabilised over the following 6 months.

Table 2
ANCOVA adjusted outcome measure estimates at each time point for the ITT sample.[a]

Time-point	Job crafting estimate (SE)	CBT estimate (SE)	Mean difference (95 % CI)	F	p
Primary outcomes	*N = 238*	*N = 227*			
OLBI total scores					
Post-treatment	39.48 (0.26)	39.00 (0.26)	0.47 (−0.25 to 1.20)	1.67	0.197
Follow-up	39.80 (0.27)	39.00 (0.27)	0.80 (0.05–1.54)	4.42	**.036**
Secondary outcomes					
OLBI disengagement subscale					
Post-treatment	18.38 (0.13)	18.39 (0.13)	−0.01 (−0.37 to 0.35)	0.01	0.940
Follow-up	18.78 (0.13)	18.31 (0.14)	0.46 (0.09–0.84)	6.02	**.015**
OLBI exhaustion subscale					
Post-treatment	21.04 (0.15)	20.63 (0.16)	0.41 (−0.02 to 0.84)	3.55	0.060
Follow-up	21.01 (0.16)	20.69 (0.16)	0.32 (−0.12 to 0.76)	2.04	0.154
WEMWBS					
Follow-up	45.80 (0.39)	47.54 (0.40)	−1.73 (−2.83 to −0.64)	9.68	**.002**

SE; standard error; NHS; National Health Service; OLBI; Oldenburg Burnout Inventory; WEMWBS; Warwick-Edinburgh Mental Wellbeing Scale.
[a] Estimates adjusted for baseline severity at time 1. Measurement time points: post-intervention measurement = 6-weeks after baseline; Follow-up measurement = 6-months post-intervention (30-weeks after baseline). Higher OLBI scores = greater levels of burnout; Higher WEMWBS scores = greater levels of wellbeing.

Although the present trial lacked a no-intervention control group, the magnitude of pre-post intervention change in burnout ($d = 0.43$ to 0.48, moderate effect sizes) exceeded the change observed in an 8-week waitlist control group ($\sim d = 0.35$) of another trial of burnout interventions delivered during the COVID-19 pandemic using the OLBI measure (Laker et al., 2023). Hence, it is unlikely that the magnitude of burnout reduction observed in this study could simply be explained by the passage of time.

Contrary to our hypothesis, JC was less effective than CBT, based on a pre-specific MCID margin for non-inferiority. Data collected six months after the end of interventions indicated that CBT was associated with better long-term outcomes compared to JC, with an effect size advantage of $d = 0.09$ for burnout and $d = -0.26$ for wellbeing. The advantage of CBT for improved wellbeing was highly robust, since this comparison remained statistically significant in the per-protocol analysis ($d = -0.27$). Although this magnitude of effect sizes is conventionally interpreted as "small" according to Cohen's criteria (Cohen, 1988), this difference is clinically important for the following reasons. Effect sizes of $d = 0.09$ and $d = -0.26$ can be transformed to a number-needed-to-treat (Furukawa & Leucht, 2011) of approximately 19.71 and 6.60, respectively. Based on this logic, routine access to CBT instead of JC would result in better burnout outcomes for one in nineteen (~5 %) and better wellbeing outcomes for one in six healthcare professionals (~15 %). Considering that the NHS employs around 1.6 million people across the United Kingdom (The King's Fund, 2020), of whom 480,000 (30 %) may be experiencing burnout, around 15,360 additional professionals would have better burnout outcomes and 46, 080 would have improved wellbeing outcomes if CBT was accessed instead of JC, assuming a modest participation rate of 64 % (307,200).

The findings described above have important theoretical implications. The general orientation of JC is to guide participants to amplify aspects of their job that are consistent with their personal values and goals, so as to redress the demands–rewards imbalance. This intervention also aims to redress the demands–resources imbalance by

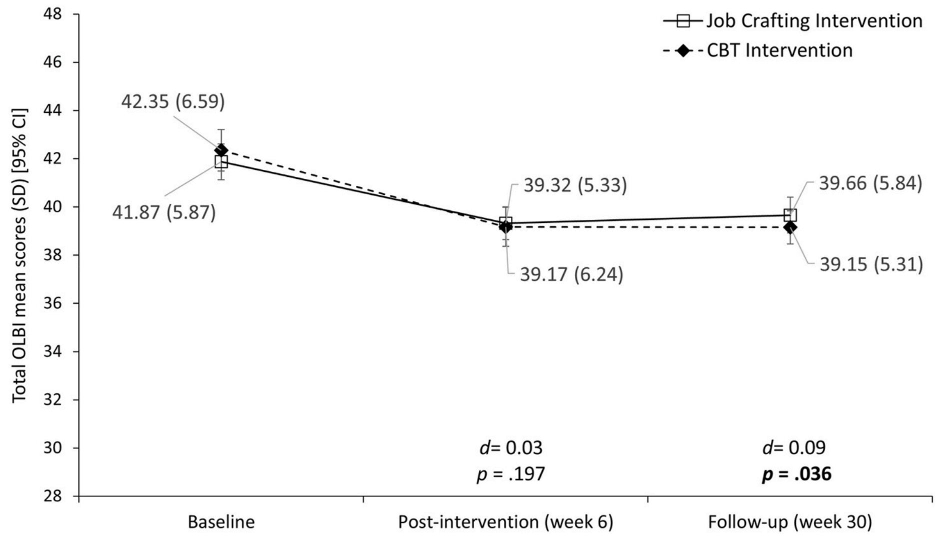

Fig. 2. Unadjusted mean total OLBI scores and between-groups effect size (*d*) at each time point for the ITT sample (error bars represent 95 % CI). Statistical significance of group differences (*p*) based on ANCOVA analysis controlling for baseline severity.

