Understanding the impact of Job Crafting on healthcare staff wellbeing.

Aaminah Aqeel

A thesis submitted in partial fulfilment of the requirements for the degree of Doctorate in Clinical Psychology

Clinical Psychology Unit, Department of Psychology

The University of Sheffield

June 2025

Declaration

I, the author, confirm this thesis is my own work and that I am aware of the University of Sheffield guidance on unfair means (www.sheffield.ac.uk/new-students/unfairmeans). This thesis is submitted in partial fulfilment of the requirements for the degree of Doctorate in Clinical Psychology. This work has not been submitted for any other degree or to any other institution. No funding has been received for this thesis. No conflicts of interests stated. For any enquiries about data or code sharing, please contact aaqeel1@sheffield.ac.uk or r.k.webster@sheffield.ac.uk.

Structure and Word Count

Section One: Literature Review

Excluding references and tables:	6679
Including references and tables:	10399

Section Two: Empirical Study

Excluding references and tables:	6970
Including references and tables:	9449

Total

Excluding references and tables:	13649
Including references and tables:	19848

Lay Summary

Healthcare staff experience high levels of burnout and poor wellbeing. Services need to find effective ways to support them. Job Crafting (JC) interventions make people's work feel more meaningful by changing work tasks, building better relationships or changing the way they view their work to fit more with their values. It is important to explore whether JC is effective in improving healthcare staff personal wellbeing and burnout.

Chapter one of this thesis is a systematic literature review which includes studies exploring the effect of JC on healthcare staff personal wellbeing and burnout. Some of the studies were experimental delivering JC as an intervention while others were observational measuring JC as a spontaneous employee-initiated behaviour. The narrative synthesis found that JC was associated with better wellbeing, reduced burnout and distress, increased happiness and better mental and physical health. This suggests JC is a promising intervention for improving personal wellbeing, although more high-quality research is required to confirm associations and long-term effects.

Chapter two is an empirical research project which explored whether different subtypes of burnout could predict who benefits from JC. A machine learning method was used to identify 12 subtypes of burnout based on answers to a burnout questionnaire. However, it was concluded that burnout subtype did not predict who improved with JC. Job role or ethnicity did not predict outcomes either. Instead, the best predictor or improvement was burnout level at the start. People who had higher

levels of burnout at the start were more likely to get better after JC. This suggests that services should tailor JC to people who have the most severe burnout.

Together, these chapters show that JC is beneficial for improving healthcare staff wellbeing however more research should be done to understand more about it and how to deliver it most effectively.

Acknowledgements

First, I want to thank my supervisor, Dr. Jaime Delgadillo, for teaching me so much and helping me make sense of a complex machine learning approach. You broke everything down so clearly and guided me through it step by step – I've learned more than I could have imagined. Thank you also to my new supervisor, Dr. Rebecca Webster, for stepping in last minute and picking things up so quickly. I really appreciate your support and guidance.

A massive thank you to Amareen, Ammara, and Sophia – I honestly couldn't have done this without you. Thank you for being there through all the stress and for keeping each other going. We really did this together.

To my family – thank you for your unwavering support, love and patience throughout my life and my entire educational journey. A special thanks to my mum, dad, Haleema, Zulaika and Zak for taking the time to learn what a Doctorate in Clinical Psychology even is, just so you could proudly tell everyone! Thank you to Ted for keeping me sane with endless cuddles and my grandma for all your prayers. And especially, thank you to my husband Saaim. Thank you for riding this rollercoaster with me and for never giving up on me. You encouraged me through every doubt, kept me fed, and always found a way to make me smile when I needed it most.

Last but by no means least – Alhamdulillah.

Contents - edit page numbers

Part One: Literature Review

The effects of job crafting on healthcare professional's personal wellbeing: A systematic review of intervention and observational studies

Abstract

Background: Burnout is common in healthcare staff due to their high workloads, emotional demands, and complex work environments. This negatively affects staff wellbeing as well as the quality of patient care and organizational efficiency. Job Crafting (JC) is a proactive strategy where people alter areas of their work so that they align more with their personal strengths and values. JC has shown promise in improving staff wellbeing in various sectors. However there has not yet been a systematic review exploring its impact on healthcare staff wellbeing specifically.

Methods: This systemic review (PROSPERO ID: CRD420251040496) was conducted following the PRISMA 2020 checklist. Studies were identified by searching five databases (PubMed, PsycNet, PsycInfo, Scopus, Web of Science) in April 2025 for any that investigated the effects of JC on healthcare staff personal wellbeing. Studies were checked for eligibility using the inclusion criteria (Experimental or observational studies exploring the effect of JC on personal wellbeing or burnout of healthcare staff written in English) and exclusion criteria developed through the PICOS framework A total of 17 studies were eligible to be included in the review, 14 of which were cross sectional and the others cohort or quasi-experimental. As there was heterogeneity in study designs, outcome measures, a narrative synthesis was conducted. The CASP checklists were used to assess risk of bias of the studies, 53% of which were dual reviewed.

Results: There was a total of 6945 healthcare staff in the 17 studies included, from a range of countries. The majority of the samples were nurses. Personal wellbeing outcomes included psychological wellbeing, burnout, happiness, distress, physical health and life satisfaction. Results showed that JC was associated with improved

wellbeing and reduced burnout and distress. Effect sizes ranged from small to large. There were two interventional studies which had comparator control groups which found JC improved health and reduced exhaustion. One cohort study found there wasn't a significant effect on longitudinal outcomes. There were several limitations, such as studies mostly being cross-sectional, using self-report measures and some risk of bias. Nevertheless, findings were consistent and supported the positive effect of JC.

Conclusion: JC is associated with improved healthcare staff personal wellbeing. It is an approach which can be developed at an individual or organisational level, which makes it flexible and potentially scalable. However, further experimental and longitudinal studies with more diverse groups of healthcare professionals need to be done to confirm causal relationships and identify the longer-term effects. This would also help to identify specific JC strategies which may be more suited to different roles and settings.

Keywords: *Job crafting, intervention, burnout, healthcare professionals, wellbeing, systematic review, narrative review, health.*

Practitioner Points

- JC is consistently associated with higher healthcare staff wellbeing
- JC may improve wellbeing, happiness, mental and physical health.
- JC could be delivered as an intervention or informally encouraged
- JC would be tailored to the context and supported by wider organizational strategies
- Further research should include experimental controlled designs and longitudinal outcomes.

Introduction

Prevalence of Burnout in General Workforce

Burnout—a state of emotional exhaustion, depersonalization, and reduced personal accomplishment—has become increasingly prevalent across various professions. Reed (2023) found that in the UK, 85% of professionals have experienced some sort of burnout symptoms; 47% of employees have taken some time off due to mental health concerns; and younger adults (18 to 34 year olds), have the highest levels of burnout severity, including fatigue and cognitive difficulties. Although awareness of burnout is increasing, stigma around mental health problems continue, which prevent staff from disclosing or asking for help for their mental health (Reed, 2023).

Burnout and Personal Wellbeing Among Healthcare Professionals

Healthcare professional roles are particularly emotionally demanding and high-pressured, which makes them more vulnerable to burnout (Johnson et al., 2017). They often work long shifts, have an emotional role, as well as lots of paperwork, all of which causes high stress levels (Yifan et al., 2023). They also have high caseloads of patients with often distressing situations (Drummond, 2015), further increasing their risk of burnout and negatively affecting their workplace and personal wellbeing. Woo et al. (2020) completed a meta-analysis during the COVID-19 pandemic which found increased burnout in nurses, suggesting a need for effective interventions. Around 11% of nurses and allied health professionals, experience burnout symptoms (Woo et al., 2020; de Hert, 2020). Around 50% of doctors also report being burnt out, and even medical students experience emotional exhaustion – before even starting their

qualified roles (West et al., 2018). In emergency and intensive care settings, the staff have even higher burn out severity (Woo et al., 2020; de Hert, 2020).

Staff burnout has direct implications for work life and patient care, as it is linked to low job satisfaction and engagement, increased medical errors, lower patient satisfaction, and staff turnover (Garcia et al., 2019; Maslach & Leiter, 2016; Shanafelt, 2002; Sinsky et al., 2022). Specifically with mental health professionals, it can reduce how well therapists support people with mental health problems (Morse, 2012). Not only does this add extra financial pressure on healthcare services (Han et al., 2019; Sinsky et al., 2017), but it also has negative personal consequences - it can cause mental health problems, loneliness, substance misuse, difficulties in relationships, and in some cases, suicide (Dyrbye et al., 2008; Shanafelt et al., 2012).

To be able to deliver high quality patient care, healthcare professionals also need to maintain their own personal wellbeing. Personal wellbeing includes emotional, psychological and physical health as well as overall life satisfaction and happiness. However, their highly stressful and emotional roles impact their personal wellbeing. Studies have shown that healthcare professionals have higher levels of stress, exhaustion, and psychological problems, along with reduced levels of happiness and life satisfaction compared to other work roles (Shanafelt et al., 2012; Dyrbye et al., 2008). Due to the chronic stress, healthcare staff can develop worse physical symptoms, such as struggling to sleep, headaches, and weaker immune systems (Garcia et al., 2019; Sinsky et al., 2022). Due to these negative consequence on staff wellbeing, patient wellbeing and NHS resources, tackling these issues is important in healthcare research.

Interventions to Reduce Burnout and Improve Wellbeing

Several intervention strategies have been implemented to combat burnout and improve wellbeing in healthcare staff. There are two main types of interventions used to reduce burnout. One of these is organisational changes, which include improving work conditions or reducing workloads. Organisational changes seem to be effective in improving how accomplished staff feel at work (Busireddy et al., 2017; Panagioti et al., 2017). However, these changes, such as reducing work hours, aren't always feasible, especially in busy settings like the NHS.

There are also individual approaches. These include mindfulness-based stress reduction (MBSR), relaxation and stress management, resilience training, and cognitive-behavioural therapy (CBT) (Irving et al., 2009). Past studies (e.g., Lee et al., 2016; Dreison et al., 2018; Shin et al., 2014) have shown that individual strategies like CBT can reduce emotional exhaustion and depersonalization. Although these interventions might be helpful, studies have usually found small to moderate effects and burnout can be caused by variables such as job demands and stress outside of work (Demerouti et al., 2001). Additionally individual approaches might be limited if the organisation is still the same and this is the factor reducing staff wellbeing.

A review by Maricutoiu et al. (2016) concluded that there isn't a solution which fits everyone, highlighting the need to continue to understand the causes of burnout and continue to investigate the effectiveness of possible interventions and match them to different people's needs and work settings.

Job Crafting: A Proactive Approach

One new promising approach is Job Crafting (JC). JC is a more individualized, proactive alternative, which combines both individual and organisational elements to reduce burnout and enhance wellbeing (Tims & Bakker, 2010). JC can be defined as

the way in which staff modify their tasks, relationships, or cognitive framing of their work so that they better match their personal strengths and values (Wrzesniewski & Dutton, 2001). JC includes three main dimensions: task crafting (tasks they do), relational crafting (how they interact with others), and cognitive crafting (how they think about their job). The aim is that by making changes in these three areas, staff can experience increased engagement and a stronger sense of purpose, which can then reduce burnout and improve personal wellbeing (Tims et al., 2013). This can be encouraged via a JC intervention.

Evidence on Job Crafting's Impact

Previous research conducted in different professional settings/roles, has shown that JC can be helpful for staff wellbeing and work performance (Slemp & Vella-Brodrick, 2015; van Wingerden et al., 2017). Two large trials in the NHS have added to the evidence. The UpLift1 trial (Delgadillo et al., 2025a, manuscript in preparation) involved 465 healthcare staff who took part in either JC or CBT. Both were delivered by trained professionals over six weeks. JC helped reduce burnout and improve wellbeing. The results were similar to CBT immediately after treatment, and many of the benefits lasted six months, though CBT had slightly better outcomes at 6 months follow-up. The UpLift2 trial (Delgadillo et al., 2025b, manuscript in preparation) compared job crafting to a waitlist control group. In this study, 135 psychological therapists received job crafting over six weeks. Those in the JC group reported improvements in burnout, while those on the waitlist reported no change in burnout. When the waitlist group later received the same intervention, they also improved.

A systematic review by Pimenta de Devotto & Wechsler (2019) including eight studies concluded that JC interventions improve wellbeing and work performance.

Additionally, a meta-analysis found that job crafting was strongly associated with proactive personality, promotion regulatory focus, and work engagement (Rudolph et al., 2017). However, these literature reviews as well as others on the effectiveness of JC included different working populations, not specifically healthcare staff. Therefore, the applicability of these findings to healthcare staff's personal wellbeing is limited.

Current Study

Given the prevalence of burnout in healthcare settings and the emerging promise of job crafting interventions, the main objective of this systematic review is to synthesize the available evidence on the effects of job crafting—whether as an intervention or observed behaviour—on personal wellbeing and burnout among healthcare professionals. This will be the first known review to focus specifically on the healthcare staff population.

The secondary aim is to examine how the findings might be used in real life settings. Insights from this review could help to reduce costs and find easier to use strategies for improving healthcare staff wellbeing and burnout. Consequently, this could improve healthcare staff's personal lives, indirectly improving workforce retention and the quality-of-care patients receive.

Method

Study Protocol

This review has been conducted and written in accordance with the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al., 2021). Full details of the PRISMA checklist are provided in Appendix A to ensure transparency. The review protocol was registered prior to

commencing data collection with the International Prospective Register of Systematic Reviews (PROSPERO) (Registration ID: PROSPERO 2025 CRD420251040496).

There were 2 small amendments made to the original protocol before the review was started. Firstly, the focus was narrowed to personal wellbeing outcomes only, not work-related outcomes, to keep it clear and manageable in the time frame. Secondly it was made clear that JC could be measured as a spontaneous employee-initiated behaviour or delivered as an intervention, and only quantitative studies would be included. This was the original aim and the changes were made early so findings were not biased.

No financial support was received for this review and there are no competing interests of review authors.

Eligibility Criteria

As per Eriksen and Frandsen (2018), the Patient, Intervention, Comparison, Outcomes and Study (PICOS) framework was used to check if studies were eligible for inclusion. The criteria under each domain is shown in Table 1.

Table 1

Inclusion and Exclusion Criteria

	Inclusion Criteria	Exclusion Criteria
Patients/ participants	Staff in any healthcare role in any setting	Not healthcare roles
	Aged 18 years or older	Below 18 years old
Intervention	Job Crafting level measured at baseline or delivered as an intervention	Any other interventions
Comparator	May include control conditions such as waitlist groups, care-as-usual, or baseline-only	No job crafting interventions or behaviours as a dependent variable

	assessments, as well as active comparators.	
Outcomes	Outcomes related to personal psychological or physical health/ wellbeing or burnout will be considered.	Studies focused only on outcomes not related to wellbeing, such as performance, work engagement, productivity, or organisational efficiency
Study	Experimental and non-experimental designs	Articles published in non-academic sources such as newspapers, editorials, or other media formats
	Interventional and non-interventional studies that assess job crafting and its relationship with personal wellbeing outcomes	Non-accessible articles
	Studies may assess job crafting at baseline, as an exposure, or deliver it as an intervention	Publications not written in English
		Grey literature, including unpublished reports, theses, or conference abstracts

Search Strategy

Searches were completed on five electronic databases—PubMed, PsycNet, PsycInfo, Scopus and Web of Science—on 27th April 2025, using a range of search terms for healthcare staff roles, job crafting and study design. The complete search syntax is presented in Appendix B, along with how many papers were captured in each block separately from PsycINFO as a representative example. A subsequent search was not undertaken as the initial search was less than a month before the review was written.

Article Selection

Database results were all added to EndNote 21 to keep track of the results. All of the results were combined into one group and any duplicate studies were removed. All titles and abstracts of articles identified were then screened for eligibility by the

primary reviewer. A second reviewer screened 50% of these titles and abstracts to check inter-rater agreement and they agreed on all of the studies. Full texts of the remaining articles were accessed and checked against the eligibility criteria by the primary reviewer. Forward and backward reference searching was conducted by the primary reviewer for all included studies to identify any additional articles missed by the database search. The first reviewer first identified records based on title screening, then abstract screening and then full text screening. Study selection is presented in a PRISMA flow diagram (Moher et al., 2009). Full-text articles identified as potentially eligible were then reviewed further by two reviewers to confirm inclusion, they agreed on all texts included.

Data extraction

The Cochrane Collaboration Data Collection form (Higgins & Green, 2011) was used as a template to create a simple data extraction form tailored to the review objectives and inclusion/exclusion criteria. One reviewer used the standardized form to record the following data: authors, year, study design, sample size, population (healthcare roles), intervention, comparator, wellbeing outcome measures, study setting, effect measures, effect sizes and interpretation. Results of individual studies are visually displayed in a table.

Quality Assessment

Two reviewers independently assessed eligible studies against CASP checklists (CASP, 2022) specifically using the cross-sectional studies form and cohort studies form (Appendices C and D). The CASP checklists do not have specific steps to categorise risk of bias. However, summarising the number of ‘yes’ answers and

sorting into low/medium/high ratings is common practise in systematic reviews when a scoring system is required for narrative comparison. The CASP website (CASP, n.d.) FAQ's state "Classifying quality (or risk of bias) as high, moderate or low, based on the CASP tool would be perfectly acceptable." This modified scoring approach is used to support transparency and consistency in synthesising the quality of study methods. Therefore, the total number of yes or no responses given for each question in the checklists was used as a guide to categorise risk of bias level. In both checklists, the answers given were 'yes', 'partial', 'can't tell' or 'no'. 'Yes' responses were good so the more yes answers meant the lower risk of bias. For a study to be rated as low risk of bias, it had to have mostly yes answers, particularly in key areas such as randomization, blinding and group similarity (few no, partial or can't tell in non-key areas). For medium risk of bias, some partial or can't tell and possibly one no in less critical areas, however major elements still had to be mostly yes. For high risk of bias, studies had multiple no or can't tell responses or a no in any key area.

A second reviewer independently assessed risk of bias for 53% (nine of the 17) of the studies included in the review. A Cohen's kappa (κ) statistic was calculated to check inter-rater reliability. This gave a value of $\kappa = 0.41$ (95% CI [–0.32, 1.14]), $p < .001$, suggesting 'moderate agreement'. This highlights some of the lack of clarity in reporting of studies. Any discrepancies in risk of bias scoring were discussed and resolved.

Data Synthesis

A detailed narrative synthesis was conducted and presented to summarise and explain the results of the included studies. All studies were included. No methods were required to prepare the data as it was ready for synthesis. Findings were sorted and

discussed based on different factors such as the type of study design (experimental vs. non-experimental), whether JC was spontaneous employee-initiated behaviour or delivered as an intervention, and outcome measured (e.g., burnout or general wellbeing). A meta-analysis was not conducted due to the heterogeneity in the designs and outcome measures used in the studies, meaning they were too different to apply meta-analytic methods.

Instead, the narrative synthesis grouped and discussed different factors which might influence how much of an effect JC behaviours have on personal wellbeing. Some of the factors grouped and discussed narratively were which healthcare role someone did, (e.g., nurses, doctors, etc), the type of JC behaviour (e.g. whether it was spontaneous employee-initiated behaviour or an intervention), how a JC was delivered (e.g, online or in-person), the design of the study (experimental or non-experimental), or the outcome measure used (eg. OLBI, MBI, etc). These subgroup discussions may help to look at what might explain differences in study results.

Because this review was based on a narrative synthesis and did not include a meta-analysis, there are no sensitivity analyses and a formal assessment of certainty of evidence was not done (eg. the GRADE tool was not applicable).

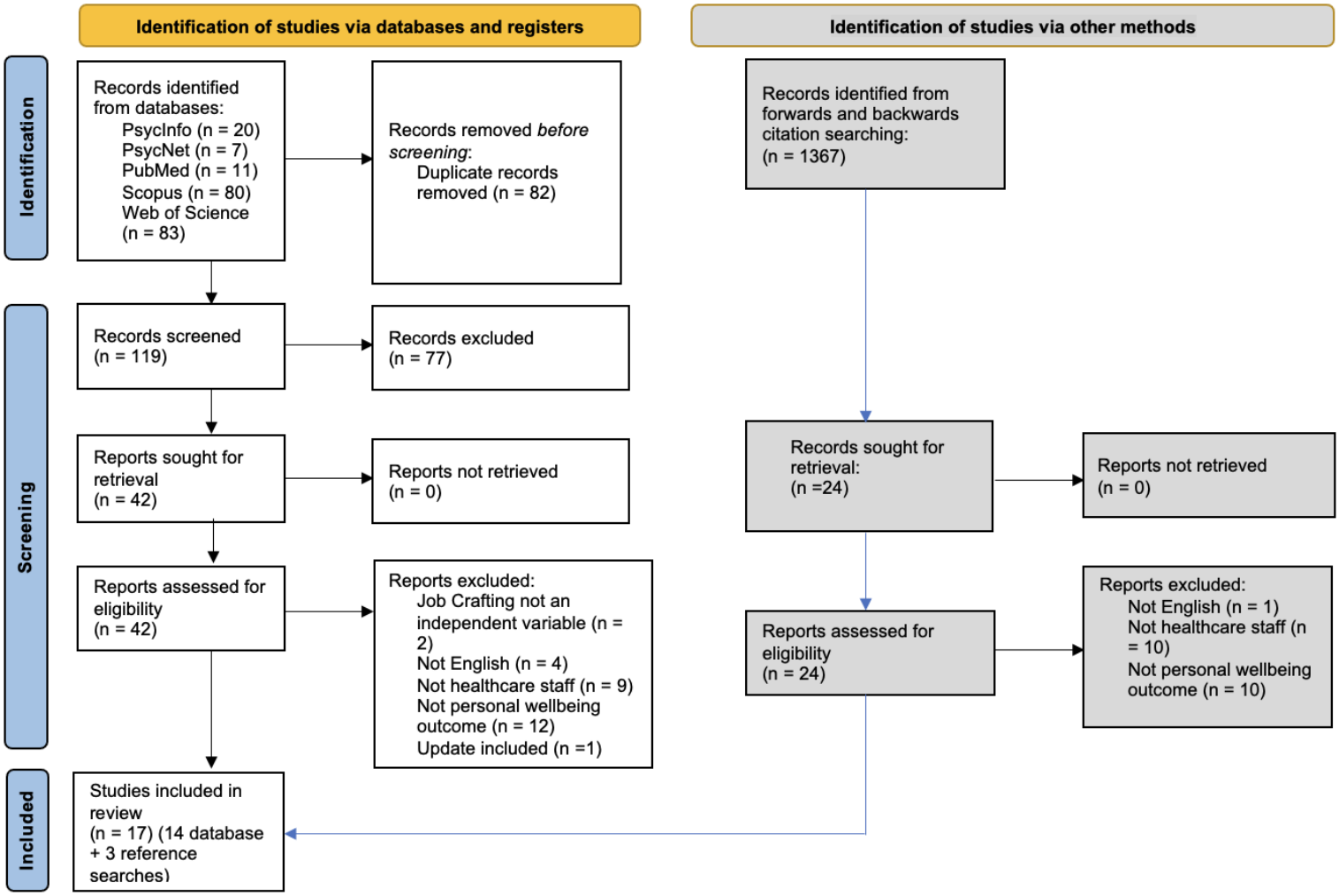
Results

The initial database search gave 201 articles. Titles and abstracts were reviewed against the inclusion and exclusion criteria. Many of the studies were excluded due to not being healthcare staff, not having wellbeing focused outcomes, not having quantitative methodology, or measuring JC as an outcome rather than as an independent variable. 42 full texts were retrieved and assessed for eligibility. They were then excluded if they didn’t meet the inclusion criteria. 28 texts were excluded

for not meeting the inclusion criteria. Reasons for exclusion (appendix E) were JC was not an independent variable, article was not available in English, not healthcare staff participants, not a personal wellbeing focused outcome, and one was excluded due being a duplicate (an updated version of the text was available). This left 14 articles to be included in the review. Forwards and backwards reference searching was conducted to identify further studies from the ones already included. 1367 further articles were found and had their titles, abstracts and full texts screened. This gave three texts to include in the review. These processes identified a total of 17 articles to include in the systematic review. A PRISMA diagram was drawn to summarise the articles selected and reasons for the texts that were excluded (Figure 1).

Figure 1

PRISMA Diagram for Selection of Articles



Study Characteristics

There was a total of seventeen interventional and observational studies in the review. Most of the settings were hospitals (including general and psychiatric), but some studies reported other settings such as residency programmes, nursing homes, and an academic medical centre but one of the studies stated “different settings”. Studies were conducted across a range of countries such as Saudi Arabia, UAE, Columbia, Lebanon, Netherlands, China, South Korea, Egypt, Japan, USA, Spain,

Sweden, India. 14 studies used a cross-sectional design, mostly measuring job crafting as a spontaneous employee-initiated behaviour, rather than delivering it as an intervention. Of the remaining three studies, two of these were quasi-experimental and the other was a prospective cohort design. Self-report questionnaires were used to measure job crafting levels and wellbeing outcomes. Sample sizes varied from 14 to 1235 participants.

Healthcare professional studies were mainly nurses, but some of the studies included residents, medical specialists, occupational therapy professionals, nursing home employees (providing direct care) and healthcare leaders. Genders reported were predominantly female, especially the nurses, however there were also males included. The general range of reported participant ages was around 28 to 51 years old. A total sample size was calculated, summing participants of all 17 studies, which gave 6945 participants.

15 of the studies measured job crafting as spontaneous employee-initiated behaviour, however, two of the papers looked at the effects of job crafting as an intervention (one of these used results from two quasi-experimental studies). The article which included two-quasi experimental studies included control groups in both parts however the other quasi-experimental article didn't have a control group, only a pre/post design. None of the 15 observational studies had comparators. For the independent variable of level of JC, most studies used the Job Crafting Scale (JCS), some using adapted versions specific to their country. There were many different outcome measures for different wellbeing outcomes, including burnout (e.g., MBI, CBI), general wellbeing (e.g., WHO-5, GHQ-12), life satisfaction (e.g., SWLS), psychological distress (e.g., DASS-21, K6), and self-rated health. General or

psychological wellbeing were frequently explored, however some other studies assessed life satisfaction, happiness or perceived health.

Table 2

Study Characteristics

Author(s) and year	Country	Study Design	Sample Size (N)	Age: M (SD), Gender	Population (N)	Study Setting	Intervention Condition (Measure)	Comparator Condition	Wellbeing Outcome (Measure)
Alharthi et al. (2023)	Saudi Arabia	quantitative cross-sectional study	441	Not reported?	Nurses	Hospitals	JC behaviour (JCS)	No comparator group	Happiness (OHQ)
Alkhraishi & Yesiltas (2024)	Abu Dhabi, UAE	Descriptive cross-sectional study.	348	unknown	Nurses	Hospitals	Spontaneous employee-initiated behaviour (JCQ)	No comparator	Psychological capital (PCQ)
Dominguez et al. (2018)	Columbia	cross sectional study	202	unknown	Residents	Residency programs	Spontaneous employee-initiated JC(DJCS)	None	Burnout (MBI-HSS)
Ghazzawi et al. (2021)	Lebanon	Cross sectional study	547	30.65 (7.05), 124 males, 384 females	Nurses	Hospitals	Spontaneous employee-initiated JC (JCS)	None	well-being (SWLS)
Gordon et al. (2018)	Netherlands	2 quasi experimental studies	Study 1: medical specialists: experimental group N = 48, control group N = 71,	Study 1: experimental group age 50.8 (8.1), 58.3% male, control group age 51.3 (7.3), 81.8% male.	119 medical specialists and 58 nurses	“different settings”	Intervention (JCS)	2 Control groups	Health, exhaustion (OLBI, SF-36 Health Survey)

			Study 2: nurses: total N = 58, experimental group N = 32, control group N = 26,	Study 2: experimental group age 41.2 (11.3), 12.5% male, control group age 31.2 (8.8), 7.7% male					
Guo et al. (2024)	China	Cross sectional survey study	1235	Over half were 30–39 years old (N = 734). Women (95.8%).	Nurses	four tertiary hospitals	Spontaneous employee-initiated JC (JCS)	None	Burnout (MBI-GS)
Han (2023)	South Korea	Cross sectional survey study	207	33.5 years, and most (93.2%) were females.	Nurses	2 general hospitals	Spontaneous employee-initiated JC (JCS)	none	Wellbeing (MHC-SF)
Ibrahim et al. (2025)	Egypt	Cross sectional	100	Average age 35.4 years, 70% females	Nurses	Zagazig General Hospital	Spontaneous employee-initiated JC (JCS)	none	Mental and physical health (DASS-21,, SF-36 health survey)
Iida et al. (2024)	Japan	multilevel prospective cohort study	391	most (78.5%) were female.	Nurses	5 hospitals	Spontaneous employee-initiated JC (Japanese JCS)	none	Psychological distress (Japanese K6 questionnaire)
Kato et al. (2023)	Japan	cross-sectional study	309	43.3 years (10.7), 54.7% were female	Nurses	psychiatric hospitals	JC (JCS)	none	Mental health (WHO-5-J)

Lynner et al. (2024)	45 states across the United States	Cross-sectional survey.	400	women (65.8%)	Occupational therapy professionals	Pediatrics, long-term care or skilled nursing facility, home health, and hospital	Spontaneous employee-initiated JC (JCS)	none	Burnout (CBI)
Pan et al. (2021)	China	Cross-sectional survey design	263	28.76 years (SD = 7.04).	Nurses	hospitals	Spontaneous employee-initiated JC (JCS)	none	Life satisfaction (SWLS)
Romeo et al. (2018)	Spain	cross-sectional design	353	44.62 years	Nurses	Residential nursing homes	Spontaneous employee-initiated JC (JCQ)	none	Wellbeing (adapted GHQ-12)
Yepes-Baldó, et al. (2018)	Spain and Sweden	cross-sectional design	530	Age 44.48 (11.77), gender women 462 (87.2)	Nursing home employee	Elderly/Nursing homes	Spontaneous employee-initiated JC (JCQ)	none	Wellbeing (GHQ-12)
Zahoor et al. (2023)	India	Cross sectional	773	unknown	Nurses	hospitals	Spontaneous employee-initiated JC (JCQ)	none	Psychological and subjective wellbeing) mental health continuum, GSE, LOT-R)
Zhang et al. (2024)	Beijing	Cross sectional survey	655	30.22 years (SD = 5.48). female (92.5%)	Nurses	ICU	Spontaneous employee-initiated JC (JCS)	none	Personal perceived health (COPSOQ II-short Chinese version)

Zmijewski et al. (2023)	United States	quasi-experimental design.	14	Half (N=7) female.	Healthcare leaders	Academic medical center	Spontaneous employee-initiated JC (JCS)	No control group	Wellbeing (WBI, PSS)

Note. JCS = Job Crafting Scale; OHQ = Oxford Happiness Questionnaire; JCQ = Job Crafting Questionnaire; PCQ = Psychological Capital Questionnaire; DJCS = Dutch Job Crafting Scale; MBI-HSS = Maslach Burnout Inventory – Human Services Survey; SWLS = Satisfaction With Life Scale; ISTJR = Increasing Structural Job Resources; ICJD = Increasing Challenging Job Demands; ISOJR = Increasing Social Job Resources; OLBI = Oldenburg Burnout Inventory; SF-36 = 36-Item Short Form Survey; MBI-GS = Maslach Burnout Inventory – General Survey; MHC-SF = Mental Health Continuum – Short Form; DASS-21 = Depression Anxiety Stress Scales–21; HLM = Hierarchical Linear Modelling; WHO-5-J = Japanese version of the World Health Organization 5-item Well-Being Index; CBI = Copenhagen Burnout Inventory; RWA = Relative Weights Analysis; LSAT = Life Satisfaction; GHQ-12 = General Health Questionnaire–12; GSE = General Self-Efficacy Scale; LOT-R = Revised Life Orientation Test; SEM = Structural Equation Modelling; COPSOQ = Copenhagen Psychosocial Questionnaire; SWB = Subjective Well-Being; PWB = Psychological Well-Being; WBI = Well-Being Index; PSS = Perceived Stress Scale.

Risk of Bias Assessment

This literature review included 17 studies which looked at the effect of JC on healthcare professionals' wellbeing. Most of the studies (n =14) were cross-sectional measuring JC as spontaneous employee-initiated behaviour. The other three studies were cohort or quasi experimental studies which looked at the effect of JC delivered as an intervention.

Although their study designs were similar, there were some differences in 14 cross sectional studies, such as different sample sizes (from 100 to 1235), different study settings (ranging from ICU departments and hospitals to nursing homes) and they measured different outcomes such as wellbeing, burnout, life satisfaction, happiness, wellbeing and psychological capital.

Of the remaining three cohort and quasi-experimental studies, one of them had control groups (Gordon et al., 2018) in both of the study results analysed. The other two did not have control groups – Zmijewski et al. (2023) had a pre-post study design and Iida et al. (2024) was a multilevel prospective cohort study.

4 out of the 14 cross-sectional studies were rated as low risk of bias (Alkhraishi & Yesiltas, 2024; Dominguez et al., 2018; Ghazzawi et al., 2021; Ibrahim et al., 2025). These studies had robust methods, accurately measured job crafting and wellbeing outcomes and had clear conclusions. Key areas were mostly met, such as focus of study, recruitment, accurate measurement of exposure and outcomes, and appropriate statistical analyses. There were 10 other cross-sectional articles, which were all scored as medium risk - although major elements were mostly met, there were some partial or unclear responses (P or CT) in less critical areas such as clarity if results presentation, transparency of findings, relevance to local population, fit with

existing evidence and implications for practise. None of the cross-sectional studies was deemed to be high risk of bias.

There were three cohort studies. One of them (Gordon et al., 2018) had a few ‘can’t tell’ answers in some key areas so it was rated as high risk of bias. The others (Zmijewski et al., 2023; Iida et al., 2024) also had some insufficient answers for aspects such as confounding variables or follow-up information, so they were scored as medium risk.

Overall, some of the most common problems which contributed to increased risk of bias were unclear recruitment methods, missing follow-up details, using self-report measures, and the absence of power calculations or it wasn’t clear whether interventions were delivered as initially planned. However, most of the articles used validated outcome measures and answered the main aims well. See appendix F for full details of the risk of bias assessments.

Table 3

The results of Job crafting on healthcare professional's wellbeing from included studies

Authors and year	JC assessed?	Outcomes (Measures)	Effect measure	Effect size/stats	Interpretation of Results
Alharthi et al. (2023)	Baseline using JCS	Happiness (OHQ)	Pearson correlation coefficient (r)	r = 0.252, p < .001 (Total JCS)	Small-to-moderate positive correlation; statistically significant
Alkhraishi & Yesiltas (2024)	Baseline using JCQ	Psychological capital (PCQ)	Regression coefficient (β)	TC → PsyCap: β = 0.522, p < .001 CC → PsyCap: β = 0.666, p < .001 RC → PsyCap: β = 0.537, p < .001	All job crafting dimensions positively associated with PsyCap. Effects are moderate to strong.
Dominguez et al. (2018)	Baseline using DJCS	Burnout (MBI-HSS)	Regression coefficient (β)	β = –0.38, p = .04	Moderate, statistically significant negative effect; higher job crafting predicts lower burnout (controlling for other variables)
			Pearson correlation (r))	r = –0.16 (social crafting), r = –0.20 (reducing hindering demands); both p < .05	Small-to-moderate negative associations between specific job crafting dimensions and burnout
Ghazzawi et al. (2021)	Baseline using JCS	Well-being (SWLS)	Standardised regression coefficient (β)	Increasing Structural Job Resources (ISTJR) → Significantly predicted SWB (β, p < .05). Increasing Challenging Job Demands (ICJD) → Significantly predicted SWB (β, p < .05). Increasing Social Job Resources (ISOJR) → Did not significantly predict SWB	Job crafting positively predicts subjective well-being, particularly through structural and challenging job crafting behaviours. Effects are moderate and statistically significant. Social resources do not.
Gordon et al. (2018)	Interventions vs control groups using JCS	Health, exhaustion (OLBI, SF-36 Health Survey)	Repeated measures ANOVA	Study 1: JC reducedexhaustion: F(1,117) = 5.00, p = .03. JC improved health (1,117) = 5.83, p = .02	Job crafting significantly reduced exhaustion in both studies and improved health in Study 1 only. Effects were

				Study 2: JC reduced exhaustion: F(1,56) = 14.33, p < .001 but had no significant effect on health.	statistically significant and small to moderate in size.
Guo et al. (2024)	Baseline using JCS	Burnout (MBI-GS)	Correlation coefficient (r); binary logistic regression; machine learning model importance	Negative correlation with burnout (r, p < .01); job crafting predicted burnout in logistic regression; top predictor in SVM, RF, and GBT models	Job crafting is a consistent and strong predictor of lower burnout across statistical and machine learning analyses.
Han (2023)	Baseline using JCS	Wellbeing (MHC-SF)	Standardised regression coefficient (β)	Task crafting effect on well-being (β = 0.25, p = .001); all JC types effected all well-being areas through work engagement (β = 0.05–0.17, p ≤ .045)	Task crafting directly improves psychological well-being; all JC types indirectly enhance well-being through work engagement
Ibrahim et al. (2025)	Baseline using JCS	Mental and physical health (DASS-21,, SF-36 health survey)	Standardised regression coefficient (β)	JC predicted lower mental distress (β = –0.45, p < .001) and better physical health (β = 0.40, p < .001); indirect effect on mental health via work engagement: β = 0.105, p < .01	JC improves physical health and reduces mental distress, both directly and indirectly via work engagement.
Iida et al. (2024)	Baseline using Japanese JCS	Psychological distress (Japanese K6 questionnaire)	Hierarchical linear modelling (HLM)	No significant association between JC and psychological distress at T2 or T3	JC did not significantly influence changes in psychological distress over time.
Kato et al. (2023)	Baseline using JCS	Mental health (WHO-5-J)	Structural Equation Modelling (SEM)	JC indirectly effected mental health via work engagement (β = 0.07, 95% CI [0.03, 0.12], p < .01)	.JC improved mental health through its effect on work engagement; no direct effect was reported.
Lynner et al. (2024)	Baseline using JCS	Burnout (CBI)	Correlation, ANOVA and RWA	JC negatively correlated with all burnout types (r not reported); ANOVA: burnout M = 2.37–3.81 across roles; RWA: workload (21%), identity strain (11%), role conflict (7%)	Greater job crafting linked to lower burnout. RWA highlighted job demands—not JC—as stronger burnout predictors, but JC varied by role and setting.

Pan et al. (2021)	Baseline using JCS	life satisfaction (SWLS)	Structural path coefficients + Sobel mediation tests	JC → LSAT: Individual JC β = 0.213, p = .014; Collaborative JC β = 0.271, p = .008 (Sobel Z = 2.45 and 2.65)	Both types of JC had significant, positive indirect effects on life satisfaction;
Romeo et al. (2018)	Baseline using JCQ	Wellbeing (adapted GHQ-12)	Simple regression	Cognitive JC: β = .236, R^2 = .056; Task JC: β = .199, R^2 = .040; Relational JC: β = .169, R^2 = .029; all p < .001	All JC dimensions positively predicted well-being. Cognitive JC was the strongest predictor.
Yepes-Baldó, et al. (2018)	Baseline using JCQ	Wellbeing (GHQ-12)	Hierarchical linear regression	Spain: JC → ↑ well-being (significant); Sweden: JC → ↓ well-being at high/low levels (nonlinear); ΔR^2 = small, p < .01	Job crafting positively predicted well-being in Spain, but not in Sweden. Country moderated the JC–well-being relationship. Effect sizes were small.
Zahoor et al. (2023)	Baseline using JCQ	Psychological and subjective wellbeing (Keyes' (2007) mental health continuum, GSE, LOT-R)	Structural equation modeling (SEM)	Task crafting → SWB (β = 0.33); PWB (β = 0.37); Relational crafting → SWB (β = 0.38); PWB (β = 0.35); all p < .05	Task and relational crafting significantly predicted higher subjective and psychological well-being.
Zhang et al. (2024)	Baseline using JCS	Personal perceived health (COPSOQ II-short Chinese version)	Moderated mediation model	JC × Personal Health → Work WB (b = 0.011, 95% CI [0.006, 0.015]); index of moderated mediation: b = -0.007, 95% CI [–0.010, –0.003]	JC significantly moderates the link between perceived health and work well-being, suggesting a buffering role for health outcomes.
Zmijewski et al. (2023)	Baseline using JCS	Wellbeing (WBI, PSS)	Pre-post intervention using Wilcoxon signed-rank tests	46% ↑ structural/social JC (p = .03); 85% ↓ hindrance demands (p = .02); ↑ meaningful work (p = .04); no sig. change in WBI; 30% improved WBI distress score	JC led to limited well-being gains present in some participants.

Primary Aim: Effects of Job Crafting on Healthcare Staff Wellbeing and Burnout

In accordance with the published protocol for this literature review, a narrative synthesis was conducted to summarize the findings. A meta-analysis was not conducted. This was because of differences in the study designs, populations and outcome measures of the articles included.

Overall, it seemed that JC had a positive impact on personal wellbeing outcomes in healthcare professionals. Of the 14 cross-sectional studies included in the review, 13 of these concluded a statistically significant positive associations between JC and wellbeing. Some of the studies reported relationships between JC and specifically psychological or general wellbeing (Zahoor et al., 2023; Han, 2023; Kato et al., 2023). Other studies found significant effects on burnout, with higher JC linked to lower burnout severity (Guo et al., 2024; Dominguez et al., 2018; and Lynner et al., 2024). Pan et al. (2021) and Alharti et al., (2003) found that JC was positively associated with higher happiness and life satisfaction scores. Ibrahim et al. (2025) and Zhang et al. (2024) also found that JC was linked with better physical and perceived health. However, one of the cross-sectional studies by Iida et al. (2024) found there wasn't a significant effect of JC on psychological distress over time, which means that any benefits of JC might not be sustained over longer periods of time.

There were three experimental studies with JC provided as an intervention. There were two quasi-experimental studies in Gordon et al. (2018)'s paper. Both of the studies found that JC significantly reduced exhaustion, and one of the studies found better perceived health. Zmijewski et al. (2023) did a pre-post study which found that JC reduced stress but did not statistically significantly improve overall wellbeing.

There was one longitudinal cohort study by Iida et al. (2024) which concluded that there wasn't a significant effect on psychological distress over time.

The effect sizes of the studies were explored to see if there were any themes in study groups. It seemed that JC had the strongest relationships with psychological wellbeing and mental distress. Zahoor et al. (2023) looked at the effect on subjective and psychological wellbeing and found moderate to strong effect sizes (beta coefficient values from 0.33 to 0.38). Ibrahim et al. (2025) found a moderate effect size on mental health reduction ($\beta = -0.45$) and moderately better physical health ($\beta = 0.40$). The components of JC which had the biggest associations with better outcomes were task and relational crafting behaviours.

Secondary Aim: Implications for Practice and Real-World Settings

Healthcare role and work settings were also explored and differences were found. Most of the study samples were nurses who had the most substantial improvements, compared to other roles. Some of the settings were higher intensity, for example intensive care units in Zhang et al. (2024) or hospital wards in Guo et al. (2024). In these settings, the associations between JC and wellbeing were consistently substantial. However, other less stressful settings such as care homes or academic settings had more variable results.

Also, the country and cultural context of studies appeared to have an impact on the benefits of JC. Yepes-Baldó et al. (2018)'s study found that although JC significantly predicted wellbeing in a sample in Spain, it did not predict wellbeing in the Sweden sample. These results show that it is important to consider contextual and demographic variables when looking at the effectiveness of JC.

It was also found that different aspects of job crafting had different effects on wellbeing. For example, Ghazzawi et al. (2021) found that increasing structural and challenging demands significantly improved wellbeing, however increasing social job resources did not have a significant effect.

Methodological Quality and Certainty of Evidence

No meta-analysis was conducted, therefore a formal assessment of certainty of evidence was not conducted. However, confidence in the overall findings was considered based on consistency, design type and risk of bias. There were different factors which contributed to this, such as the majority of the studies being cross sectional and therefore cause and effect could not be concluded, only correlation. In addition, many studies had a moderate risk of bias and one even had high risk of bias, meaning results should be interpreted with caution. Additionally, the majority of the studies relied on self-report data so response bias could play a role in the scores. Furthermore, the studies investigated different job roles, settings and used different outcome measures, therefore it is not clear how consistently JC affects healthcare staff's wellbeing.

Finally, more positive findings appeared to be in less robust cross-sectional studies and the more robust experimental/longitudinal studies didn't find as favourable findings for JC. Therefore JC might not be as effective at improving wellbeing as the cross-sectional studies suggest therefore there needs to be more randomised controlled trials or experimental or cohort studies to investigate this further.

Despite these limitations, the results were fairly consistent, with most showing that JC is linked to better wellbeing. Because of this consistency, we can be

moderately confident in the overall conclusion, but the findings should still be interpreted with caution.

Discussion

This literature review found that JC is positively associated with the personal wellbeing of healthcare professionals. This fits with existing literature showing that JC is effective for improving wellbeing and reducing burnout in professionals (Slemp & Vella-Brodrick, 2015; Rudolph et al., 2017; van Wingerden et al., 2017). Previous reviews have demonstrated that JC can be helpful in different occupational settings (e.g., Pimenta de Devotto & Wechsler, 2019; Lichtenthaler & Fischbach, 2019) however this is the first one to focus specifically on the effects of JC on personal wellbeing of healthcare professionals. This is important to assess due to the demanding and emotional nature of healthcare roles (Johnson et al., 2017; Drummond, 2015).

This review supports earlier conclusions that JC could be particularly helpful in high-stress settings such as healthcare services, where staff experience high burnout levels and traditional organisational levels are not feasible (eg healthcare services can’t reduce workloads). The positive relationships between JC and wellbeing was consistent across different healthcare staff roles, which was also observed in recent NHS trials (Delgadillo et al., 2025a, 2025b, manuscripts in preparation), where JC significantly improved wellbeing and reduced burnout in a large number of healthcare staff. In these trials, the effects of JC were also comparable to cognitive behavioural therapy (CBT) which shows JC is very beneficial and a cost-effective intervention.

Additionally, this review supports the growing arguments that interventions aimed at reducing burnout should address individual changes as well as contextual

support. Traditional approaches have either worked on individual techniques like CBT pr mindfulness or systematic changes like reducing workloads (Irving et al., 2009; Lee et al., 2016) but these may be more effective delivered in combination. JC offers a solution in the middle ground, where proactive behavioural and cognitive individual changes are encouraged but is also compatible with wider organisational strategies, which is an important aspect in the Job Demands-Resources model (Demerouti et al., 2001).