increasing resources/support or reducing demands if possible. Here, the focus in on making changes to the job itself, including tasks and work relationships. Taking a different orientation, the CBT intervention guides participants to make changes to how they think about and respond to work-related challenges. Here, the focus is on striving to enhance one's ability to cope with work demands, while compensating for these demands through restorative activities outside of work. It may be that the enhanced CBT effects on wellbeing could be explained by the latter emphasis on *compensation*, particularly given the intense demands of healthcare and the relatively limited degree of autonomy that staff have to make fundamental changes to their demands and roles. The effectiveness of CBT coping skills on stress, anxiety and mood management is well established (Hofmann et al., 2012), hence an alternative interpretation could be that the CBT intervention had a more generalised effect on emotion regulation within and outside of the work context. Ultimately, process-oriented research is necessary to understand the extent to which the effects of these interventions may be driven by similar or distinctive mechanisms. Moreover, burnout is known to be influenced by multiple risk factors including organisational factors (e.g., high workload; Morse et al., 2012), contextual factors (e.g., quality of relationships at work; O'Connor et al., 2018) and individual differences (e.g., overcommitment; Avanzi et al., 2014). It may be that people with different combinations of risk factors respond differentially to these burnout interventions and future research could potentially advance targeted prescription models (e.g., recommending either CBT or JC) or personalised interventions combining specific modules that are matched to each person's risk factors (e.g., combining some CBT and some JC modules).

The present study has a number of methodological strengths, including the large multisite population providing a representative and generalisable sample, random allocation to interventions, a 6-month follow-up period, pre-registration of the statistical analysis plan and blinded data analysis. This study also has several limitations. Outcomes were self-reported and no observer-rated or workforce data (e.g., actual sickness absence records) were available. A major limitation concerns loss to follow-up (~55 %), which necessitated multiple imputation of missing data in order to minimise the influence of reporting bias. The available data do not shed light on any factors that may be associated with adherence and loss to follow-up. No process measures were collected, such as those regarding group cohesion. The infrequent assessment of wellbeing (WEMWBS) is a limitation, though the results at six months follow-up are consistent with the primary outcome. Furthermore, the study lacked appropriate data and measures to examine the potential health economic impact of burnout interventions on participants' quality of life and organisational costs related to sickness absence. Despite the inclusion of numerous NHS healthcare organisations, the sample was self-selected and it is possible that the effect of these interventions may differ in wider healthcare professional samples outside of the confines of a clinical trial. It is also possible that the results may differ across specific professional groups (e.g., nurses, medical doctors), although the sample was not powered to test a non-inferiority hypothesis in these subgroups.

In conclusion, the present findings indicate that brief and accessible digital health interventions are effective for the alleviation of occupational burnout and the enhancement of psychological well-being in healthcare professionals. The effects of these interventions was maintained at 6-months follow-up, although CBT was more clinically effective and led to better long-term outcomes compared to JC.

CRediT authorship contribution statement

Jaime Delgadillo: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Victoria Laker:** Writing – review & editing, Supervision, Project administration, Data curation, Conceptualization. **Melanie Simmonds-Buckley:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Amy Southgate:** Writing – review & editing, Project administration, Conceptualization. **Laura Parkhouse:** Writing – review & editing, Resources, Project administration, Conceptualization. **Ben Davis:** Writing – review & editing, Resources, Project administration, Investigation, Conceptualization. **Jessica Furlong-Silva:** Writing – review & editing, Resources, Project administration, Investigation, Conceptualization. **Nicole King:** Writing – review & editing, Resources, Project administration, Formal analysis, Data curation, Conceptualization. **Sarah Keeble:** Writing – review & editing, Resources, Project administration, Data curation, Conceptualization. **Oliver Davis:** Writing – review & editing, Resources, Project administration, Data curation, Conceptualization. **Poppy Royal:** Writing – review & editing, Resources, Project administration, Conceptualization. **Mike Lucock:** Writing – review & editing, Supervision, Resources, Conceptualization. **Elisa Aguirre:** Writing – review & editing, Supervision, Resources. **Richard Thwaites:** Writing – review & editing, Supervision, Resources. **Beverley Flint:** Writing – review & editing, Supervision, Resources. **Thomas Osborne:** Writing – review & editing, Supervision, Resources. **Fiona Bell:** Writing – review & editing, Supervision, Resources. **Madeleine Devon:** Writing – review & editing, Supervision, Resources.

Michael Barkham: Writing – review & editing, Supervision, Resources.

Data sharing policy

In line with the requirements of the ethics review board for this study, requests for access to data are to be made in writing to the corresponding author.

Funding

This study was part-funded by MindLife UK [REF: 12082020]. The funder was not involved in the data analysis, interpretation or decision to publish the results.

Declaration of competing interest

MindLife UK funded the website development for the adjunct digital health skills modules that supplemented telehealth (video webinar) interventions. None of the authors have contractual, financial or personal relationships with MindLife UK, and do not benefit from any direct payment or company shares related to the website technology.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.brat.2025.104919.

Data availability

Data will be made available on request.

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