Previous literature demonstrates that JC may not work equally for all individuals (Maricutoiu et al., 2016) which is supported by this review. There was variation in the strength of associations in the studies included in this review – depending on role, setting, and country. For example, it was found that JC was more beneficial for nurses in intensive care or hospital environments compared to academic settings and there were differences depending on country (e.g., Yepes-Baldó et al., 2018). Therefore, there may be underlying differences in the amount of autonomy different roles have, workplace culture, and work demands, which may shape the way job crafting behaviours are conducted and experienced.

This literature review supports the growing body of evidence which suggests that JC is an important factor for healthcare staff personal wellbeing and burnout, especially due to healthcare staff persistent stressors like understaffing, high patient numbers, and emotionally taxing work. This review also reflects the results of the Uplift trials in which JC reduced healthcare professional burnout and improved wellbeing (Delgadillo et al., 2025a, 2025b, manuscripts in preparation). In conclusion the results of this narrative synthesis suggest JC could be a practical, cost-effective intervention

which helps healthcare staff to gain some control and find some meaning in their tasks as well as buffer against the harmful effects of burnout.

Strengths and Limitations

This review has strengths and limitations at the study level. One of the strengths was the fact that it included studies from different countries, settings and staff roles. This gives a broad understanding of the effect of JC across different countries and healthcare contexts. Additionally, most outcome measures used were well validated, which increases the belief in the findings.

Nevertheless, the studies also have several limitations. Most of them were cross-sectional which means causality cannot be established. Additionally, outcome measures were self-report measures, so social desirability could have affected the scores. Additionally, some of the studies used convenience sampling which means other samples weren't represented and therefore results cannot be generalized. Also, some other staff members may have been underrepresented, such as male nurses or people on sick or maternity leave or those too stressed to engage in the study.

Some of the studies reported difficulties with having small sample sizes, high dropout rates or not having much control over other variables which may have affected the results (such as organisational support, workload or leadership style). Gordon et al. (2028) conducted interventional studies however groups were not randomly assigned and staff members worked in the same setting so there may have been contamination between experimental and control groups. Some of the studies also mentioned the need for more studies to investigate follow up effects, to check if improvements were maintained longitudinally.

This review itself also had strengths and limitations. One of the strengths of this review was the search of five well known databases to gather as many relevant studies as possible. The protocol was written and published to PROSPERO before the review was written, which gave clear explanation of what was planned and reduced the risk of bias in study analysis. Also, a second reviewer independently checked a high proportion of the risk of bias ratings (53% of included studies), which increases inter-rater reliability. Another strength was that the review included studies from different countries and settings, which gives an international understanding of JC effects. Although JC interventions weren't exactly the same, they did follow core JC theory and explored similar wellbeing outcomes so they could be compared.

However, there were also some limitations of the review. The search terms used were broad and sometimes vague, meaning the studies captured may have been inconsistent and this may have also meant lower inter-rater reliability during screening. Future reviews could improve this by both raters developing clearer key constructs together before study selection and rating. A further limitation is the inclusion criteria only included papers published in English and peer-reviewed journal articles. This meant that studies in other languages or grey literature was not included. Studies with non-significant results are less likely to be published, therefore there is a risk of publication bias as these studies have not been included. In addition, quantitative analyses were not conducted as a meta-analysis was not done due to differences in designs, populations, outcome measures and effect size measurements', therefore effect sizes could not be quantified. Additionally, although a second reviewer checked a large proportion of the risk of bias assessments, they did not double check of the full texts which were screened against the inclusion criteria so inclusion of studies may

not be consistent. Lastly, this review reports a narrative synthesis which could be biased as there is no statistical synthesis.

Clinical and research implications

The findings of this review show that JC has a positive effect on healthcare staff personal wellbeing, including their happiness, psychological capital, burnout, psychological and subjective wellbeing, exhaustion, mental and physical health, psychological distress and life satisfaction. The results of this review can be implemented practically to improve healthcare staff wellbeing while they complete high-demand roles. In clinical practice, JC principles could be incorporated into staff and leadership training. These JC strategies could improve staff wellbeing and therefore their morale and attention, which could reduce costs for health services. JC doesn't even need to be delivered as an intervention as spontaneous employee-initiated JC behaviours had the same positive association with wellbeing. Therefore, JC approaches could even be encouraged informally, such as encouraging autonomy, flexibility and reflection on work tasks. However, some JC aspects seemed to be more feasible and effective than others in certain settings and certain roles (Lynner et al., 2024). For example, one aspect of JC is relational crafting. Healthcare leaders more commonly did this as they had the power to influence workplace interactions. Whereas occupational therapists engaged more in task crafting, as they could modify their patient care. Also staff working in academic or administrative settings didn't have as much access to tools or training meaning they couldn't increase structural resources as much compared to those work in clinical environments. Therefore, it may be better to tailor JC interventions to specific roles or settings.

JC might also work well with the way healthcare organisations are already trying to improve wellbeing by encouraging staff to shape their own work experiences, increasing resilience and engagement at work. However, it is important to note that JC should not be an alternative to addressing broader problems like understaffing and high workloads. To improve wellbeing the most, individuals should be encouraged to increase their JC skills at the same time as their organizational context is promoting wellbeing more broadly.

Regarding the evidence base on JC and wellbeing in healthcare staff, the literature is growing however there are still some gaps. Most of the studies found were cross sectional designs so cause and effect directional relationships could not be established. There needs to be more research using experimental and longitudinal designs to be able to establish causality and look at long term effects of JC over time.

Also the majority of the studies used nurses as participants. Future studies need to include more diverse roles. It should also consider other factors which might play a role in the effects of JC, such as organisational culture or leadership style. More robust designs, such as randomized controlled trials should be used with longer follow up periods. Finally, it would be helpful to explore which dimensions of JC specifically, e.g. task crafting, cognitive crafting or relational aspects, help improve different aspects of wellbeing. This could help with making JC interventions more effective and efficient.

Conclusion

This systematic review included interventional and observational studies to explore the effects of JC behaviours on healthcare staff's personal wellbeing. Some of the JC behaviours were self-initiated while others were guided by an intervention.

Whichever way they were gained, JC behaviours were positively associated with personal wellbeing outcomes. These results support the use of JC as a strategy for improving healthcare staff personal wellbeing.

However, the majority of includes studies used a cross-sectional design and used self-report outcome measures, which limits the strength of conclusions. Despite this, the positive effect of JC was consistent, suggesting that JC is a promising predictor of staff wellbeing in demanding healthcare roles. Healthcare organizations and policies should consider ways to support JC to improve staff wellbeing, while future studies should focus on experimental designs with long follow up periods to be able to establish the causal pathway and check if wellbeing improvements are maintained over time.

References

Alharthi, N., Elseesy, N., & Aljohani, W. (2023). The relationship between job crafting and nurses' happiness in Bisha Region, Kingdom of Saudi Arabia. *Cureus Journal of Medical Science, 15*(3), e35697. https://doi.org/10.7759/cureus.35697

Alkhraishi, M. Y., & Yesiltas, M. (2024). The impact of job crafting dimensions on work engagement among nurses: The mediating role of psychological capital. *Asia Pacific Journal of Health Management, 19*(2), Article 3313. https://doi.org/10.24083/apjhm.v19i2.3313

Busireddy, K. R., Miller, J. A., Ellison, K., Ren, V. J., Qayyum, R., & Panda, M. (2017). Efficacy of interventions to reduce resident physician burnout: A systematic review. *Journal of Graduate Medical Education, 9*(3), 294–301. https://doi.org/10.4300/JGME-D-16-00372.1

Critical Appraisal Skills Programme (CASP). (n.d.). *FAQs*. https://casp-uk.net/faqs/

de Hert, S. (2020). Burnout in healthcare workers: Prevalence, impact and preventative strategies. *Local and Regional Anesthesia, 13*, 171–183. https://doi.org/10.2147/LRA.S240564

Delgadillo, J., et al. (2025a). The UpLift1 Trial: Comparing job crafting and CBT for reducing burnout among NHS staff. [*Manuscript in preparation]*.

Delgadillo, J., et al. (2025b). The UpLift2 Trial: Evaluating job crafting vs. waitlist in NHS therapists. [*Manuscript in preparation]*.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499

Dominguez, L. C., Stassen, L., de Grave, W., Sanabria, A., Alfonso, E., & Dolmans, D. (2019). Taking control: Is job crafting related to the intention to leave surgical training? *PLoS ONE, 13*(6), e0197276. https://doi.org/10.1371/journal.pone.0197276

Dreison, K. C., Luther, L., Bonfils, K. A., Sliter, M. T., McGrew, J. H., & Salyers, M. P. (2018). Job burnout in mental health providers: A meta-analysis of 35 years of intervention research. *Journal of Occupational Health Psychology, 23*(1), 18–30. https://doi.org/10.1037/ocp0000047

Drummond, D. (2015). Physician burnout: Its origin, symptoms, and five main causes. *Family Practice Management, 22*(5), 42–47.

Dyrbye, L. N., Thomas, M. R., & Shanafelt, T. D. (2008). Systematic review of depression, anxiety, and other indicators of psychological distress among U.S. and Canadian medical students. *Academic Medicine, 83*(4), 354–373. https://doi.org/10.1097/ACM.0b013e3181662c2e

Dyrbye, L. N., Thomas, M. R., & Shanafelt, T. D. (2008). Systematic review of depression, anxiety, and other indicators of psychological distress among US and Canadian medical students. *Academic Medicine, 83*(4), 354–373.

Eriksen, M. B., & Frandsen, T. F. (2018). The impact of patient, intervention, comparison, outcome (PICO) as a search strategy tool on literature search quality: a systematic

review. *Journal of the Medical Library Association, 106*(4), 420–431. https://doi.org/10.5195/jmla.2018.345

Garcia, C. L., Abreu, L. C., Ramos, J. L. S., Castro, C. F. D., Smiderle, F. R. N., Santos, J. A. D., & Bezerra, I. M. P. (2019). Influence of burnout on patient safety: Systematic review and meta-analysis. *Medicina, 55*(9), 553. https://doi.org/10.3390/medicina55090553

Garcia, C. L., Abreu, L. C., Ramos, J. L. S., Castro, C. F. D., Smiderle, F. R. N., Santos, J. A. D., & Bezerra, I. M. P. (2019). Influence of burnout on patient safety: Systematic review and meta-analysis. *Medicina, 55*(9), 553. https://doi.org/10.3390/medicina55090553

Ghazzawi, R., Bender, M., Daouk-Oyry, L., van de Vijver, F. J. R., & Chasiotis, A. (2021). Job crafting mediates the relation between creativity, personality, job autonomy and well-being in Lebanese nurses. *Journal of Nursing Management, 29*(7), 2163–2174. https://doi.org/10.1111/jonm.13357

Gordon, H. J., Demerouti, E., Le Blanc, P. M., Bakker, A. B., Bipp, T., & Verhagen, M. A. M. T. (2018). Individual job redesign: Job crafting interventions in healthcare. *Journal of Vocational Behavior, 104*, 98–114. https://doi.org/10.1016/j.jvb.2017.07.002

Guo, Y. F., Wang, S. J., Plummer, V., Du, Y., Song, T. P., & Wang, N. (2024). Effects of job crafting and leisure crafting on nurses' burnout: A machine learning-based prediction analysis. *Journal of Nursing Management,* 2024, Article 9428519. https://doi.org/10.1155/2024/9428519

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews, 18*(2), e1230. https://doi.org/10.1002/cl2.1230

Han, S. (2023). Nurses' job crafting, work engagement, and well-being: A path analysis. *BMC Nursing*, *22*(1), Article 1573. https://doi.org/10.1186/s12912-023-01573-6

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., Trockel, M., & Goh, J. (2019). Estimating the attributable cost of physician burnout in the United States. *Annals of Internal Medicine, 170*(11), 784–790. https://doi.org/10.7326/M18-1422

Higgins, J. P., & Green, S. (2011). *Cochrane Handbook for Systematic Reviews of Interventions (vol. 4*). John Wiley and Sons.

Ibrahim, A. M., Zaghamir, D. E. F., Elsehrawy, M. G., Abdel-Aziz, H. R., Elgazzar, S. E., Hassabelnaby, F. G. E., et al. (2025). Impact of job crafting and work engagement on the mental and physical health of palliative care nurses. *BMC Nursing*, *24*(1), Article 3058. https://doi.org/10.1186/s12912-025-03058-0

Iida, M., Sakuraya, A., Watanabe, K., Imamura, K., Sawada, U., Akiyama, H., et al. (2024). The association between team job crafting and work engagement among nurses: A prospective cohort study. *BMC Psychology, 12*(1), Article 1538. https://doi.org/10.1186/s40359-024-01538-7

Irving, J. A., Dobkin, P. L., & Park, J. (2009). Cultivating mindfulness in health care professionals: A review of empirical studies of mindfulness-based stress reduction

(MBSR). *Complementary Therapies in Clinical Practice, 15*(2), 61–66. https://doi.org/10.1016/j.ctcp.2009.01.002

Johnson, J., Louch, G., Dunning, A., Johnson, O., Grange, A., Reynolds, C., ... & Hall, L. H. (2017). Burnout mediates the association between symptoms of depression and patient safety perceptions: A cross-sectional study in hospital nurses. *Journal of Advanced Nursing, 73*(7), 1667–1680. https://doi.org/10.1111/jan.13251

Kato, Y., Chiba, R., Shimazu, A., Hayashi, Y., & Sakamoto, T. (2023). Antecedents and outcomes of work engagement among psychiatric nurses in Japan. *Healthcare, 11*(3), 295. https://doi.org/10.3390/healthcare11030295

Lee, R. T., & Ashforth, B. E. (2016). A meta-analytic examination of the correlates of the three dimensions of job burnout. *Journal of Applied Psychology, 81*(2), 123–133. https://doi.org/10.1037/0021-9010.81.2.123

Lichtenthaler, P. W., & Fischbach, A. (2019). A meta-analysis on promotion- and prevention-focused job crafting. *European Journal of Work and Organizational Psychology, 28*(1), 30–50. https://doi.org/10.1080/1359432X.2018.1527767

Lynner, B., Stoa, R., Fisher, G., del Pozo, E., & Lizerbram, R. (2025). Feel the burn, heal the burn: Job crafting and burnout among occupational therapy professionals. *American Journal of Occupational Therapy, 79(*1), 050731. https://doi.org/10.5014/ajot.2025.050731

Maricutoiu, L. P., Sava, F. A., & Butta, O. (2016). The effectiveness of controlled interventions on employees' burnout: A meta-analysis. *Journal of Occupational and Organizational Psychology, 89*(1), 1–27. https://doi.org/10.1111/joop.12099

Maslach, C., & Leiter, M. P. (2016). Understanding the burnout experience: Recent research and its implications for psychiatry. *World Psychiatry, 15*(2), 103–111. https://doi.org/10.1002/wps.20311

Millar, R. (2019). Staff care: How the NHS treats its people. *The Health Foundation*. https://www.health.org.uk/publications/staff-care

Morse, G., Salyers, M. P., Rollins, A. L., Monroe-DeVita, M., & Pfahler, C. (2012). Burnout in mental health services: A review of the problem and its remediation. *Administration and Policy in Mental Health and Mental Health Services Research, 39*(5), 341–352. https://doi.org/10.1007/s10488-011-0352-1

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pan, J., Chiu, C. Y., & Wu, K. S. (2021). Leader–member exchange fosters nurses' job and life satisfaction: The mediating effect of job crafting. *PLoS ONE, 16*(4), e0250789. https://doi.org/10.1371/journal.pone.0250789

Panagioti, M., Panagopoulou, E., Bower, P., Lewith, G., Kontopantelis, E., Chew-Graham, C., ... & Esmail, A. (2017). Controlled interventions to reduce burnout in physicians: A systematic review and meta-analysis. *JAMA Internal Medicine, 177*(2), 195–205. https://doi.org/10.1001/jamainternmed.2016.7674

Pimenta de Devotto, R., & Wechsler, S. M. (2019). Job crafting interventions: Systematic review. *Temas em Psicologia, 27*(2), 371–383. https://doi.org/10.9788/TP2019.2-06

Reed. (2023). 85% of UK workforce experiencing burnout. *The Times*. Retrieved from https://www.thetimes.co.uk/article/85-percent-workforce-burnout-mental-health-reed-pvcqwt3l3

Robertson, R., Wenzel, L., Thompson, J., & Charles, A. (2017). Understanding NHS financial pressures. *The King's Fund*. https://www.kingsfund.org.uk/publications/understanding-nhs-financial-pressures

Romeo, M., Yepes-Baldó, M., Piñeiro, M. Á., Westerberg, K., & Nordin, M. (2019). Job crafting and well-being in the elderly care sector: The effect of over-commitment. *Employee Relations: The International Journal, 41*(3), 405–419. https://doi.org/10.1108/ER-04-2018-0117

Rudolph, C. W., Katz, I. M., Lavigne, K. N., & Zacher, H. (2017). Job crafting: A meta-analysis of relationships with individual differences, job characteristics, and work outcomes. *Journal of Vocational Behavior, 102*, 112–138. https://doi.org/10.1016/j.jvb.2017.05.008

Shanafelt, T. D. (2002). Burnout and self-reported patient care in an internal medicine residency program. *Annals of Internal Medicine, 136*(5), 358–367. https://doi.org/10.7326/0003-4819-136-5-200203050-00008

Shanafelt, T. D., Balch, C. M., Bechamps, G., Russell, T., Dyrbye, L., Satele, D., ... & Freischlag, J. (2012). Burnout and career satisfaction among American surgeons. *Annals of Surgery, 250*(3), 463–471. https://doi.org/10.1097/SLA.0b013e3181ac4dfd

Shanafelt, T. D., Balch, C. M., Bechamps, G., Russell, T., Dyrbye, L., Satele, D., Collicott, P., Novotny, P. J., Sloan, J., & Freischlag, J. (2012). Burnout and career satisfaction

among American surgeons. *Annals of Surgery, 250*(3), 463–471. https://doi.org/10.1097/SLA.0b013e318185a4d0

Sinsky, C. A., Brown, R. L., Stillman, M. J., & Linzer, M. (2022). COVID-related stress and work intentions in a sample of US health care workers. *Mayo Clinic Proceedings: Innovations, Quality & Outcomes, 6*(3), 272–279. https://doi.org/10.1016/j.mayocpiqo.2022.03.002

Sinsky, C. A., Brown, R. L., Stillman, M. J., & Linzer, M. (2022). COVID-related stress and work intentions in a sample of US health care workers. *Mayo Clinic Proceedings: Innovations, Quality & Outcomes, 6*(3), 272–279. https://doi.org/10.1016/j.mayocpiqo.2021.08.007

Sinsky, C. A., Dyrbye, L. N., West, C. P., Satele, D., Tutty, M., & Shanafelt, T. D. (2017). Professional satisfaction and the career plans of US physicians. *Mayo Clinic Proceedings, 92*(11), 1625–1635. https://doi.org/10.1016/j.mayocp.2017.08.017

Slemp, G. R., Kern, M. L., & Vella-Brodrick, D. A. (2015). Workplace well-being: The role of job crafting and autonomy support. *Psychology of Well-Being, 5*(1), 7. https://doi.org/10.1186/s13612-015-0034-y

Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *South African Journal of Industrial Psychology, 36*(2), 1–9. https://doi.org/10.4102/sajip.v36i2.841

Tims, M., Bakker, A. B., & Derks, D. (2013). The impact of job crafting on job demands, job resources, and well-being. *Journal of Occupational Health Psychology, 18*(2), 230–240. https://doi.org/10.1037/a0032141

van Wingerden, J., Derks, D., & Bakker, A. B. (2017). Fostering employee well-being via a job crafting intervention. *Journal of Vocational Behavior, 100*, 164–174. https://doi.org/10.1016/j.jvb.2017.03.008

West, C. P., Dyrbye, L. N., & Shanafelt, T. D. (2018). Physician burnout: Contributors, consequences and solutions. *Journal of Internal Medicine, 283*(6), 516–529. https://doi.org/10.1111/joim.12752

Woo, T., Ho, R., Tang, A., & Tam, W. (2020). Global prevalence of burnout symptoms among nurses: A systematic review and meta-analysis. *Journal of Psychiatric Research, 123*, 9–20. https://doi.org/10.1016/j.jpsychires.2019.12.015

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review, 26*(2), 179–201. https://doi.org/10.5465/amr.2001.4378011

Yepes-Baldó, M., Romeo, M., Westerberg, K., & Nordin, M. (2018). Job crafting, employee well-being, and quality of care. *Western Journal of Nursing Research, 40*(1), 52–66. https://doi.org/10.1177/0193945916680614

Yifan, W., Rojik, L., & Owusu, E. (2023). Burnout among nurses during the COVID-19 pandemic: A systematic review and meta-analysis. *arXiv preprint*. https://arxiv.org/abs/2312.14853

Zahoor, A., Khan, D., & Fazili, S. (2023). Cultivating well-being of nurses through job crafting: The moderating effect of job and personal resources. *Journal of Health Management.* Advance online publication. https://doi.org/10.1177/09720634231216024

Zhang, X., Zhang, C., Gou, J., & Lee, S. Y. (2024). The influence of psychosocial work environment, personal perceived health and job crafting on nurses' well-being: A cross-sectional survey study. *BMC Nursing, 23*(1), Article 2041. https://doi.org/10.1186/s12912-024-02041-5

Zmijewski, P., Lindeman, B., & Rogers, D. A. (2023). The impact of a job crafting intervention on wellbeing in health care leaders. *The American Surgeon, 89*(12), 5655–5659. https://doi.org/10.1177/00031348231167392

Appendices

Appendix A

PRISMA 2020 Checklist

PRISMA 2020 Main Checklist

Topic	No.	Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Abstract, page 4
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist	
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Introduction, page 10
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Introduction, page 10
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Method, page 11-12

Topic	No.	Item	Location where item is reported
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Method, page 12
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Appendix B
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Method, page 12-13
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Method, page 13

Topic	No.	Item	Location where item is reported
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Method, page 13
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Method page 13,
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Method, page 13-14
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Results, page 25-27
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item 5)).	Method, page 14-15

Topic	No.	Item	Location where item is reported
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Method, page 14
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Method, page 13
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Method, page 14-15
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Method, page 15
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Method, page 15
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Method, page 13-14
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Method, page 15

Topic	No.	Item	Location where item is reported
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Results, page 15-17
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Results page 16 & Appendix E
Study characteristics	17	Cite each included study and present its characteristics.	Results, page 19-22
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Results, page 23-24
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Results, page 25-27
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Results, page 28-29

Topic	No.	Item	Location where item is reported
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Results, page 28-29
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Results, page 30
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Results, page 31-31
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Results, page 31
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Results, page 31-32
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Discussion, page 32-34
	23b	Discuss any limitations of the evidence included in the review.	Discussion, page 34

Topic	No.	Item	Location where item is reported
	23c	Discuss any limitations of the review processes used.	Discussion, page 35
	23d	Discuss implications of the results for practice, policy, and future research.	Discussion, page 36-37
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Method, page 11
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Method, page 11
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Method, page 11
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Method, page 11
Competing interests	26	Declare any competing interests of review authors.	Method, page 11

Topic	No.	Item	Location where item is reported
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	N/A

PRIMSA Abstract Checklist

Topic	No.	Item	Reported?
TITLE			
Title	1	Identify the report as a systematic review.	Yes
BACKGROUND			
Objectives	2	Provide an explicit statement of the main objective(s) or question(s) the review addresses.	Yes
METHODS			
Eligibility criteria	3	Specify the inclusion and exclusion criteria for the review.	Yes
Information sources	4	Specify the information sources (e.g. databases, registers) used to identify studies and the date when each was last searched.	Yes
Risk of bias	5	Specify the methods used to assess risk of bias in the included studies.	Yes

Topic	No.	Item	Reported?
Synthesis of results	6	Specify the methods used to present and synthesize results.	Yes
RESULTS			
Included studies	7	Give the total number of included studies and participants and summarise relevant characteristics of studies.	Yes
Synthesis of results	8	Present results for main outcomes, preferably indicating the number of included studies and participants for each. If meta-analysis was done, report the summary estimate and confidence/credible interval. If comparing groups, indicate the direction of the effect (i.e. which group is favoured).	Yes
DISCUSSION			
Limitations of evidence	9	Provide a brief summary of the limitations of the evidence included in the review (e.g. study risk of bias, inconsistency and imprecision).	Yes
Interpretation	10	Provide a general interpretation of the results and important implications.	Yes
OTHER			
Funding	11	Specify the primary source of funding for the review.	No
Registration	12	Provide the register name and registration number.	Yes

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. MetaArXiv. 2020, September 14. DOI: 10.31222/osf.io/v7gm2. For more information, visit: www.prisma-statement.org

Appendix B

Search Strategy

PUBMED

(("job crafting" OR "work role redesign" OR "task redefinition" OR "proactive work behavior" OR "employee-initiated change")

AND

(nurs OR doctor* OR psycholog* OR "healthcare staff" OR "healthcare professional*" OR "NHS staff" OR therapist* OR clinician* OR "allied health" OR "mental health therapist*" OR "advanced clinical practitioner*" OR "medical associate professional*" OR "nursing associate*" OR "speech and language therapist*" OR "occupational therapist*" OR anesthetist* OR anaesthetist* OR "general practitioner*" OR surgeon* OR consultant* OR cardiologist* OR oncologist* OR dermatologist* OR neurologist* OR "respiratory therapist*" OR "emergency medical technician*" OR "social worker*" OR "physician assistant*" OR "care worker*" OR "health visitor*" OR "clinical psychologist*" OR psychiatrist* OR "community nurse*" OR "home care worker*" OR "rehabilitation specialist*" OR "clinical nurse specialist*" OR "public health professional*" OR "medical laboratory scientist*" OR "biomedical scientist*" OR "genetic counselor*" OR counsellor* OR "forensic nurse*" OR "critical care nurse*" OR "perioperative nurse*" OR "intensive care nurse*" OR "palliative care specialist*" OR podiatrist* OR radiographer* OR dentist* OR pharmacist* OR prosthetist* OR orthotist* OR dietician* OR osteopath* OR physiotherapist*)*

AND

("randomized controlled trial" OR RCT OR "clinical trial" OR "controlled trial" OR "control group" OR "intervention study" OR "observational study" OR "non-experimental" OR "quasi-experimental" OR "before and after study" OR "comparative study" OR "cohort study" OR "cross-sectional study" OR "survey study" OR "pilot study" OR "feasibility study"))

PSYCINFO (VIA OVID)

"job crafting" OR "work role redesign" OR "task redefinition" OR "proactive work behavior" OR "employee-initiated change"

AND

nurs* OR doctor* OR psycholog* OR "healthcare staff" OR "healthcare professional*" OR "NHS staff" OR therapist* OR clinician* OR "allied health" OR "mental health therapist*" OR "advanced clinical practitioner*" OR "medical associate professional*" OR "nursing associate*" OR "speech and language therapist*" OR "occupational therapist*" OR anesthetist* OR anaesthetist* OR "general practitioner*" OR surgeon*

OR consultant* OR cardiologist* OR oncologist* OR dermatologist* OR neurologist* OR "respiratory therapist*" OR "emergency medical technician*" OR "social worker*" OR "physician assistant*" OR "care worker*" OR "health visitor*" OR "clinical psychologist*" OR psychiatrist* OR "community nurse*" OR "home care worker*" OR "rehabilitation specialist*" OR "clinical nurse specialist*" OR "public health professional*" OR "medical laboratory scientist*" OR "biomedical scientist*" OR "genetic counselor*" OR counsellor* OR "forensic nurse*" OR "critical care nurse*" OR "perioperative nurse*" OR "intensive care nurse*" OR "palliative care specialist*" OR podiatrist* OR radiographer* OR dentist* OR pharmacist* OR prosthetist* OR orthotist* OR dietician* OR osteopath* OR physiotherapist*

AND

"randomized controlled trial" OR RCT OR "clinical trial" OR "controlled trial" OR "control group" OR "intervention study" OR "observational study" OR "non-experimental" OR "quasi-experimental" OR "before and after study" OR "comparative study" OR "cohort study" OR "cross-sectional study" OR "survey study" OR "pilot study" OR "feasibility study"

Search block	Example search terms	Records captured (PsycINFO)
Block 1 – Job crafting	“job crafting” OR “task crafting” OR “cognitive crafting” OR ….	888
Block 2 – Healthcare staff	“nurse*” OR “doctor*” OR “healthcare professional*” OR ….	1471851
Block 3 – Study design	“randomized controlled trial” OR RCT OR “cross-sectional study” OR “cohort study” OR …	298064

PSYCNET

("job crafting" OR "work role redesign" OR "task redefinition" OR "proactive work behavior" OR "employee-initiated change")

AND

("nurse" OR "doctor" OR "psychologist" OR "healthcare staff" OR "healthcare professional" OR "NHS staff" OR "therapist" OR "clinician" OR "allied health" OR

"mental health therapist" OR "advanced clinical practitioner" OR "medical associate professional" OR "nursing associate" OR "speech and language therapist" OR "occupational therapist" OR "anesthetist" OR "anaesthetist" OR "general practitioner" OR "surgeon" OR "consultant" OR "cardiologist" OR "oncologist" OR "dermatologist" OR "neurologist" OR "respiratory therapist" OR "emergency medical technician" OR "social worker" OR "physician assistant" OR "care worker" OR "health visitor" OR "clinical psychologist" OR "psychiatrist" OR "community nurse" OR "home care worker" OR "rehabilitation specialist" OR "clinical nurse specialist" OR "public health professional" OR "medical laboratory scientist" OR "biomedical scientist" OR "genetic counselor" OR "counsellor" OR "forensic nurse" OR "critical care nurse" OR "perioperative nurse" OR "intensive care nurse" OR "palliative care specialist" OR "podiatrist" OR "radiographer" OR "dentist" OR "pharmacist" OR "prosthetist" OR "orthotist" OR "dietician" OR "osteopath" OR "physiotherapist")

AND

("randomized controlled trial" OR "RCT" OR "clinical trial" OR "controlled trial" OR "control group" OR "intervention study" OR "observational study" OR "non-experimental" OR "quasi-experimental" OR "before and after study" OR "comparative study" OR "cohort study" OR "cross-sectional study" OR "survey study" OR "pilot study" OR "feasibility study")

SCOPUS

(("job crafting" OR "work role redesign" OR "task redefinition" OR "proactive work behavior" OR "employee-initiated change")

AND

(nurs* OR doctor* OR psycholog* OR "healthcare staff" OR "healthcare professional*" OR "NHS staff" OR therapist* OR clinician* OR "allied health" OR "mental health therapist*" OR "advanced clinical practitioner*" OR "medical associate professional*" OR "nursing associate*" OR "speech and language therapist*" OR "occupational therapist*" OR anesthetist* OR anaesthetist* OR "general practitioner*" OR surgeon* OR consultant* OR cardiologist* OR oncologist* OR dermatologist* OR neurologist* OR "respiratory therapist*" OR "emergency medical technician*" OR "social worker*" OR "physician assistant*" OR "care worker*" OR "health visitor*" OR "clinical psychologist*" OR psychiatrist* OR "community nurse*" OR "home care worker*" OR "rehabilitation specialist*" OR "clinical nurse specialist*" OR "public health professional*" OR "medical laboratory scientist*" OR "biomedical scientist*" OR "genetic counselor*" OR counsellor* OR "forensic nurse*" OR "critical care nurse*" OR "perioperative nurse*" OR "intensive care nurse*" OR "palliative care specialist*" OR podiatrist* OR radiographer* OR dentist* OR pharmacist* OR prosthetist* OR orthotist* OR dietician* OR osteopath* OR physiotherapist*)

AND

("randomized controlled trial" OR RCT OR "clinical trial" OR "controlled trial" OR "control group" OR "intervention study" OR "observational study" OR "non-

experimental" OR "quasi-experimental" OR "before and after study" OR "comparative study" OR "cohort study" OR "cross-sectional study" OR "survey study" OR "pilot study" OR "feasibility study"))

WEB OF SCIENCE

TS=(("job crafting" OR "work role redesign" OR "task redefinition" OR "proactive work behavior" OR "employee-initiated change")

AND

(nurs* OR doctor* OR psycholog* OR "healthcare staff" OR "healthcare professional*" OR "NHS staff" OR therapist* OR clinician* OR "allied health" OR "mental health therapist*" OR "advanced clinical practitioner*" OR "medical associate professional*" OR "nursing associate*" OR "speech and language therapist*" OR "occupational therapist*" OR anesthetist* OR anaesthetist* OR "general practitioner*" OR surgeon* OR consultant* OR cardiologist* OR oncologist* OR dermatologist* OR neurologist* OR "respiratory therapist*" OR "emergency medical technician*" OR "social worker*" OR "physician assistant*" OR "care worker*" OR "health visitor*" OR "clinical psychologist*" OR psychiatrist* OR "community nurse*" OR "home care worker*" OR "rehabilitation specialist*" OR "clinical nurse specialist*" OR "public health professional*" OR "medical laboratory scientist*" OR "biomedical scientist*" OR "genetic counselor*" OR counsellor* OR "forensic nurse*" OR "critical care nurse*" OR "perioperative nurse*" OR "intensive care nurse*" OR "palliative care specialist*" OR podiatrist* OR radiographer* OR dentist* OR pharmacist* OR prosthetist* OR orthotist* OR dietician* OR osteopath* OR physiotherapist*)

AND

("randomized controlled trial" OR RCT OR "clinical trial" OR "controlled trial" OR "control group" OR "intervention study" OR "observational study" OR "non-experimental" OR "quasi-experimental" OR "before and after study" OR "comparative study" OR "cohort study" OR "cross-sectional study" OR "survey study" OR "pilot study" OR "feasibility study"))

Appendix C

CASP Checklist: Cohort Studies

CASP Checklist:
For Cohort Studies

Reviewer Name:	
Paper Title:	
Author:	
Web Link:	
Appraisal Date:	

During critical appraisal, never make assumptions about what the researchers have done. If it is not possible to tell, use the "Can't tell" response box. If you can't tell, at best it means the researchers

have not been explicit or transparent, but at worst it could mean the researchers have not undertaken a particular task or process. Once you've finished the critical appraisal, if there are a large number of "Can't tell" responses, consider whether the findings of the study are trustworthy and interpret the results with caution.

Section A: Are the results valid?	
1. Did the study address a clearly focused issue?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: *A question can be 'focused' in terms of* • *the population studied* • *the risk factors studied* • *is it clear whether the study tried to detect a beneficial or harmful effect* • *the outcomes considered*	
2. Was the cohort recruited in an acceptable way?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *Look for selection bias which might compromise the generalisability of the findings:* • *was the cohort representative of a defined population* • *was there something special about the cohort* • *was everybody included who should have been*	
3. Was the exposure accurately measured to minimise bias?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: *Look for measurement or classification bias:* • *did they use subjective or objective measurements* • *do the measurements truly reflect what you want them to (have they been validated)* • *were all the subjects classified into exposure groups using the same procedure*	
4. Was the outcome accurately measured to minimise bias?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: *Look for measurement or classification bias:* • *did they use subjective or objective measurements* • *do the measurements truly reflect what you want them to (have they been validated)* • *has a reliable system been established for detecting all the cases (for measuring disease occurrence)*	

• *were the measurement methods similar in the different groups* • *were the subjects and/or the outcome assessor blinded to exposure (does this matter)*	
5. (a) Have the authors identified all important confounding factors?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *list the ones you think might be important, and ones the author missed*	
b) Have they taken account of the confounding factors in the design and/or analysis?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *look for restriction in design, and techniques e.g. modelling, stratified-, regression-, or sensitivity analysis to correct, control or adjust for confounding factors*	
6. a) Was the follow up of subjects complete enough?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *the persons that are lost to follow-up may have different outcomes than those available for assessment* • *in an open or dynamic cohort, was there anything special about the outcome of the people leaving, or the exposure of the people entering the cohort*	
b) Was the follow up of subjects long enough?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *the good or bad effects should have had long enough to reveal themselves*	
Section B: What are the results?	
7. What are the results of this study?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *what are the bottom line results* • *have they reported the rate or the proportion between the exposed/unexposed, the ratio/rate difference* • *how strong is the association between exposure and outcome (RR)* • *what is the absolute risk reduction (ARR)*	
8. How precise are the results?	☐ Yes ☐ No ☐ Can't Tell

CONSIDER: • *look for the range of the confidence intervals, if given*	
9. Do you believe the results?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *big effect is hard to ignore* • *can it be due to bias, chance or confounding* • *are the design and methods of this study sufficiently flawed to make the results unreliable* • *Bradford Hills criteria (e.g. time sequence, dose-response gradient, biological plausibility, consistency)*	
Section C: Will the results help locally?	
10. Can the results be applied to the local population?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *Is a cohort study the appropriate method to answer this question* • *If the subjects covered in this study could be sufficiently different from your population to cause concern* • *If your local setting is likely to differ much from that of the study* • *If you can quantify the local benefits and harms*	
11. Do the results of this study fit with other available evidence?	☐ Yes ☐ No ☐ Can't Tell
12. What are the implications of this study for practice?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *one observational study rarely provides sufficiently robust evidence to recommend changes to clinical practice or within health policy decision making* • *for certain questions, observational studies provide the only evidence* • *recommendations from observational studies are always stronger when supported by other evidence*	

APPRAISAL SUMMARY: *List key points from your critical appraisal that need to be considered when assessing the validity of the results and their usefulness in decision-making.*		
Positive/Methodologically sound	**Negative/Relatively poor methodology**	**Unknowns**

Referencing recommendation:

CASP recommends using the Harvard style referencing, which is an author/date method. Sources are cited within the body of your assignment by giving the name of the author(s) followed by the date of publication. All other details about the publication are given in the list of references or bibliography at the end.

Example:

Critical Appraisal Skills Programme (2024). CASP (insert name of checklist i.e. qualitative studies Checklist.) [online] Available at: insert URL. Accessed: insert date accessed.

Creative Commons

Need further training on evidence-based decision making? Our online training courses are helpful for healthcare educational researchers and any other learners who:

- Need to critically appraise and stay abreast of the healthcare research literature as part of their clinical duties.
- Are considering carrying out research & developing their own research projects.
- Make decisions in their role, whether that be policy making or patient facing.

Benefits of CASP Training:

⇒ Affordable – courses start from as little as £6
⇒ Professional training – leading experts in critical appraisal training
⇒ Self-directed study – complete each course in your own time
⇒ 12 months access – revisit areas you aren't sure of and revise
⇒ CPD certification - after each completed module

Scan the QR code below or visit https://casp-uk.net/critical-appraisal-online-training-courses/ for more information and to start learning more.

Appendix D

CASP Checklist: Cross-Sectional Studies

CASP Checklist:
For Descriptive/Cross-Sectional Studies

Reviewer Name:	
Paper Title:	
Author:	
Web Link:	
Appraisal Date:	

During critical appraisal, never make assumptions about what the researchers have done. If it is not possible to tell, use the "Can't tell" response box. If you can't tell, at best it means the researchers have not been explicit or transparent, but at worst it could mean the researchers have not undertaken a particular task or process. Once you've finished the critical appraisal, if there are a large

number of “Can’t tell” responses, consider whether the findings of the study are trustworthy and interpret the results with caution.

Section A: Are the results valid?	
13. Did the study address a clearly focused issue?	☐ Yes ☐ No ☐ Can’t Tell
CONSIDER: *A question can be ‘focused’ in terms of* • *the population studied* • *the risk factors studied* • *is it clear whether the study tried to detect a beneficial or harmful effect* • *the outcomes considered*	
14. Did the authors use an appropriate method to answer their question?	☐ Yes ☐ No ☐ Can’t Tell
CONSIDER: • *Is a descriptive/cross-sectional study an appropriate way of answering the question* • *did it address the study question*	
15. Were the subjects recruited in an acceptable way?	☐ Yes ☐ No ☐ Can’t Tell
CONSIDER: *We are looking for selection bias which might compromise the generalisability of the findings:* • *Was the sample representative of a defined population* • *Was everybody included who should have been included*	
16. Were the measures accurately measured to reduce bias?	☐ Yes ☐ No ☐ Can’t Tell
CONSIDER: *Look for measurement or classification bias:* • *did they use subjective or objective measurements* • *do the measurements truly reflect what you want them to (have they been validated)*	
17. Were the data collected in a way that addressed the research issue?	☐ Yes ☐ No ☐ Can’t Tell

CONSIDER: • *if the setting for data collection was justified* • *if it is clear how data were collected (e.g., interview, questionnaire, chart review)* • *if the researcher has justified the methods chosen* • *if the researcher has made the methods explicit (e.g. for interview method, is there an indication of how interviews were conducted?)*	
18. Did the study have enough participants to minimise the play of chance?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *if the result is precise enough to make a decision* • *if there is a power calculation. This will estimate how many subjects are needed to produce a reliable estimate of the measure(s) of interest.*	
19. How are the results presented and what is the main result?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *if, for example, the results are presented as a proportion of people experiencing an outcome, such as risks, or as a measurement, such as mean or median differences, or as survival curves and hazards* • *how large this size of result is and how meaningful it is* • *how you would sum up the bottom-line result of the trial in one sentence*	
20. Was the data analysis sufficiently rigorous?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *if there is an in-depth description of the analysis process* • *if sufficient data are presented to support the findings*	
21. Is there a clear statement of findings?	☐ Yes ☐ No ☐ Can't Tell
CONSIDER: • *if the findings are explicit* • *if there is adequate discussion of the evidence both for and against the researchers' arguments* • *if the researchers have discussed the credibility of their findings* • *if the findings are discussed in relation to the original research questions*	
22. Can the results be applied to the local population?	☐ Yes ☐ No ☐ Can't Tell

CONSIDER: • *the subjects covered in the study could be sufficiently different from your population to cause concern.* • *your local setting is likely to differ much from that of the study*

23. How valuable is the research?	☐ Yes ☐ No ☐ Can't Tell

CONSIDER: • *one descriptive/cross-sectional study rarely provides sufficiently robust evidence to recommend changes to clinical practice or within health policy decision making* • *if the researcher discusses the contribution the study makes to existing knowledge (e.g., do they consider the findings in relation to current practice or policy, or relevant research-based literature?)* • *if the researchers have discussed whether or how the findings can be transferred to other populations*

APPRAISAL SUMMARY: *List key points from your critical appraisal that need to be considered when assessing the validity of the results and their usefulness in decision-making.*		
Positive/Methodologically sound	**Negative/Relatively poor methodology**	**Unknowns**

Referencing recommendation:

CASP recommends using the Harvard style referencing, which is an author/date method. Sources are cited within the body of your assignment by giving the name of the author(s) followed by the date of publication. All other details about the publication are given in the list of references or bibliography at the end.

Example:

Critical Appraisal Skills Programme (2024). CASP (insert name of checklist i.e. cross sectional Checklist.) [online] Available at: insert URL. Accessed: insert date accessed.

Creative Commons

Need further training on evidence-based decision making? Our online training courses are helpful for healthcare educational researchers and any other learners who:

- Need to critically appraise and stay abreast of the healthcare research literature as part of their clinical duties.
- Are considering carrying out research & developing their own research projects.
- Make decisions in their role, whether that be policy making or patient facing.

Benefits of CASP Training:

⇒ Affordable – courses start from as little as £6
⇒ Professional training – leading experts in critical appraisal training
⇒ Self-directed study – complete each course in your own time
⇒ 12 months access – revisit areas you aren't sure of and revise
⇒ CPD certification - after each completed module

Scan the QR code below or visit https://casp-uk.net/critical-appraisal-online-training-courses/ for more information and to start learning more.

Appendix E

Table Of Ineligible Studies With Reasons For Exclusion

Author(s)	Year	Title	Exclusion Criteria
Baghdadi et al.	2021	The relationship between nurses' job crafting behaviours and their work engagement -	not a personal wellbeing outcome
Bakker	2018	Job crafting among health care professionals: The role of work engagement	not personal wellbeing outcome
Bakker et al.	2016	Modelling job crafting behaviours: Implications for work engagement	not healthcare staff
Boettcher & Kauffeld	2025	Enhancing workplace support digitally: evaluating the impact of a job crafting and a wise intervention	not healthcare staff
Chung & Han	2023	Effects of job crafting, burnout, and job satisfaction on nurses' turnover intention: A path analysis	not a personal wellbeing outcome
Dominiguez et al.	2018	Taking control: Is job crafting related to the intention to leave surgical training?	duplicate/update available

Elsayed et al.	2023	Effect of Job Demands-Resources and Job Crafting on Nurses Work Engagement –	not a personal wellbeing outcome
Gillet et al.	2025	A Longitudinal Person-Centered Investigation of the Multidimensional Nature of Employees' Perceptions of Job Crafting	not healthcare staff
Hassan et al.	2020	Relation between Job Crafting and Job Satisfaction among Staff Nurses	not a personal wellbeing outcome
Hommelhoff et al.	2021	The role of cognitive job crafting in the relationship between turnover intentions, negative affect, and task mastery	not a personal wellbeing outcome
Hyun	2021	Development of Job Crafting Intervention Program for Hospital Nurses: Effects on Organizational Commitment, Embeddedness, and Organizational Well-being	not English
Jutengren et al.	2020	The potential importance of social capital and job	not a wellbeing outcome

		crafting for work engagement and job satisfaction among health-care employees	
Kim	2021	Effects of Job Crafting on the Quality of Nursing Services among Clinical Nurses: The Mediating Effect of Work Engagement	not English
Kılıç et al.	2020	A research on the relationship between job crafting, psychological empowerment and turnover intention	not healthcare staff
Kuijpers et al.	2020	Align your job with yourself: The relationship between a job crafting intervention and work engagement, and the role of workload	not a personal wellbeing outcome
Leeuwen et al.	2021	A Career Crafting Training Program: Results of an Intervention Study	JC not an IV
Leeuwen et al.	2022	Stimulating Employability and Job Crafting Behaviour of Physicians: A Randomized Controlled Trial	JC not an IV

Liu	2022	Job Crafting and Nurses' Presenteeism: The Effects of Job Embeddedness and Job Irreplaceability	not a personal wellbeing outcome
Mohamed & Ahmed	2024	Relation between Job Crafting, Staff Nurses' Job Satisfaction and Counterproductive Work Behaviors	not a personal wellbeing outcome
Nwanzu	2024	Employee Job Crafting Behaviour and its Antecedents: A Study of Psychological Safety, Psychological Autonomy, and Task Competence	not healthcare staff
Perez-Marques et al.	2023	Effects of three personal resources interventions on employees' burnout	not healthcare staff
Plomp et al.	2016	Effects of three personal resources interventions on employees' burnout	not healthcare staff
Rafiq et al.	2023	Linking job crafting, innovation performance, and career satisfaction: The mediating role of work engagement	not healthcare staff

Rodríguez-García	2024	The Influence of Job Crafting on Nurses' Intent to Stay: A Cross-Sectional Study –	not a personal wellbeing outcome
Sakuraya et al.	2020	Effects of a job crafting intervention program on work engagement among Japanese employees: A randomized controlled trial	not healthcare staff
Sakuraya et al.	2023	Corrigendum: Effects of a job crafting intervention program on work engagement among Japanese employees: A randomized controlled trial	not healthcare staff
Sakuraya et al.	2016	Effects of a job crafting intervention program on work engagement among Japanese employees: A pretest-posttest study	not healthcare staff
Saleh et al.	2024	Appreciative Leadership, Workplace Belongingness, and Affective Commitment of Nurses: The Mediating Role of Job Crafting	not a personal wellbeing outcome
Seo et al.	2024	Effects of Clinical Nurses' Grit, Social Support, Job Crafting, and Evidence-	not English

		Based Practice Competency on Job Satisfaction	
Shaheen & Mahmoud	2021	Relation between job crafting, nurses' job satisfaction and counterproductive work behaviors	not a personal wellbeing outcome
Shi et al.	2022	Job crafting and employees' general health: the role of work–nonwork facilitation and perceived boundary control	not healthcare staff
Sidin et al.	2021	Do Ethical Climate Have Impact on Job Satisfaction of Staff in West Sulawesi Hospital, Indonesia?	not a personal wellbeing outcome
Sidin et al.	2021	How is the correlation job crafting to job satisfaction of hospital staff at disruption era in hospital industries	not a personal wellbeing outcome
Tadić Vujčić	2019	Personal resources and work engagement: A two-wave study on the role of job resources crafting among nurses	not a personal wellbeing outcome

Tang et al.	2024	Mediating Role of Job Crafting in the Relationship Between Creativity and Work Exhaustion	not healthcare staff
Tims et al.	2014	Daily job crafting and the self-efficacy–performance relationship	not healthcare staff
Tims et al.	2013	Job crafting at the team and individual level: Implications for work engagement and performance	not a personal wellbeing outcome
Tong et al.	2024	Job Crafting and Work Engagement of Nurses in Affiliated Hospitals of Harbin Medical University, the People’s Republic of China	not a personal wellbeing outcome
Topa & Aranda-Carmena	2022	Job crafting in nursing: mediation between work engagement and job performance in a multisample study	not a personal wellbeing outcome
Uglanova & Dettmers	2023	Improving employee mental health through an internet-based job crafting intervention: A randomized controlled study	not healthcare staff

Van de Heuvel	2015	The job crafting intervention: Effects on job resources, self-efficacy, and affective well-being	not healthcare staff
van Hooff & van Hooft	2014	Improving employee mental health through an internet-based job crafting intervention: A randomized controlled study	not healthcare staff
Van Wingerden	2017	The impact of personal resources and job crafting interventions on work engagement and performance	not healthcare staff
Wijngaards et al.	2022	Cognitive crafting and work engagement: A study among remote and frontline health care workers during the COVID-19 pandemic	not a personal wellbeing outcome
Wingerden	2016	A test of a job demands-resources intervention	not a personal wellbeing outcome
Won	2024	Factors Influencing the Field Adaptation of New Nurses in General Hospitals	not English
Xiong et al.	2025	Work engagement among new nurses in China: a latent profile analysis	not a personal wellbeing outcome

Yasin Ghadi	2024	The impact of personal resources and job crafting interventions on work engagement and performance	not healthcare staff
Zhang et al.	2024	The relationship between job crafting and work engagement among nurses in China: A latent profile analysis	not a personal wellbeing outcome

Appendix F

Summary Of Risk Of Bias Assessment

Overview Risk of Bias Assessment – Cross-sectional Studies

Study	*Clearly focused research question?*	*Appropriate study method?*	*Cases recruited in an acceptable way?*	*Controls recruited in an acceptable way?*	*Measures accurately measured to minimise bias?*	*Data collection addressed the research issue?*	*Enough participants to minimise chance?*	*How are results presented and what is main result?*	*Rigorous data analysis?*	*Clear findings?*	*Results applicable to local population/your context?*	*Valuable research?*	**Risk of Bias**
Alharthi et al. (2023)	Y	Y	CT	Y	Y	Y	Y	Clearly presented, significant positive correlation between job crafting and happiness.	Y	Y	Y	Y	**MEDIUM**
Alkhraishi & Yesiltas (2024)	Y	Y	Y	Y	Y	Y	Y	Clearly presented, significant relationships	Y	Y	P	Y	**LOW**
Dominguez et	Y	Y	Y	Y	Y	Y	Y	Clear results, JC	Y	Y	P	Y	**LOW**

al. (2018)								relates indirectly to intention to leave via burnout and engagement.				
Ghazzawi et al. (2021)	Y	Y	Y	Y	Y	Y	Y	Clear results, JC mediates the effect of creativity and job autonomy on subjective well-being.	Y	Y	P	Y	**LOW**
Guo et al. (2024)	Y	Y	P	Y	Y	Y	Y	Clearly presented, job crafting was predictor of burnout	Y	Y	P	Y	**MEDIUM**
Han (2023)	Y	Y	P	Y	Y	Y	Y	Clearly presented, JC was	Y	Y	P	Y	**MEDIUM**

							correlated with wellbeing					
Ibrahim et al. (2025)	Y	Y	Y	Y	Y	Y	Y	Clearly presented, JC positively impacts the physical and mental well-being of palliative care nurses	Y	Y	P	Y	**LOW**
Kato et al. (2023)	Y	Y	P	Y	Y	Y	Y	Clearly presented, JC could help enhance work engagement, which could contribute to improving attitudes, mental health.	Y	Y	P	Y	**MEDIUM**

Lynner et al. (2024)	Y	Y	P	Y	Y	Y	Y	Clearly presented, JC reduced burnout	Y	Y	P	Y	**MEDIUM**
Pan et al. (2021)	Y	Y	P	Y	Y	Y	Y	Clearly presented, LMX will affect job satisfaction and life satisfaction through a partial mediating effect of both individual and collaborative JC.	Y	Y	P	Y	**MEDIUM**
Romeo et al. (2018)	Y	Y	P	Y	Y	Y	CT	Clearly presented, a direct and simple effect was observed between cognitive crafting	Y	Y	P	Y	**MEDIUM**

								and well-being					
Zahoor et al. (2023)	Y	Y	P	Y	Y	Y	CT	Clearly presented, JC significantly ameliorates nurses' hedonic and eudaimonic WB.	Y	Y	P	Y	**MEDIUM**
Zhang et al. (2024)	Y	Y	P	Y	Y	Y	Y	Clearly presented, job crafting moderated perceived health's impact on work well-being	Y	Y	P	Y	**MEDIUM**

Note. N – No (item not adequately addressed), Y – Yes (item adequately addressed), CT – Can't tell if item adequately addressed, P – Partially (Item partially addressed).

Overview Risk of Bias Assessment – Cohort Studies

Study	*Clearly focused research question?*	*Cohort recruited in an acceptable*	*Exposure accurately measured to*	*Outcome accurately measured to*	*All important confounding factors*	*Were confounding factors considered*	*FU of subjects complete enough?*	*FU of subjects long enough?*	*Study results*	*Were results precise?*	*Do you believe the results?*	*Results applicable to local population/*	*Do results fit with other available*	*What are the implications of this study for practice?*	**Risk of Bias**
Gordon et al. (2018)	Y	CT	Y	Y	CT	Y	CT	CT	JC associated with increases in well-being	CT	Y	Y	Y	JC is a promising job redesign intervention strategy that individual employees can use to improve their well-being	**HIGH**
Iida et al. (2024)	Y	CT	Y	Y	CT	Y	N	Y	No significant association between JC and	Y	CT	CT	P	JC is insufficient	**MEDIUM**

									distress						
Zmijewski et al. (2023)	Y	CT	Y	Y	Y	N	Y	N	No significant. Hange in burnout risk but improved distress scores.	CT	Y	CT	Y	Supports JC to enhance job meaning	**MEDIUM**

Note. N – No (item not adequately addressed), Y – Yes (item adequately addressed), CT – Can't tell if item adequately addressed, P – Partially (Item partially addressed).

Part Two: Empirical Study

Do NHS staff with different occupational burnout profiles respond differently to a Job Crafting intervention?

Abstract

Burnout is a growing problem amongst NHS healthcare staff. While interventions like Job Crafting (JC) show promise in reducing burnout and improving well-being, it remains unclear why outcomes vary between individuals. This study aimed to explore whether distinct burnout profiles—identified using Self-Organising Maps (SOM)—could predict who benefits most from JC. A secondary data analysis was conducted using data from two randomised controlled trials: UpLift1 (n=238), comparing the effectiveness of JC versus cognitive behavioural therapy, and UpLift2 (n=135), testing the effectiveness of JC against a waitlist control group. Participants completed the Occupational Burnout Inventory (OLBI), and item-level baseline questionnaires were analysed using SOM. The best-fitting SOM model identified 12 clusters of burnout subtypes. A logistic regression was then run to examine whether cluster membership predicted reliable improvement (defined as ≥7 point reduction in OLBI score). After controlling for baseline severity, cluster membership was not significantly associated with reliable improvement. However, baseline severity strongly predicts treatment response, with people who were more burnt out at the start more likely to benefit from JC. Demographic factors (e.g. gender, gob role, ethnicity) did not significantly predict treatment response. Overall, while different people have different configurations of burnout symptoms, the overall level of burnout severity is the most clinically meaningful predictor of treatment outcomes with JC.

Keywords: *Occupational Burnout, Job Crafting Intervention, NHS Professionals, Machine Learning, Self-Organizing Maps (SOM), Burnout Subtypes, Healthcare Staff Well-being, Psychological Interventions, Secondary Data Analysis, Clinical Trial*

Introduction

Presently, the National Health Service (NHS) in the UK is facing financial difficulties (Robertson et al., 2017) as well as a high number of patients with complex care needs (Millar, 2019). This has increased the risk of NHS professionals experiencing burnout, and the situation has been exacerbated by the impact of the COVID-19 pandemic (Rotenstein et al., 2023).

The latest revision of the International Classification of Diseases (ICD-11) defines burnout as a syndrome that includes three domains: emotional exhaustion, depersonalization, and reduced sense of accomplishment. Burnout affects all professionals in different fields; however, healthcare staff appear to have the most significant risk (Johnson et al., 2017) due to constantly working with a high workload of patients in distress (Drummond, 2015). Research from around the world shows that occupational burnout impacts approximately 11% of nursing and allied health professionals and around 30% of medical staff. The prevalence is even higher among the critical care workforce such as those working in emergency departments (A&E) and intensive care units (ICU) (Woo et al., 2020; de Hert, 2020). More recent studies show that the Covid-19 pandemic has further increased burnout among healthcare staff. Rotenstein et al. (2023) conducted a study exploring levels of burnout in 43,026 healthcare professionals (including physicians, nurses, other clinical staff, and non-clinical staff). Alarmingly, they found the overall burnout prevalence was 49.9%.

Burnout syndrome has many individual consequences, such as staff feeling dissatisfied with their jobs, feeling unhappy, increased mental health problems, more isolated, substance misuse, relationship problems and breakdowns including divorce, or even suicide (Dyrbye et al., 2008; Shanafelt et al., 2012). This affects the level of

care healthcare staff provide to patients (Garcia et al., 2019) and reduces the effectiveness of psychological therapists supporting clients with mental health problems (Morse, 2012). Consequences are increased staff turnover (Sinsky et al., 2022) and frequency of medical errors (Shanafelt, 2002), which not only affect the department they work in but also have significant financial costs for caregivers, hospitals, and the NHS (Han et al., 2019; Sinsky et al., 2017), making research into burnout a priority.

Current interventions for burnout include individual (e.g., mindfulness-based/relaxation skills, Cognitive Behavioural Therapy, mind management skills) and organizational approaches (e.g., increasing resources, changing the culture, adjustment of workload). Studies investigating burnout interventions typically find small to moderate effect sizes and burnout influenced by multiple risk factors, such as workload, organisational stress, and conflict at home or the workplace (Demerouti et al., 2001; Davis, 2020). Therefore, different interventions and components may be effective for different people. There is currently little research evidence to understand what works for whom. Due to the prevalence and consequences of burnout in healthcare staff, there is a need for research on burnout prevention and intervention programs, with attention to what works for whom, so we can target available interventions to those who might benefit most from them.

Job crafting is a novel intervention that combines both individual and organizational approaches to reduce burnout (Tims & Bakker, 2010). It involves the consideration and implementation of three key elements: (1) task crafting, (2) relational crafting, and (3) cognitive/psychological crafting. The aim is to empower individuals to proactively reshape their roles in ways that restore a balance between the demands of work and the resources available to meet these demands.

A meta-analysis of observational studies provides some preliminary support for job crafting (Frederick & VanderWeele, 2020), with 16 studies demonstrating its potential effectiveness. However, large-scale randomised controlled trials (RCTs) in healthcare settings remain limited. A recent study completed the first job crafting multi-centre RCT in an NHS setting, called the UpLift1 Trial (Delgadillo et al., 2025a). A total of 465 healthcare professionals accessed either job crafting or cognitive behavioural therapy (CBT), both delivered by psychological professionals over the course of 6 weeks. Findings indicate that job crafting reduced average levels of burnout and increased wellbeing levels in participants. Furthermore, post-treatment effects of job crafting on burnout were not significantly different from those of CBT, and these improvements were largely maintained over a six-month follow-up period, although CBT outcomes were more favourable at 6 months follow-up.

A second trial, UpLift2 (Delgadillo et al., 2025b), tested the efficacy of job crafting compared to a waitlist control group. In this study, psychological professionals delivered a six-week job crafting intervention to 135 psychological therapists working in the NHS. Burnout levels significantly decreased in the intervention group, while remaining unchanged in the waitlist group. When the waitlist group later received job crafting, they experienced similar improvements. However, maintenance of gains at six months varied between groups—one retained its progress, while the other did not.

While prior studies (e.g., Lee et al., 2016; Dreison et al., 2018; Shin et al., 2014) have found that individual-level strategies such as CBT and stress management reduce emotional exhaustion and depersonalisation, organisational interventions tend to be more effective for improving personal accomplishment (Busireddy et al., 2017; Panagioti et al., 2017). Yet, changes like reducing working hours—though beneficial—are often unfeasible in high-demand environments like the NHS.

In summary, while job crafting appears to be a promising intervention for burnout in healthcare professionals, not all individuals experience the same benefits. Further research is needed to determine “what works for whom” in occupational burnout. The present study aims to contribute to this by investigating whether healthcare professionals’ initial burnout profile—specifically their unique combination of burnout symptoms—can help predict who is most likely to benefit from job crafting.

Further rationale for investigating burnout subtypes comes from depression research, where distinct clinical presentations have been identified. Lamers et el. (2010) identified three profiles: ‘a severe melancholic class (prevalence, 46.3%), a severe atypical class (prevalence, 24.6%), and a class of moderate severity (prevalence, 29.1%). They found that as well as depression severity, the type of depressive symptoms were also important differentiators between subtypes. Nunez et al. (2024) used items from Patient Health Questionnaire – 9 items (PHQ-9) to identify symptom subtypes. This is important as research has found that people who receive their optimal treatment based on their specific symptoms and personal characteristics more significantly reduced their depression (DeRubeies et al., 2014; Kappelmann et al., 2020; Webb et al., 2019). This suggests that clustering baseline symptom patterns it may be possible to find clinically meaningful subtypes which might respond differently to treatments and predict outcomes. Therefore we hypothesized we may find different burnout subtypes based on the items of a measure of burnout, which may predict response to a job crafting intervention.

Potential burnout subtypes may occur due to many factors, such as situational factors (different workplace environments and roles mean people may exhibit different levels of demand and control), individual differences (people may be more prone to exhaustion or depersonalization due to different traits and characteristics and coping

strategies), occupational fields (people may experience burnout differently due to the field they work in), temporal dynamics (people may experience burnout differently as they progress in their careers). This study aims to identify subtypes in an empirical way, rather than conceptualising a specific number of domains.

Aim, Objectives and Hypotheses

The overall aim of this study was to investigate the presence and clinical relevance of subtypes of occupational burnout. The primary objective was to identify burnout subtypes using the Oldenburg Burnout Inventory (OLBI) and the secondary objective was to determine if people with different subtypes respond differently to the Job Crafting (JC) intervention.

Theory in the occupational burnout field indicates that the OLBI measure is characterized by two domains (exhaustion; disengagement). However, we hypothesised that there will be more than two distinctive burnout subtypes among NHS and psychological therapy staff. No upper boundary on the number of latent subtypes was specified a priori, as this study followed a data-driven and inductive research paradigm. The second hypothesis was that people with distinct burnout subtypes will respond differently to JC, such that some will have better treatment outcomes after controlling for baseline severity of burnout.

Ethical approval

Ethical approval for the secondary analysis of data from clinical trials was sought and granted by the University of Sheffield Ethics Committee (see Appendix A).

Method

Design and Setting

This study was based on a secondary analysis of data collected in the UpLift1 and UpLift2 Trials (Delgadillo et al., 2025a, 2025b). The study followed the Transparent Reporting of Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD + AI), which are recommended for studies that use machine learning to develop clinical prediction models (Collins et al., 2015; see Appendix B).

UpLift1 included 465 NHS staff members from 20 NHS trusts across England. Participants were identified during triage**,** assessed for eligibility, and invited to participate after providing written informed consent. Overall, 238 of these participants received the Job Crafting intervention so the data from these participants was used for this study (others received CBT).

UpLift2 included 135 staff members working in Improving Access to Psychological Therapy (IAPT) services. This included psychological wellbeing practitioners, cognitive-behavioral therapists, counsellors, psychotherapists, psychologists, and other professionals who deliver psychological interventions. As in Uplift1, participants underwent an eligibility check before being invited and providing written informed consent**.**

The interventions in both trials were delivered remotely, as six-session (1 hr. each) group-based interventions, using video conference software that enabled multiple participants to attend. Participants could remain anonymous, as they didn't have to have their cameras on or show their real names on screen. The facilitators for both trials were psychological wellbeing practitioners, counsellors and clinical psychology trainees, supervised by the developer of the treatment protocol for the job crafting intervention.

Inclusion and Exclusion Criteria

If participants met the inclusion criteria below (Table 1), they were invited to take part in the study and randomly allocated to a group.

Table 1

Inclusion and Exclusion Criteria by Trial

Criteria	Common to Both Trials	Trial 1 Specific	Trial 2 Specific
Inclusion			
Working in the healthcare system	Must have been employed by the NHS or IAPT services at the time of the trial.	Must have had direct patient contact, either in a clinical or administrative capacity.	Must have been a psychological professional delivering psychological interventions in IAPT services.
Employment type	Could have worked full-time or part-time.	Included receptionists and administrators with direct patient contact.	Could have included those delivering therapy or providing management/clinical supervision to psychological therapists.
Active service	Must have been in active service at the time of the trial (not on extended leave or suspended).	-	-
Age	Must have been 18 or older.		
Qualification status	-	-	Qualified staff and trainees were eligible.
Exclusion			

Concurrent psychological intervention	Participants accessing or referred to any concurrent psychological intervention delivered by a professional were excluded.	-	-
Not in active service	Participants on extended leave (e.g., sick leave, maternity leave) or suspended were excluded.	-	-
Temporary contracts	Participants on temporary contracts, such as bank or agency contracts, were excluded.	-	-
Recent CPM trial participants	-	Participants who had taken part in the recent CPM Trial and were still in a 6-month follow-up period were excluded.	-
Non-relevant roles	-	-	Participants whose roles did not involve delivering or managing psychological therapy were excluded.

Participant characteristics

The study included a majority of female participants (89.5%), with 9.7% identifying as male and 0.8% preferring not to disclose their gender. Most participants were from a White British background (83.6%), which aligns with population trends reported by the Office for National Statistics, estimating 16–18% of the UK population as ethnic minorities. Due to small sample sizes in other ethnic groups, the analysis focused on White British and "Other" categories for reliability. The average age of participants was 42.4 years, with ages ranging from 23 to 73, spanning a 50-year range. Participants worked across 20 NHS Trusts in regions including Cumbria, Northumberland, Yorkshire and the Humber, Lincolnshire, and Merseyside, among others. Job roles were diverse, with 68.5% in clinical roles, 28.4% in mental health professions, and 3.2% in administrative positions. Of the 238 individuals recruited, subgroup analysis was based on the 155 participants (65.4%) who attended the sessions. Table 2 includes a breakdown or participant characteristics.

Table 2

Participant Characteristics

Variable	Category	n (%)
Gender	Female	212 (89.5)
	Male	23 (9.7)
	Prefer not to say	2 (0.8)
Ethnicity	White British	199 (83.6)
	Other	39 (16.4)

NHS Trust	Number of trusts (North East London, Bradford District, Rotherham, Doncaster and South Humber, Cumbria, Northumberland, Yorkshire and the Humber, Lincolnshire, Merseyside, etc.)	20
Job Role area	Clinical	163 (68.5)
	Mental Health	68 (28.4)
	Administrative	7 (3.2)

Sampling procedures

Common elements

Participants were recruited through NHS trusts and IAPT services. Different materials were used, such as newsletters, posters, participant information sheets, and videos. People could contact the research team if they wanted to ask anything. Written consent was obtained using a secure online system and participants remained anonymous by using pseudonyms. Participants were randomly allocated to a group and emailed to notify them of which one they were in. The interventions were delivered online at different times to fit around participants schedules.

Unique elements for each trial

For UpLift1, participants were recruited through NHS trust investigators and at NHS team meetings, and the study was actively promoted for 4 weeks before participants gave consent to take part. However, UpLift2 was promoted within IAPT services. In Uplift1, participants accessed either CBT or a JB intervention. In contrast, Uplift2 participants accessed JB or a waitlist initially.

Sample Size

SOM sample size calculation

SOM is a form of unsupervised machine learning, which aims to discover subgroups in data without prior specification of the number of subgroups to be identified.

We chose the SOM machine learning approach because a methodological study by Kiang et al. (2006) shows that the SOM method outperforms more traditional clustering methods such as k-means cluster analysis and factor analysis, even at relatively small sample sizes - SOM produced more stable and reliable clusters. Also traditional clustering methods like k-means require assumptions of number of clusters prior to analyses which is not ideal when the aim is to find unknown patterns in data. Other classical methods also rely on some statistical assumptions (e.g., data distribution, distance metrics) and can be unstable in small or complex datasets. However, SOM detects patterns without prior assumptions. Furthermore, Kiang et al. (2006) demonstrated that the performance of the SOM method is insensitive to larger sample sizes above the minimum threshold of N=50; results remain stable even when compared to a sample size as large as N=1600. Maximum performance is consistently better than other methods. This is because neural network models are not dependent on traditional statistical assumptions, therefore results are consistent across different

sample sizes. Therefore, following the methodological guidelines by Kiang et al. (2006), we proposed a minimum sample of N=50 cases to train an SOM clustering model.

Logistic regression sample size calculation

To perform logistic regression, we it was expected a minimum of 82 cases would be be necessary to detect a medium effect size. Using the sample size calculation guidance by Hsieh et al. (1998), assumptions were made to calculate the necessary sample size.

Firstly, an effect size converter was used to equate a Cohen's d effect size of 0.5 (considered a medium effect size) to a log odds ratio (effect size metric for logistic regression). The log odds ratio is the effect size metric for logistic regression analysis, a measure of the strength and direction of the association between variables. The converted odds ratio for a medium effect size was 2.48.

A conservative assumption that if group membership was predictive of clinical outcomes, a medium effect size would be expected. Cohen’s d was used as an estimate, which equates to 2.48 on the odds ratio scale (effect size that corresponds to logistic regression) and assumed around 50% will experience reliable improvement (0.5 in the proportion of sample 1). Based on these assumptions, and considering we would be controlling for baseline severity, it was expected 82 participants would be required using the sample size criteria by Hsieh et al. (1998).

Measures and covariates

Data collected from participants in both trials completing the Occupational Burnout Inventory (OLBI; Appendix C) was used: This is a validated 16-item questionnaire that assesses the 2 core areas of burnout: exhaustion and

disengagement (Demerouti, 1999; Demerouti & Nachreiner, 1998). Participants rated the frequency or intensity of their experiences on a series of items relating to burnout symptoms. Each item on the measure is scored from 1 (strongly agree) to 4 (strongly disagree). It includes 8 positive statements and 8 negative statements (scored reversely).

Secondary measures: Participants provided some demographic information, including age, gender, ethnicity, job role, access to clinical supervision, department, and hours worked for the NHS.

Intervention

In both of the clinical trials in this a “blended care” approach was used to deliver a JC intervention to NHS healthcare professionals and psychological practitioners. This meant participants attended live online group sessions and also had access to an interactive app to support them to apply the learning to their day-to-day lives. The intervention was based on key burnout and wellbeing models including the Job Demands-Resources (JD-R) model (Demerouti et al., 2001), the Effort-Reward Imbalance model (Siegrist, 1996), and multiple job crafting theories (Wrzesniewski & Dutton, 2001; Tims & Bakker, 2010; Bruning & Campion, 2018).

In UpLift1, participants assigned to the JC condition attended hourly sessions delivered online by trained facilitators, which took place over six weeks. Between the sessions, participants were encouraged to use an app which had short videos, reflective tools, practice exercises, and guided prompts, allowing them to practice techniques between sessions, making it easier to build habits.

Session content was focused on empowering staff to make five areas of change to make their job align better with their values and, strengths and needs. Each session

targeted specific workplace behaviours and challenges. Firstly, the intervention focused on reframing their tasks; encouraging staff to think about whether they could organise their workload differently or approach repetitive duties in a way that felt more rewarding or manageable. The second part focused on Improving workplace relationships – exploring how their connections with colleagues or supervisors affected their day and were supported to find ways to build stronger, more supportive relationships or reduce unhelpful interactions. Thirdly, there was time to shift perspectives – sometimes the stress of daily tasks can make work feel less meaningful, so the intervention helped people reconnect with what originally mattered to them in their roles and how their work fits into the bigger picture. In later session, participants created a productive environment – to think about how their physical or digital spaces might be affecting their energy, focus, or stress levels—and whether they could make small changes to improve this. Lastly, the intervention helped people to think about their personal development – to consider opportunities for learning new skills or taking on responsibilities that felt exciting or aligned with their career goals.

Each session added to the prior, with people choosing and trying different techniques at work. Between sessions, they used the mobile app to support their learning. This helped them check and set personalised goals.

In UpLift2, the same intervention was delivered to psychological professionals working in IAPT services. As the intervention was consisted, it was possible to see whether it worked similarly in different work roles.

Overall, the aim of the intervention was to support staff to have more control over how they experience their work, giving it more purpose and helping them feel more satisfied with it. Although not all aspects of a role can be changed, this

intervention focused on helping people make small, realistic and personalised adjustments to their work wellbeing.

Data collection

In both clinical trials, participants were randomly assigned to either a job crafting intervention or a control group. They completed outcome measures via an online survey issued to them via email, including the OLBI, at baseline, post-treatment (after six weeks), and six-month follow-up. Demographic information such as age, gender, ethnicity, and job role was also captured through the online survey. All data used in this study were anonymised.

Masking

Participants were randomly allocated to groups. They were aware of which intervention they were receiving and could not be blinded due to nature of intervention.

Psychometrics

The OLBI has been validated for use in longitudinal studies. Past studies have shown the OLBI is stable over multiple observations over time, with test–retest coefficients in repeated measures settings supporting its reliability (Demerouti et al., 2003; Halbesleben & Demerouti, 2005). These results show that the OLBI can correctly measure burnout at the time intervals used in this study – baseline, post-intervention and at 6 months follow up.

The OLBI has high internal consistency. Cronbach's alpha coefficients for the exhaustion subscale range from 0.74 to 0.87 and 0.70 to 0.83 for the disengagement scale. Therefore, when assessing burnout's two main dimensions, the OLBI has strong reliability. (Demerouti et al., 2003; Halbesleben & Demerouti, 2005)

A newer a more accurate measure of reliability, the McDonald's Omega, has demonstrated the OLBI exhaustion subscale value of 0.76 and disengagement subscale value of 0.85, with a value of 0.92 for the entire OLBI measure (Reis et al., 2021; Sinval et al., 2019).

The OLBI has convergent and discriminant validity as it matches results from similar burnout measures (such as the MBI subscale). It also shows low-moderate links to measures of job satisfaction and depression (Halbesleben & Demerouti, 2005).

These values indicate the OLBI is reliable when used with different occupational and cultural samples.

The OLBI has been tested on a range of different samples, which means the data can be generalised to diverse populations. Some of the populations and settings it has been tested across include working adults in the United States (Halbesleben & Demerouti, 2005), a variety different occupations in Greece (Demerouti et al., 2003), Brazil and Portugal (Sinval et al., 2019), psychologists in Australia (Smout, 2024), healthcare staff including nurses in Germany, (Reis et al., 2015), doctors in Nigeria (Ogunsuji et al., 2022).

Data Diagnostics

To prepare data, input variables were standardized, and key predictor variables were selected using filter nodes.

Clustering Analysis Using Self-Organizing Maps (SOM)

The first stage of analysis involved using Self-Organizing Maps (SOM), which is a type of unsupervised machine learning designed to group together similar cases, identifying subgroups within the data. This method was chosen because it does not

require predefining of the number of clusters, therefore spontaneous employee-initiated burnout subtypes could were discovered in a data-driven way. The clustering process was based on the individual baseline item-level data from the OLBI questionnaire for study participamnts. The software used was IBM SPSS Modeler.

SOM works by mapping input data (e.g., item-level OLBI responses) onto a two-dimensional grid, where similar cases are positioned closer together. The algorithm includes an input layer of neurons and an output layer, with adjustable weights connecting them to each other. During training, neurons in the output layer continuously adjust their weights as the model runs. This form clusters of participants with similar burnout profiles. Over time, training process keeps amending these clusters by adjusting the strength of connections based on similarity, improving cluster accuracy.

Before running the SOM analysis, data were standardized to make sure there was consistency across different measurement scales. Multiple phases were used to train the model. This meant the structure of clusters was gradually refined to give the best possible organization of similar data points. The final output was a set of clusters showing different burnout subtypes.

Data Visualization

Bar charts were created to make it easier to present differences in burnout severity across the clusters. These bar charts were created in SPSS. Visual representations of mean OLBI scores within each cluster were generated, including error bars to show variations in the data.

Logistic Regression Analysis

Once grouping participants into clusters was completed, logistic regression was conducted to see if belonging to a specific cluster was associated with treatment response. Reliable improvement was defined as the primary outcome, coded as a binary variable. To check whether participants met the criteria for reliable improvement, participants were classified based on the magnitude of change in their OLBI scores from baseline to the post-treatment assessment. The reliable change index (RCI) for the present sample was calculated following the guidelines by Jacobson and Truax (1992), using the pre-treatment sample standard deviation and Cronbach's alpha as an index of reliability, yielding a RCI value. We completed a reliability analysis on SPSS using all OLBI baseline items. The Cronbach's alpha value was 0.82, indicating good consistency and reliability between items. The standard deviation (SD) of the total OLBI score at week 0 was then calculated, which was 5.87. Both of these values were added into an online RCI calculator (Evans, 2023), which gave an RCI value of 6.94. This meant a for a person's burnout score change to count as real clinical improvement, rather than normal fluctuations, they had to improve by least 7 points. Next, a change score variable was made by taking OLBI week 6 scores away from week 0 scores. Participants then needed to be classified into two groups to change the change score into a binary variable: if someone's score improved by less than 6.94 points, they were classed as 0 (no reliable improvement), and if they improved by 6.95 points or more, they were classed as 1 (reliable improvement).

Odds ratios and statistical significance were examined to interpret the results. The logistic regression analysis was conducted using IBM SPSS.

Cross-Validation

To assess the generalisability and replicability of findings, the SOM model was trained in the dataset for UpLift1 and tested in a second dataset (UpLift Trial 2), following an external cross-validation approach. This process meant sorting participants from the test sample (UpLift2) into burnout subtypes using the same SOM algorithm developed in the training sample (UpLift1),and running the logistic regression analysis again. The consistency of cluster patterns were compared as well as their ability to predict treatment response, to check if the findings were consistent across different groups. The aim of this was to test how well the prediction model works at classifying burnout subtypes.

Exploratory Analysis

Additional analyses were done to investigate the relationship between variables such as age and gender and treatment outcome. A Logistic Regression model was used to examine whether these personal characteristics were associated with post-treatment reliable improvement.

Results

Clustering of Participants into Burnout Subtypes

SOM was used to identify distinct subgroups of participants with similar burnout symptom patterns based on their responses to the OLBI questionnaire.

Two alternative SOM model-training approaches were applied, in order to select the one which offered better goodness-of-fit indices (guided by the silhouette index). An exponential model resulted in 63 clusters. A linear model resulted in 12

subtypes. Overall, goodness-of-fit indices were similar for both options, so we retained the most parsimonious and interpretable option (linear model). The silhouette measure was used to assess how assess how well-separated the clusters were from each other, on a scale from -1 (poor separation) to +1 (complete separation). The silhouette index of cluster separation for the trained SOM model was 0.1. Each of the 12 different burnout subtypes had different levels of severity and different patterns of symptoms. To visualize these subtypes, bar charts were created to show differences in mean burnout severity across each subgroup with error bars at 95% confidence intervals (see figures 1-12).

Figure 1

Cluster 1 mean OLBI item scores at baseline

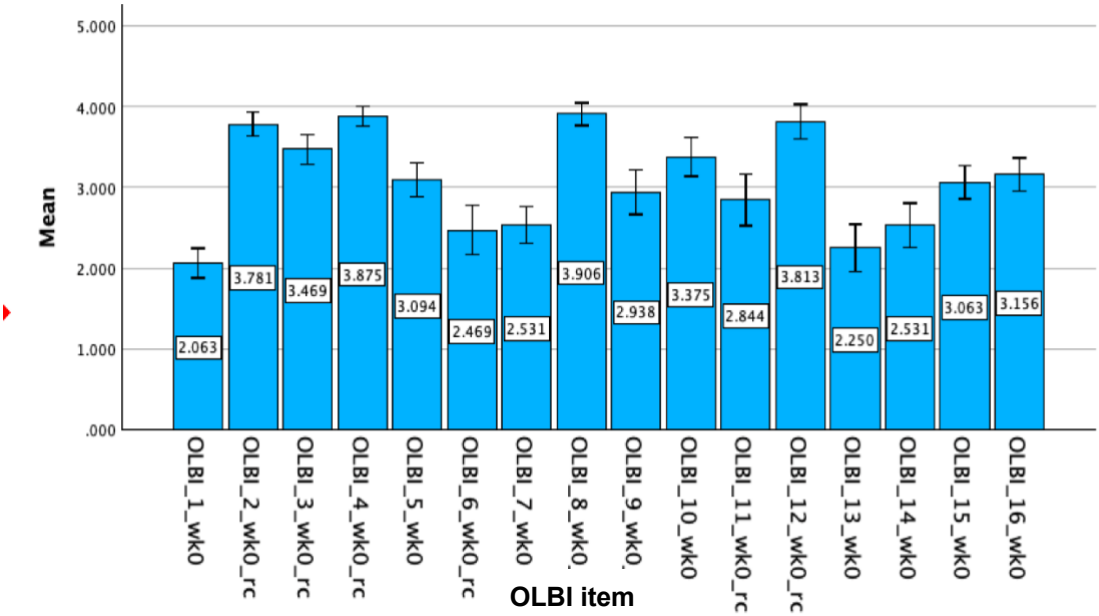


Figure 2

Cluster 2 mean OLBI item scores at baseline

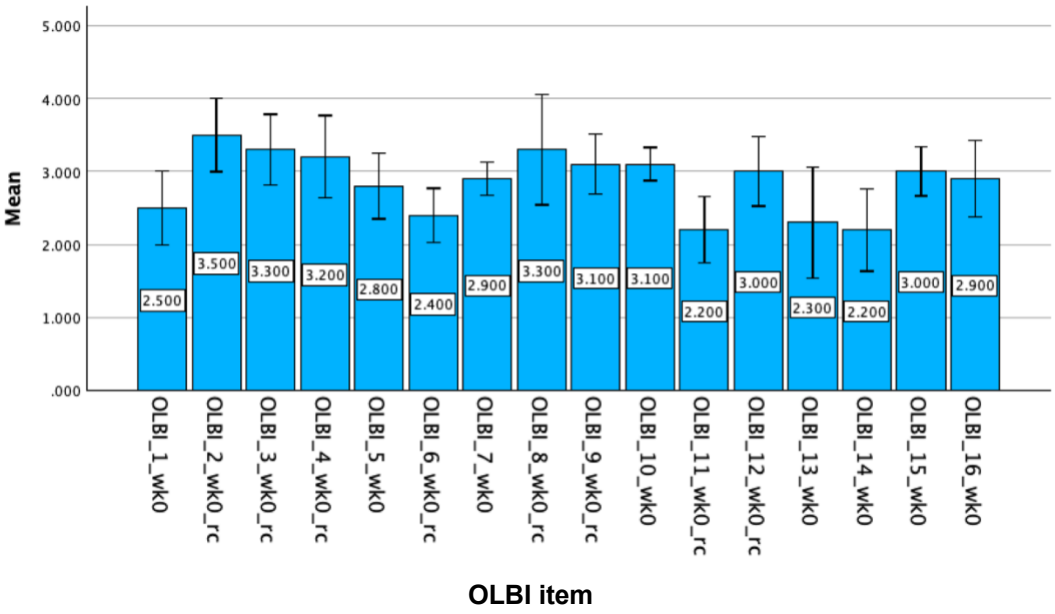


Figure 3

Cluster 3 mean OLBI item scores at baseline

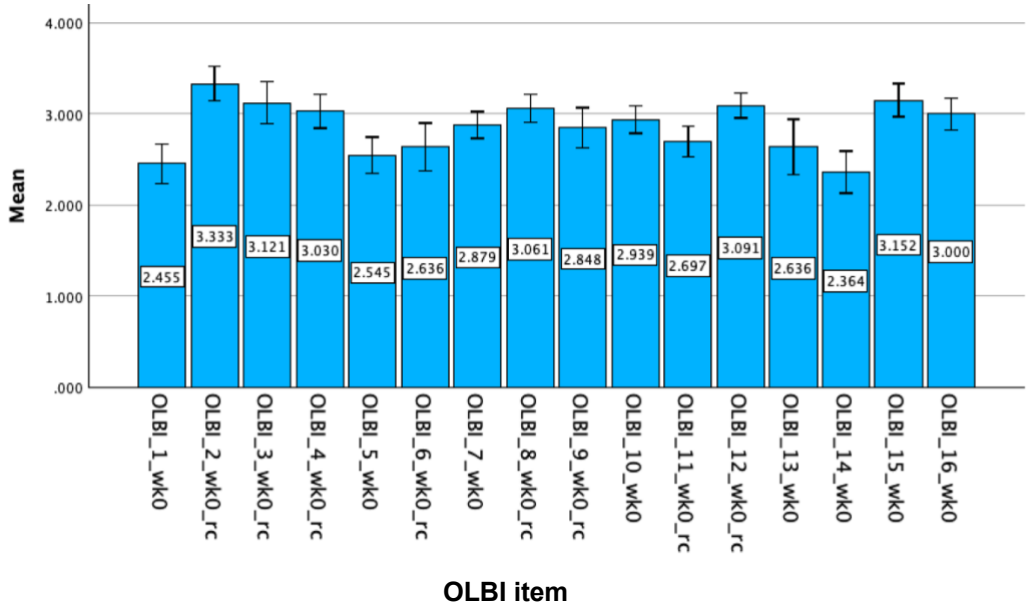


Figure 4

Cluster 4 mean OLBI item scores at baseline

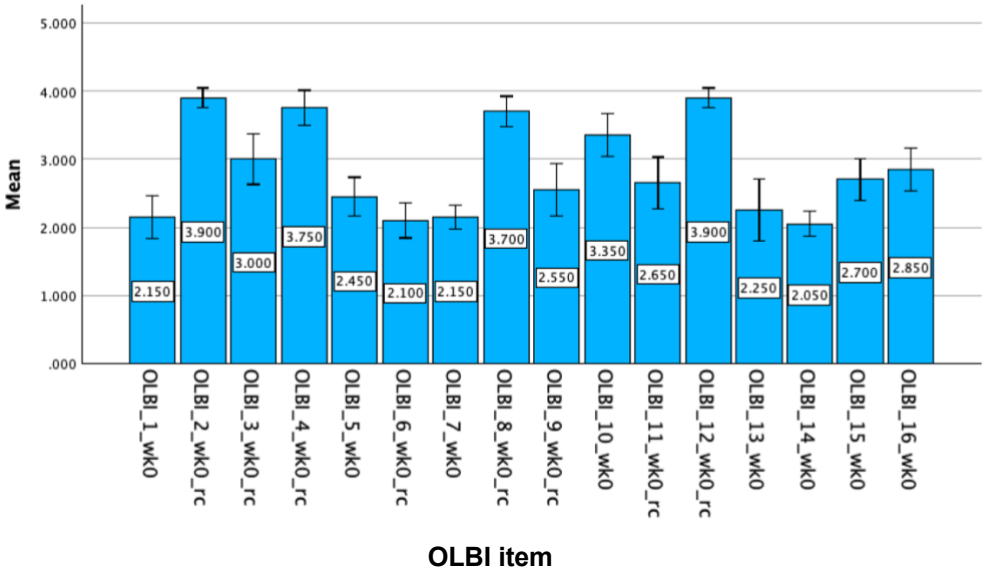


Figure 5

Cluster 5 mean OLBI item scores at baseline

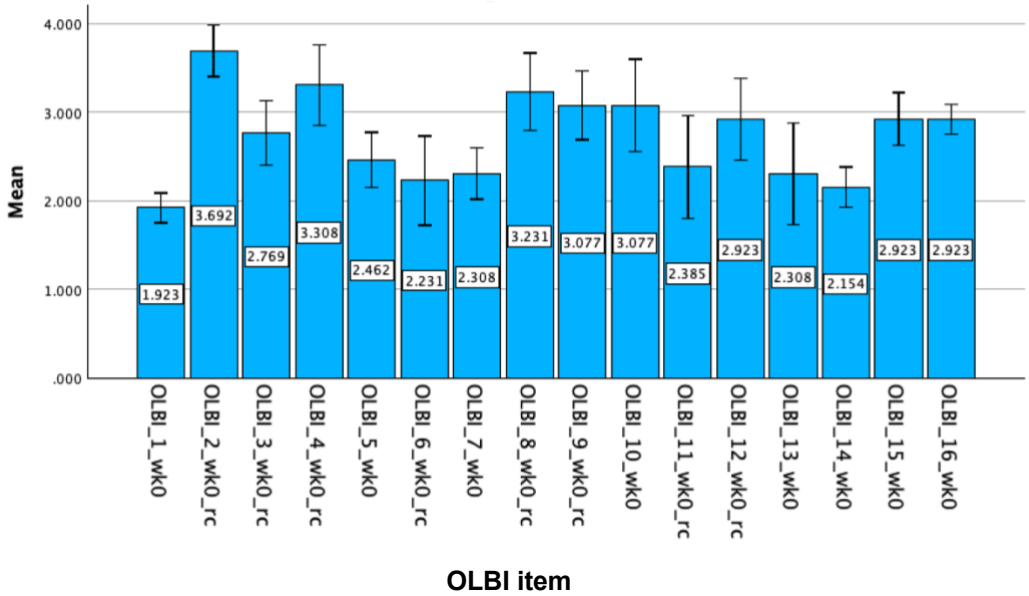


Figure 6

Cluster 6 mean OLBI item scores at baseline

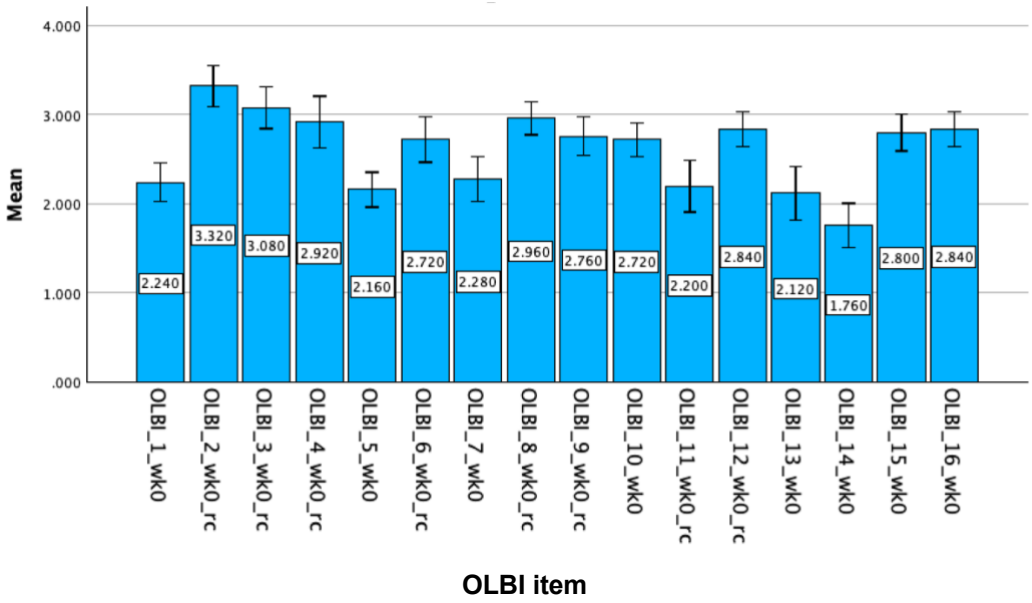


Figure 7

Cluster 7 mean OLBI item scores at baseline

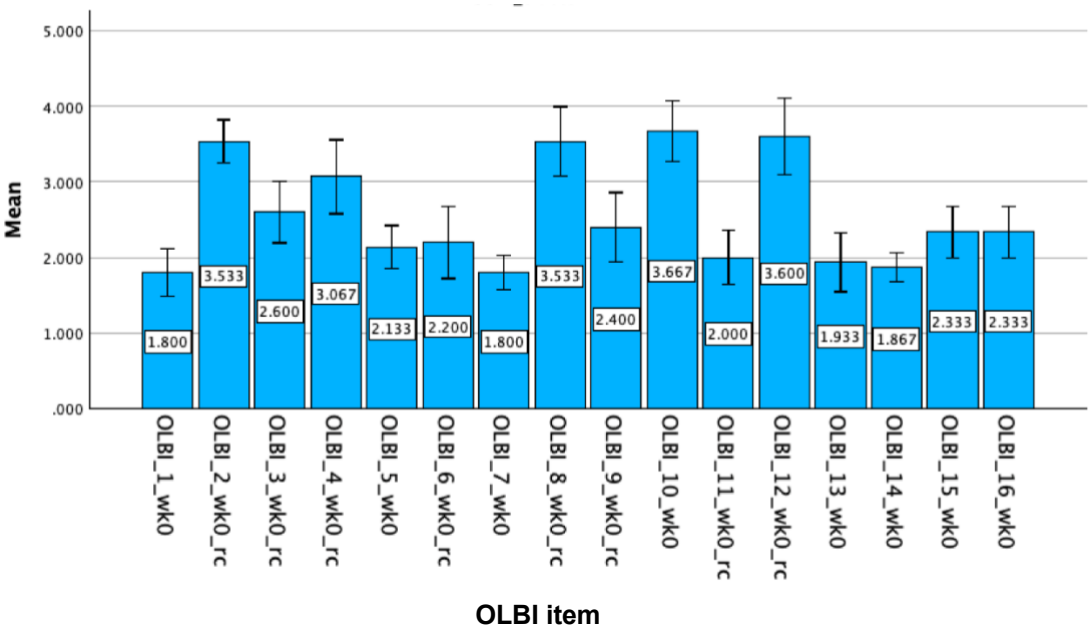


Figure 8

Cluster 8 mean OLBI item scores at baseline

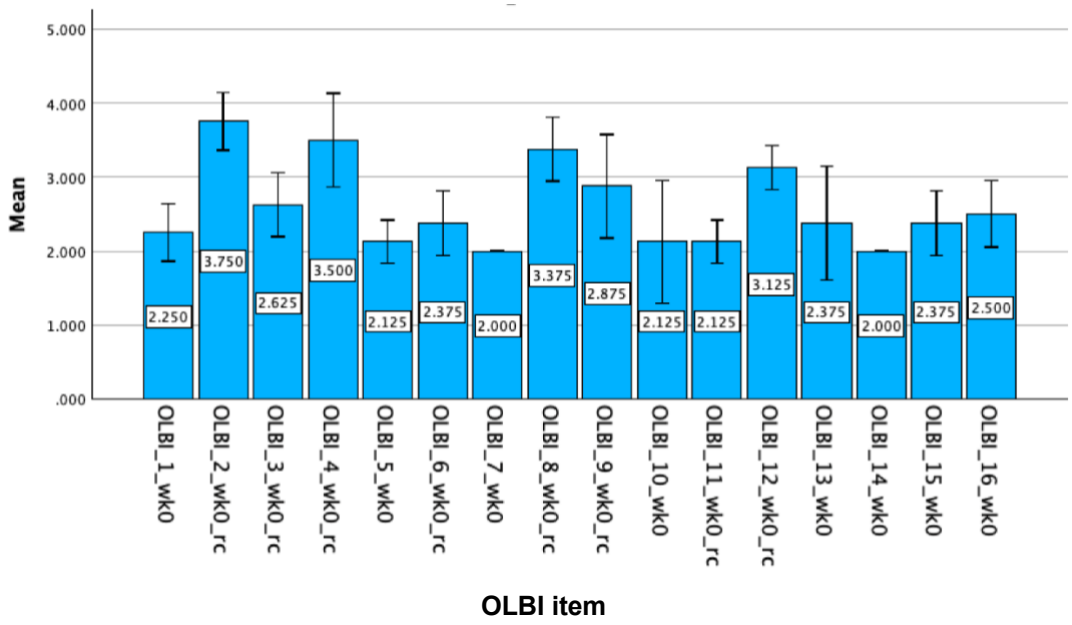


Figure 9

Cluster 9 mean OLBI item scores at baseline

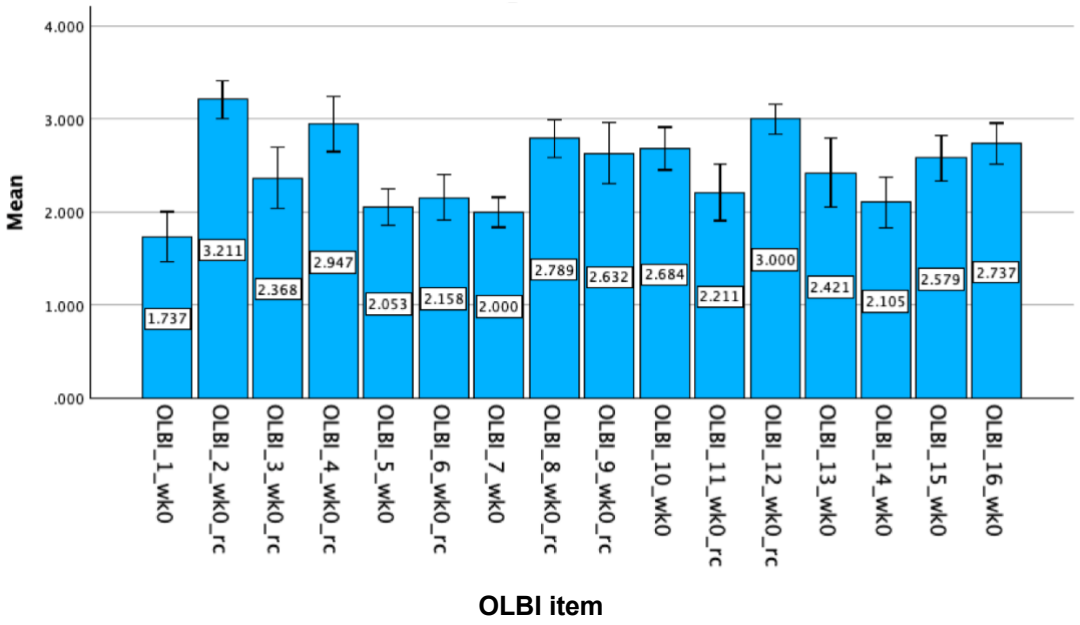


Figure 10

Cluster 10 mean OLBI item scores at baseline

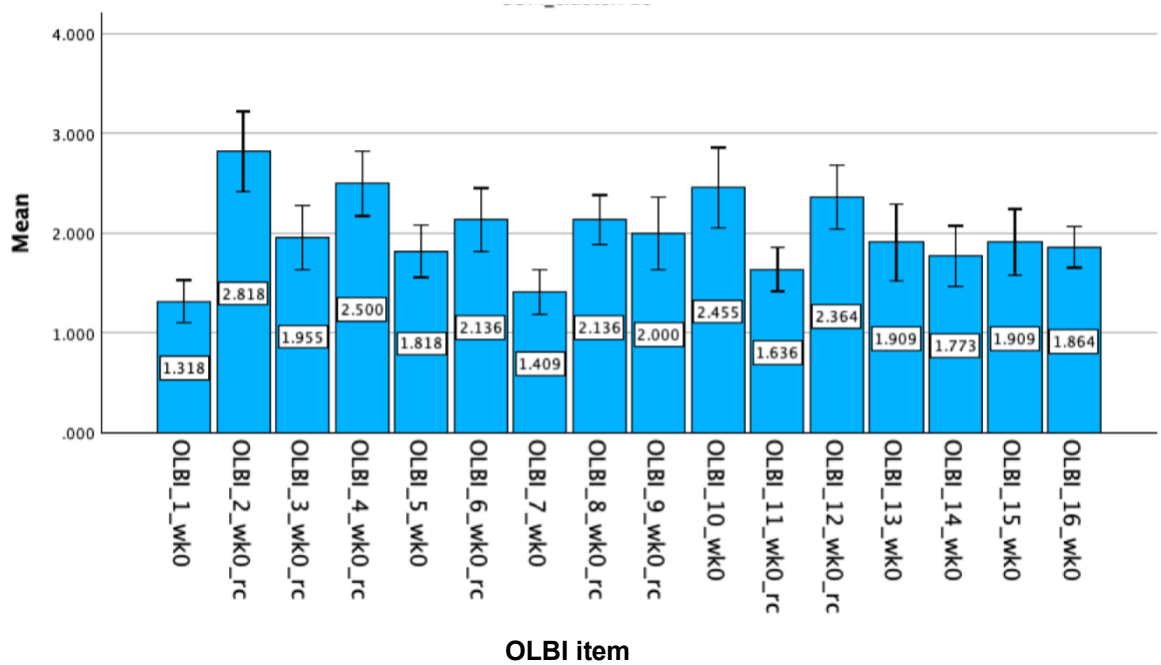


Figure 11

Cluster 11 mean OLBI item scores at baseline

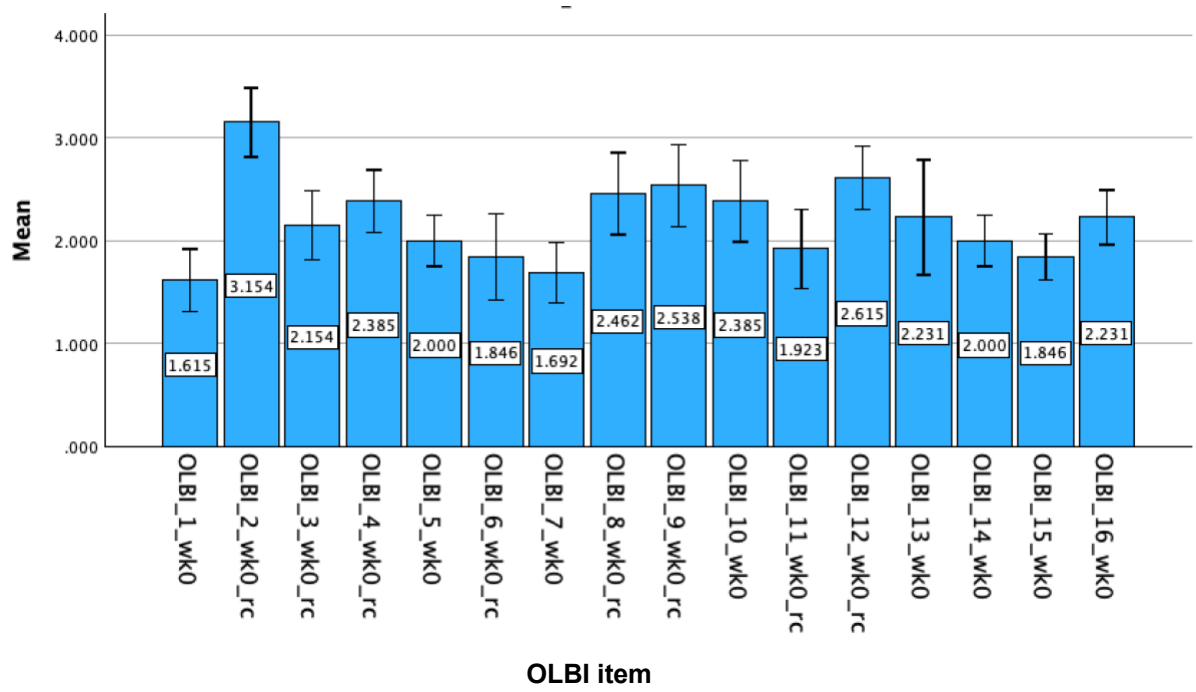


Figure 12

Cluster 12 mean OLBI item scores at baseline

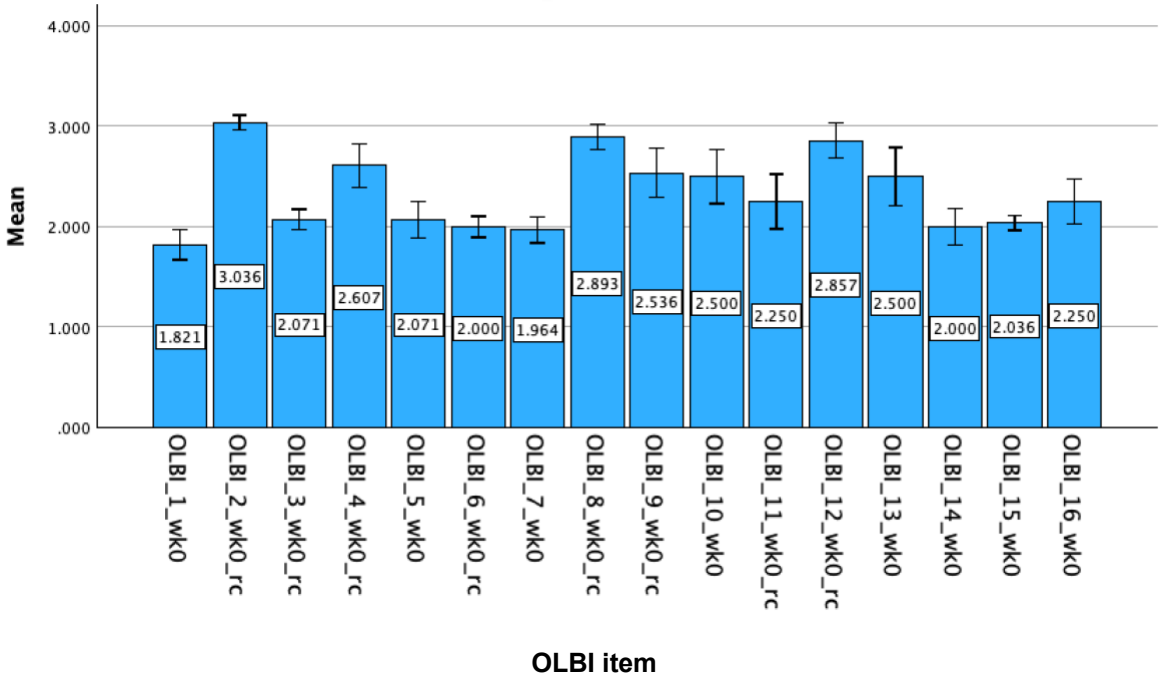


Table 3

Burnout Cluster Descriptives (Training Sample - UpLift Trial 1)

Cluster	Percentage of Training Sample (n)	OLBI Week 0 Mean (SD)	Minimum Score	Maximum Score
1	13.4% (32)	49.16 (3.30)	42	55
2	4.2% (10)	45.70 (4.37)	38	54
3	13.9% (33)	45.79 (2.39)	43	52
4	8.4% (20)	45.50 (2.70)	41	52
5	5.5% (13)	43.69 (2.90)	40	52
6	10.5% (25)	41.72 (2.37)	37	46
7	6.3% (15)	40.80 (3.71)	30	47
8	3.4% (8)	41.50 (2.27)	37	44
9	8.0% (19)	39.63 (1.92)	35	43
10	9.2% (22)	32.00 (5.17)	17	40
11	5.5% (13)	35.08 (2.30)	31	38
12	11.8% (28)	37.40 (1.83)	35	43

Table 3 shows descriptives for each burnout cluster. The overall sample mean (OLBI week 0) was 41.87 (SD = 5.87), indicating quite high variability, meaning there was a wide spread of burnout levels across participants. Each cluster had a unique pattern of burnout symptoms. Cluster 10, which included 9.2% of the sample, had the

lowest burnout levels, with a mean OLBI score of 32 (SD = 5.17). Participants in this cluster reported very little exhaustion and disengagement and also had the best treatment outcome. Most of the people in this group achieved reliable improvement. Cluster 10's mean is one SD below the sample mean, meaning members of Cluster 10 were outliers, reporting mild burnout, which may explain why they achieved the best outcomes.

Burnout severity can be categorized into three levels: low burnout (scores of 43 or below), moderate burnout (scores between 44 and 51), and high burnout (scores of 52 or higher) (Leclercq et al., 2021). Research suggests that a score of 44 or above is the clinical cutoff for burnout, based on large-scale studies (Leclercq et al., 2021; Tipa et al., 2019). Using these categories, Clusters 10, 11, 12, 9, 8, and 7 had low burnout, with average scores below 44. Clusters 6, 5, 4, 3, and 2 fell in the moderate burnout range, scoring between 44 and 51.

Cluster 2, which included 4.2% of the participants, had a mean OLBI score of 45.70 (SD = 4.37), placing it in the moderate burnout category. Meanwhile, Cluster 6, which included 10.5% of the sample, reported low burnout levels with a mean OLBI score of 41.72 (SD = 2.37). Cluster 1 had an average score of 49.16, placing it at the higher end of the moderate range, with some individuals in this group reaching the high-burnout threshold. While no cluster had an average score in the high burnout range (52 or above), the variation in scores within clusters suggests that some individuals, especially in Cluster 1, may have experienced clinically significant burnout.

Cross-Validation

To assess the generalisability of the burnout subtypes from the training sample, the clustering process was repeated and applied to an independent test dataset. This

sample included participants from the UpLift Trial 2. The overall sample mean was 41.79 (6.44). The percentages of participants assigned to each cluster in the test sample were similar to the proportions observed in the training sample, which reinforced the conclusion that the subtypes were generalisable. he distribution of participants across clusters was highly similar between the training and test samples, and the mean baseline burnout scores for each cluster remained consistent across both datasets (see Table 4), which further suggested the identified burnout profiles were consistent.

Table 4

Cluster Composition and Baseline OLBI Scores in Training and Test Samples

Cluster	Training Sample % (n)	Test Sample % (n)	OLBI Week 0 Mean (SD) Training	OLBI Week 0 Mean (SD) Test
1	13.4% (32)	12.2% (29)	49.16 (3.30)	52.07 (4.28)
2	4.2% (10)	5.5% (13)	45.70 (4.37)	47.63 (2.45)
3	13.9% (33)	14.3% (34)	45.79 (2.39)	45.38 (2.36)
4	8.4% (20)	9.7% (23)	45.50 (2.70)	45.50 (2.07)
5	5.5% (13)	3.8% (9)	43.69 (2.90)	45.00 (2.83)

6	10.5% (25)	8.8% (21)	41.72 (2.37)	42.88 (2.89)
7	6.3% (15)	5.5% (13)	40.80 (3.71)	43.50 (2.08)
8	3.4% (8)	2.5% (6)	41.50 (2.27)	43.25 (1.26)
9	8.0% (19)	7.6% (18)	39.63 (1.92)	39.88 (1.67)
10	9.2% (22)	9.2% (22)	32.00 (5.17)	31.50 (3.69)
11	5.5% (13)	3.8% (9)	35.08 (2.30)	35.27 (4.13)
12	11.8% (28)	17.2% (41)	37.40 (1.83)	37.48 (3.34)

Relationship Between Cluster Membership and Outcome

Based on the reliable change classification, descriptive statistics were completed, which found that only 32 of 238 participants (around 13%) had reliably improved, suggesting that the intervention was not very effective as most people didn't actually benefit from it. A binary logistic regression was then carried out to examine if different burnout subtypes influenced how people responded to the JC treatment. The dependent variable was a binary indicator for reliable improvement. The main predictor was the cluster group each participant belonged to. Initially, cluster 12 was taken as the reference category in the logistic regression model. In a subsequent regression model, additional covariates, such as baseline severity (based on OLBI

scores) age, gender, job role, ethnicity, and number of working hours, were also included in the analysis to adjust for confounders.

In the first model, shown in Table 6, none of the SOM clusters were statistically significant predictors of treatment response (all of the p-values were > .05), relative to the reference category. This suggests that there were no systematic differences in treatment response when comparing participants with different burnout subtypes.

The logistic regression output for cluster membership is shown below in Table 5.

Table 5

Partial logistic regression output showing clusters

Cluster	B	df	*p*	Odds ratio	95% C.I. for Odds ratio	
					Lower	Upper
SOM cluster		11	.589			
SOM Cluster 1	-.274	1	.926	.761	.002	241.260
SOM Cluster 2	2.310	1	.424	10.076	.035	2914.610
SOM Cluster 3	-.463	1	.855	.629	.004	90.132
SOM Cluster 4	-1.107	1	.715	.331	.001	124.343
SOM Cluster 5	1.268	1	.641	3.552	.017	729.808
SOM Cluster 6	1.967	1	.500	7.150	.024	2169.823
SOM Cluster 7	1.098	1	.680	7.150	.024	2169.823
SOM Cluster 8	-18.616	1	.999	.000	.000	.
SOM Cluster 9	3.943	1	.124	51.559	.339	7850.425

SOM Cluster 10	-17.564	1	.998	.000	.000	.
SOM Cluster 11	-32.390	1	.998	.000	.000	.

Exploratory Analyses: Baseline Severity and Demographics

The same binary logistic regression analysis was also used to explore whether baseline burnout severity (OLBI total at week 0), age, gender, job role, ethnicity, and working hours could predict treatment outcome, with response to treatment as the dependent variable. See appendix table (appendix D) containing the full logistic regression coefficients for all predictors. Among these variables, baseline severity (OLBI_total_wk0) was the only variable which significantly predicted treatment response (B = .322, SE = .153, *p* = .035), with people with higher initial burnout scores being more likely to show reliable improvement after JC. The odds ratio (ExpB) for baseline OLBI score was Exp(B) = 1.28. This tells us that for each additional point on the OLBI scale, there is 28% higher probability that person will achieve reliable improvement. The beta coefficient (B = 0.246) was positive, indicating that people with higher levels of burnout at the start of the intervention were more likely to improve from it.

Older participants were slightly less likely to improve however this was not statistically significant (B = –.068, p = .124). Job role had 77 categories, and some job roles appeared to have large effect sizes however none of them were statistically significant. This may have been due to each role only containing a small number of participants. Many of the roles had wide coefficient values (confidence intervals) and big standard errors, so these results should be considered with caution. Gender,

ethnicity, and working hours did not significantly predictors reliable improvement either.

The logistic regression model output gave a Nagelkerke R^2 of 0.752, showing that the model explained approximately 75% of the variation in who did or didn't reach reliable improvement, which is a strong overall fit.

Discussion

Support of Original Hypotheses

This study supports the first hypothesis that burnout does not affect everyone the same way and can appear in different subtypes. Using SOM, twelve clusters in both the training and test datasets were identified. Each cluster had different mean burnout subtypes at baseline. The test dataset had similar means across clusters when compared to the training dataset, showing they may be generalisable to other NHS professionals. These results support the idea that burnout is experienced in different ways.

The second hypothesis was that different burnout subtype would meaningly influence the likelihood of reliable improvement after the JC intervention. This study did not support hypothesis. When the logistic regression was completed, the results showed that none of the clusters were significantly associated with better outcomes. These results suggest that burnout subtype (as defined by cluster) alone does not predict the likelihood of reliable improvement after the JC intervention.

Interpretation of Results

The logistic regression model found that cluster membership was not predictive of treatment response when controlling for relevant factors. This indicated that overall

burnout subtype was not a reliable independent predictor of who reliably improved with JC.

Instead, it appeared that different responses might be due to other variables. In particular, baseline burnout severity was the strongest and only significant predictor of JC outcome. People who had higher levels of burnout at the start of the intervention tended to be more likely to achieve reliable improvement, regardless of other factors. One interpretation of this finding could be people with more sever initial symptoms having higher potential for a bigger change in scores. Another explanation could be the regression to the mean statistical effect where extremely low or high scores (eg severe burnout levels at baseline) move closer to the mean when measured again after the intervention. This can make it falsely look like someone improved when it might not actually be because of the intervention.

On the other hand, demographic characterises such as age, gender, job role, working hours and ethnicity were not reliable indicators of treatment outcome – they did not have a statistically significant effect on outcomes. This concludes that the differences in demographic variables did not influence a treatment response difference in this dataset.

Regarding the magnitude of effect size, only 13% of participants who received JC met reliable improvement (≥7-point OLBI reduction) after 6 weeks. This conservative outcome is valuable (it filters small random fluctuations), but it also means that not many people actually reached this level of improvement, which limits power and increases uncertainty in multivariable models. Descriptively, averages improved in both trials, and in UpLift2 the JC group had better outcomes than the waitlist group, however, when looking at clinically reliable change, the overall effect

size was quite small. There are a couple of likely explanations. Firstly, JC may deliver gradual benefits over six weeks that build up slowly over time. Second, part of the improvement for people who started with high baseline scores might be regression to the mean. Future research could test where extending the JC intervention over a longer period, implementing more support from managers, or also making organisational changes would increase the number of people who reliably improved.

Comparison to Previous Research

The results of this study add to previous literature examining the difficulties with reducing burnout, especially in healthcare staff. Existing meta-analyses have concluded that individual- and organisational-level interventions can be helpful, however outcomes are usually small and results vary depending on the context. For example, one study found burnout interventions including individual strategies (like CBT and mindfulness) and wider system changes (such as schedule reforms) can lead to small improvements in physician burnout, however effects were not statistically significant (West et al., 2016).

Similarly, Lee et al. (2016) found that CBT reduced burnout in nurse especially reducing emotional exhaustion, with results lasting at follow up. However broader studies have questioned whether these improvements last over time. Morse et al. (2012) reviewed studies with mental health professionals and found that lasting effects were inconclusive, highlighting that burnout is complex and has many contributing factors.

Previous literature suggests that that different components of burnout respond to different types of interventions. Dreison et al. (2018) and Shin et al. (2014) found that emotional exhaustion and depersonalisation improved the most with stress

management and emotion-focused strategies whereas personal accomplishment increased more when the intervention involved job redesign or practical problem-solving—supporting the idea that job crafting can help people find more meaning and control at work.

Additionally, organisational strategies may be more effective than individual approaches. Panagioti et al. (2017) and Busireddy et al. (2017) both concluded that interventions at the system level—such as improving leadership, reducing workload, or enhancing team functioning – had better outcomes than individual approaches alone. However, they also noted that there are barriers to these approaches, for example reducing working hours in healthcare setting would be difficult to do, meaning these solutions would not be feasible in high-demand settings.

The current study builds on existing research by demonstrating that burnout does not affect everyone in the same way even within similar burnout symptoms. Burnout clusters did not significantly predict treatment outcomes.

Strengths and Limitations

One of the main strengths of this study is the use of SOM clustering, which is a novel machine learning method which allows for burnout profiles to be found based on the data itself, without relying on pre-determined cut-offs or assumptions. Additionally, demographic, occupational factors were integrated into the predictive analysis, meaning a more accurate understanding of what factors may influence treatment outcomes.

A key strength of this study is how it measured improvement. Instead of just looking at small simple changes in OLBI scores, it looked at reliable improvement as the outcome measure. Occupational burnout can vary naturally from week to week

depending on work demands, which means small changes might not mean anything and are difficult to interpret. Therefore, by calculating and using the RCI of 7 points instead, it ensured that this study focused on meaningful clinical change, not just random ups and downs. This increased the validity and interpretability of the findings.

However, this study also has some limitations. The data may be affected by response bias, participants' expectations or understanding, as it was all gathered via self-report questionnaires. Also although the OLBI is a well-validated measure, it only records key dimensions of burnout, which may not reflect the full range of people's psychological or occupational experiences. Although the sample was diverse regarding age and ethnicity, etc, it only included NHS staff so may not be generalizable to other healthcare settings, such as in the private sector or healthcare systems in other countries.

Furthermore, another possible bias in clustering results is that unsupervised models such as SOM may sometimes detect patterns that are not clinically meaningful as they might instead pick superficial aspects of the measurement tool (eg whther the questions are worded positively or negatively). These might alter clusters rather than actual burnout symptom differences. This may be related to common method bias, where the way data is collected can create artificial patterns in results (Podsakoff et al., 203). This study used standardised data and validated clusters across two samples to try to reduce this effect however some of the cluster structures could still reflect these artefacts instead of clear clinical subtypes. The low silhouette suggests that some detected structure may reflect method effects rather than clinically distinct subtypes.

Moreover, another challenge of this study is how to interpret the characteristics of each SOM cluster, as the SOM method identifies patterns within the data but it doesn't assign clear psychological labels for each cluster. Also overall OLBI means were similar across each cluster and visual inspection of the mean OLBI item scores across clusters showed some similar patterns, no formal comparison of profiles was made. Future research could consider conducting analyses such as profile similarity analysis or centroid matching to check whether cluster subtypes really replicate across different samples.

Lastly, there are many factors which could play a role in JC success which were not measured, for example team dynamics and supportiveness, leadership style, or workplace culture.

Clinical Implications

The results of this study found that people's baseline burnout severity is the strongest and most reliable predictor of whether or not they will benefit from JC. This finding has important implications for how burnout interventions are designed and delivered in NHS settings.

Results found that it may not be useful to tailoring interventions based on burnout subtypes or demographic factors like age, gender, ethnicity, or job role as these were not linked were not significantly linked to reliable improvement in this analysis. Instead, it may be better or services to focus on how burnt out someone is before starting the intervention. For example, routinely using validated measures like the OLBI before treatment could help identify people who need the most help and may benefit the most. People with higher baseline burnout severity were more likely to reliably improve. This could be due to genuine recovery or because they had more

room to improve or due to regression to the mean. Whatever the reason, it seems these people may benefit more from early and targeted support.

If future research finds more clearly separated and stable burnout subtypes, they could have clinical implications. They could inform assessment prompts (eg it might be helpful to ask people about their meaning/purpose at work if they show high disengagement and help them with this). Different parts of the JC intervention could be focused on more for different subtypes. (eg. People who don't get on with their colleagues could do more of the 'improving workplace relationships'). Additionaly employees with more high-risk subtypes could be offered more intensive intervention (eg more JC or extra support and supervision from managers). Given clusters in this study were not very distinct, these ideas should be seen as early possibilities for future research and generating hypotheses rather than actionable guidance to be applied in practice right now.

Although previous research has suggested that job role and demographic variables could affect intervention outcomes, the present findings suggest that these factors don't make a statically significant difference on their own. Therefore, a more simple streamlined model based on burnout severity may be more effective in the NHS where time and resources are limited. Giving people with more severe burnout more detailed or longer JC interventions could improve its efficiency and impact.

In clinical practice, JC should still be used as a flexible, skills-based intervention. However, it may work more efficiently if services asses baseline burnout assessments and integrate this to adjust the intensity, duration, or type of intervention. Tailoring based on occupational or demographic characteristics might be helpful in

some cases however results from this study show that maybe it should not be the main focus when deciding how to offer interventions.

Conclusion

To conclude, this study shows that baseline severity is the most important factor in whether they get better with job crafting. People who started off more burnt out were more likely to see a reliable improvement. Other factors such as age, job role, or what type of burnout they had didn’t make a significant difference to the outcome. This means services should focus less on trying to group people by burnout type or background, and more on using burnout severity scores to decide who might benefit most from support. By doing this, help can be given more quickly and effectively to those who need it most.

References

Alzubi, J., Nayyar, A., & Kumar, A. (2018, November). Machine learning from theory to algorithms: An overview. *Journal of physics: conference series*, 1142, 012012. https://doi.org/10.1088/1742-6596/1142/1/012012

Bruning, P. F., & Campion, M. A. (2018). A role–resource approach–avoidance model of job crafting: A multimethod integration and extension of job crafting theory. *Academy of Management Journal, 61*(2), 499–522. https://doi.org/10.5465/amj.2015.0604

Busireddy, K. R., Miller, J. A., Ellison, K., Ren, V. J., Qayyum, R., & Panda, M. (2017). Efficacy of interventions to reduce resident physician burnout: A systematic review. *Journal of Graduate Medical Education*, *9*(3), 294–301. https://doi.org/10.4300/JGME-D-16-00372.1

Collins, G. S., Reitsma, J. B., Altman, D. G., & Moons, K. G. (2015). Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. *Journal of British Surgery, 102*(3), 148-158. https://doi.org/10.1111/1471-0528.13244

Davis, B. (2020). *An exploration of risk factors and consequences of occupational burnout in mental health professionals* (Doctoral dissertation, University of Sheffield).

De Hert, S. (2020). Burnout in healthcare workers: prevalence, impact and preventative strategies. *Local and regional anesthesia,* 13, 171-183. https://doi.org/10.2147/LRA.S240564

Delgadillo, J., Laker, V., Simmonds-Buckley, M., Davis, B., Furlong-Silva, J., Keeble, S., Davis, O., Southgate, A., Royal, P., Lucock, M., Booth, L., Nyamadzawo, E., Booth, G., Ludbrook, J., McDonagh, M., Webb, C., & Thwaites, R. (2025). Randomised controlled trial of job crafting as a digital health intervention for occupational burnout in psychological therapists. Submitted.

Delgadillo, J., Laker, V., Simmonds-Buckley, M., Southgate, A., Parkhouse, L., Davis, B., Furlong-Silva, J., King, N., Keeble, S., Davis, O., Royal, P., Lucock, M., Aguirre, E., Thwaites, R., Flint, B., Osborne, T., Bell, F., Devon, M., & Barkham, M. (2025). Digital health interventions for occupational burnout in healthcare professionals: a multi-site randomised controlled trial. Submitted.

Demerouti, E. (1999). *Burnout: Eine Folge konkreter Arbeitsbedingungen bei Dienstleistungsund Produktionstätigkeiten [Burnout: A consequence of specific working conditions among human services, and production tasks].* Peter Lang.

Demerouti, E., & Nachreiner, F. (1998). Zur Spezifität von Burnout für Dienstleistungsberufe: Fakt oder Artefakt [The specificity of burnout for human services: Fact or artifact]. *Zeitschrift für arbeitswissenschaft,* 52, 82-89.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The Job Demands–Resources model of burnout. *Journal of Applied Psychology*, *86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499

Demerouti, E., Bakker, A. B., Vardakou, I., & Kantas, A. (2003). The convergent validity of two burnout instruments: A multitrait-multimethod analysis. *European Journal of Psychological Assessment, 19*(1), 12–23. https://doi.org/10.1027//1015-5759.19.1.12

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

Dreison, K. C., Luther, L., Bonfils, K. A., Sliter, M. T., McGrew, J. H., & Salyers, M. P. (2018). Job burnout in mental health providers: A meta-analysis of 35 years of intervention research. *Journal of Occupational Health Psychology*, *23*(1), 18–30. https://doi.org/10.1037/ocp0000047

Drummond, D. (2015). Physician burnout: its origin, symptoms, and five main causes. *Family practice management*, *22*(5), 42-47.

Dyrbye, L. N., Shanafelt, T. D., Sinsky, C. A., Cipriano, P. F., Bhatt, J., Ommaya, A., ... & Meyers, D. (2017). Burnout among health care professionals: a call to explore and address this underrecognized threat to safe, high-quality care. *NAM perspectives*.

Dyrbye, L. N., Thomas, M. R., Massie, F. S., Power, D. V., Eacker, A., Harper, W., Durning, S., Moutier, C., Satele, D., Sloan, J., & Shanafelt, T. D. (2008). Burnout and suicidal ideation among U.S. medical students. *Annals of internal medicine,* 149(5), 334–341. https://doi.org/10.7326/0003-4819-149-5-200809020-00008

Evans, C. (2023, September 17). *Compute RCI from SD and reliability*. PSYCTC.org. Retrieved April 17, 2024, from https://shiny.psyctc.org/apps/RCI1/

Frederick, D. E., & VanderWeele, T. J. (2020). Longitudinal meta-analysis of job crafting shows positive association with work engagement. *Cogent Psychology, 7*(1). https://doi.org/10.1080/23311908.2020.1746733

Garcia, C. L., Abreu, L. C., Ramos, J. L. S., Castro, C. F. D., Smiderle, F. R. N., Santos, J. A. D., & Bezerra, I. M. P. (2019). Influence of burnout on patient safety: Systematic review and meta-analysis. *Medicina (Kaunas, Lithuania), 55*(9), 553. https://doi.org/10.3390/medicina55090553

Halbesleben, J. R. B., & Demerouti, E. (2005). The construct validity of an alternative measure of burnout: Investigating the English translation of the Oldenburg Burnout Inventory. *Work & Stress, 19*(3), 208–220. https://doi.org/10.1080/02678370500340728

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., Trockel, M., Goh, J., … West, C. P. (2019). Estimating the attributable cost of physician burnout in the United States. *Annals of internal medicine,* 170(11), 784–790. https://doi.org/10.7326/M18-1422

Hsieh, F. Y., Bloch, D. A., & Larsen, M. D. (1998). A simple method of sample size calculation for linear and logistic regression. *Statistics in medicine*, 17(14), 1623–1634. https://doi.org/10.1002/(SICI)1097-0258(19980730)17:14<1623::AID-SIM871>3.0.CO;2-S

Innstrand S. T. (2016). Occupational differences in work engagement: A longitudinal study among eight occupational groups in Norway. Scandinavian Journal of Psychology, 57(4), 338–349. https://doi.org/10.1111/sjop.12298

Izdebski, Z., Kozakiewicz, A., Białorudzki, M., Dec-Pietrowska, J., & Mazur, J. (2023). Occupational burnout in healthcare workers, stress and other symptoms of work overload during the COVID-19 pandemic in Poland. *International journal*

of environmental research and public health, 20(3), 2428. https://doi.org/10.3390/ijerph20032428

Jacobson, N. S., & Truax, P. (1992). Clinical significance: A statistical approach to defining meaningful change in psychotherapy research. In A. E. Kazdin (Ed.), *Methodological issues & strategies in clinical research* (pp. 631–648). American psychological association. https://doi.org/10.1037/10109-042

Jacobson, N. S., W. C. Follette, & D. Revenstorf (1984). Psychotherapy outcome research: Methods for reporting variability and evaluating clinical significance. *Behavior therapy,* 15(4), 336–352. https://doi.org/10.1016/S0005-7894(84)80002-7

Johnson, J., Hall, L. H., Berzins, K., Baker, J., Melling, K., & Thompson, C. (2018). Mental healthcare staff well-being and burnout: A narrative review of trends, causes, implications, and recommendations for future interventions. *International journal of mental health nursing,* 27(1), 20–32. https://doi.org/10.1111/inm.12416

Johnson, J., Louch, G., Dunning, A., Johnson, O., Grange, A., Reynolds, C., Hall, L., & O'Hara, J. (2017). Burnout mediates the association between depression and patient safety perceptions: A cross-sectional study in hospital nurses. *Journal of advanced nursing*, *73*(7), 1667-1680. https://doi.org/10.1111/jan.13251

Kappelmann, N., Rein, M., Fietz, J., Mayberg, H. S., Craighead, W. E., Dunlop, B. W., ... & Kopf-Beck, J. (2020). Psychotherapy or medication for depression? Using individual symptom meta-analyses to derive a Symptom-Oriented Therapy (SOrT) metric for a personalised psychiatry. *BMC medicine*, *18*(1), 170.

Kohonen, T. (1981). *Construction of similarity diagrams for phonemes by a self-organizing algorithm.* Teknillinen korkeakoulu.

Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biol cybern,* 43(1), 59–69. https://doi.org/10.1007/BF00337288

Kohonen, T. (2001). Self-Organizing Maps . 30 in Springer Series in Information Sciences.

Lamers, F., de Jonge, P., Nolen, W. A., Smit, J. H., Zitman, F. G., Beekman, A. T., & Penninx, B. W. (2010). Identifying depressive subtypes in a large cohort study: results from the Netherlands Study of Depression and Anxiety (NESDA). *The Journal of clinical psychiatry*, *71*(12), 1582–1589.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer publishing company.

Lee, H. F., Kuo, C. C., Chien, T. W., & Wang, Y. R. (2016). A meta-analysis of the effects of coping strategies on reducing nurse burnout. *Applied Nursing Research*, *31*, 100–110. https://doi.org/10.1016/j.apnr.2016.01.001

Maslach, C. (2003). *Burnout: The cost of caring*. Ishk.

Maslach, Christina, and Susan E. Jackson. "The measurement of experienced burnout." Journal of organizational behavior 2.2 (1981): 99-113. https://doi.org/10.1002/job.4030020205

Millar, H. L. (2019). The UK NHS Experience of Burnout: Time for Action. *International journal of person centered medicine,* 9(3), 7-18. https://doi.org/10.5750/ijpcm.v9i3.994

Morse, G., Salyers, M. P., Rollins, A. L., Monroe-DeVita, M., & Pfahler, C. (2012). Burnout in mental health services: A review of the problem and its remediation. *Administration and Policy in Mental Health and Mental Health Services Research*, *39*, 341–352. https://doi.org/10.1007/s10488-011-0352-1

Nakamura, J., & Csikszentmihalyi, M. (2009). Flow theory and research. *Handbook of positive psychology*, *195*, 206.

Ogunsuji, O., Ogundipe, H., Adebayo, O., Oladehin, T., Oiwoh, S., Obafemi, O., Soneye, O., Agaja, O., Uyilawa, O., Efuntoye, O., Alatishe, T., Williams, A., Ilesanmi, O., & Atilola, O. (2022). Internal reliability and validity of Copenhagen Burnout Inventory and Oldenburg Burnout Inventory compared with Maslach Burnout Inventory among Nigerian resident doctors: A pilot study. *Dubai Medical Journal,* *5(*2), 89–95. https://doi.org/10.1159/000521376

Panagioti, M., Panagopoulou, E., Bower, P., Lewith, G., Kontopantelis, E., Chew-Graham, C., Dawson, S., van Marwijk, H., Geraghty, K., & Esmail, A. (2017). Controlled interventions to reduce burnout in physicians: A systematic review and meta-analysis. *JAMA Internal Medicine*, *177*(2), 195–205. https://doi.org/10.1001/jamainternmed.2016.7674

Prieto, M. S., & Allen, A. R. (2009). Using self-organising maps in the detection and recognition of road signs. *Image and vision computing*, *27*(6), 673-683. https://doi.org/10.1016/j.imavis.2008.07.006

Reis, C., Tecedeiro, M., Pellegrino, P., Paiva, T., & Marôco, J. P. (2021). Psychometric Properties of the Oldenburg Burnout Inventory in a Portuguese Sample of

Aircraft Maintenance Technicians. Frontiers in Psychology, 12, 725099. https://doi.org/10.3389/fpsyg.2021.725099

Reis, D., Xanthopoulou, D., & Tsaousis, I. (2015). Measuring job and academic burnout with the Oldenburg Burnout Inventory (OLBI): Factorial invariance across samples and countries. Burnout Research, 2(1), 8-18. https://doi.org/10.1016/j.burn.2014.11.001

Robertson, R., Wenzel, L., Thompson, J., & Charles, A. (2017). Understanding NHS financial pressures. *How are they affecting patient care.* The King's Fund.

Rotenstein, L. S., Brown, R., Sinsky, C., & Linzer, M. (2023). The Association of Work Overload with Burnout and Intent to Leave the Job Across the Healthcare Workforce During COVID-19. *Journal of general internal medicine*, 1-8. https://doi.org/10.1007/s11606-023-08153-z

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of research and development*, *3*(3), 210-229. https://doi.org/10.1147/rd.33.0210

Schneider, B. (1987). The people make the place. Personnel psychology, 40(3), 437-453. https://doi.org/10.1111/j.1744-6570.1987.tb00609.x

Shanafelt, T. D., Balch, C. M., Dyrbye, L., Bechamps, G., Russell, T., Satele, D., Rummans, T., Swartz, K., Novotny, P. J., Sloan, J., & Oreskovich, M. R. (2011). Special report: suicidal ideation among American surgeons. *Archives of surgery*, *146*(1), 54-62. https://doi.org/10.1001/archsurg.2010.292

Shanafelt, T. D., Boone, S., Tan, L., Dyrbye, L. N., Sotile, W., Satele, D., West, C. P., Sloan, J., & Oreskovich, M. R. (2012). Burnout and satisfaction with work-life balance among US physicians relative to the general US population. *Archives of internal medicine*, *172*(18), 1377-1385. https://doi.org/10.1001/archinternmed.2012.3199

Shanafelt, T. D., Bradley, K. A., Wipf, J. E., & Back, A. L. (2002). Burnout and self-reported patient care in an internal medicine residency program. *Annals of internal medicine*, *136*(5), 358-367. https://doi.org/10.7326/0003-4819-136-5-200203050-00008

Shin, H., Park, Y. M., Ying, J. Y., Kim, B., Noh, H., & Lee, S. M. (2014). Relationships between coping strategies and burnout symptoms: A meta-analytic approach. *Professional Psychology: Research and Practice*, *45*(1), 44–56. https://doi.org/10.1037/a0035220

Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. *Journal of occupational health psychology, 1*(1), 27. https://doi.org/10.1037/1076-8998.1.1.27

Sinsky, C. A., Dyrbye, L. N., West, C. P., Satele, D., Tutty, M., & Shanafelt, T. D. (2017). Professional satisfaction and the career plans of US physicians. Mayo Clinic Proceedings, 92(11), 1625–1635. https://doi.org/10.1016/j.mayocp.2017.08.017

Sinsky, C. A., Shanafelt, T. D., Dyrbye, L. N., Sabety, A. H., Carlasare, L. E., & West, C. P. (2022). Health care expenditures attributable to primary care physician

overall and burnout-related turnover: A cross-sectional analysis. *Mayo Clinic Proceedings*, *97*(4), 693–702. https://doi.org/10.1016/j.mayocp.2021.09.013

Sinval, J., Queirós, C., Pasian, S., & Marôco, J. (2019). Transcultural Adaptation of the Oldenburg Burnout Inventory (OLBI) for Brazil and Portugal. *Frontiers in Psychology, 10,* 338. https://doi.org/10.3389/fpsyg.2019.00338

Smout, M. (2024). *A pragmatic pilot study of the feasibility of a common factors supervision intervention not embedded in a training program for improving confidence, burnout, and client outcomes of psychologists in routine private practice.* (Unpublished Manuscript).

Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *South African Journal of Industrial Psychology*, *36*(2), 1–9. https://doi.org/10.4102/sajip.v36i2.841

Tran, K. T., Nguyen, P. V., Dang, T. T., & Ton, T. N. (2018). The impacts of the high-quality workplace relationships on job performance: A perspective on staff nurses in Vietnam. *Behavioral sciences*, *8*(12), 109. https://doi.org/10.3390/bs8120109

UpLift Trial Research Team. (2023a). *Digital health interventions for occupational burnout in healthcare professionals: a multisite, open-label, randomised controlled trial*. UpLift Trial 1, Research Ethics Committee Reference: 20/EM/0236 (in preparation for publication).

UpLift Trial Research Team. (2023b). *Clinical trial of job crafting for occupational burnout in psychological therapists.* UpLift Trial 2, Research Ethics Committee Reference: 21/EM/0206 (in preparation for publication).

Lamers, F., de Jonge, P., Nolen, W. A., Smit, J. H., Zitman, F. G., Beekman, A. T., & Penninx, B. W. (2010). Identifying depressive subtypes in a large cohort study: results from the Netherlands Study of Depression and Anxiety (NESDA). *The Journal of clinical psychiatry*, *71*(12), 1582–1589.

Webb, C. A., Trivedi, M. H., Cohen, Z. D., Dillon, D. G., Fournier, J. C., Goer, F., ... & Pizzagalli, D. A. (2019). Personalized prediction of antidepressant v. placebo response: evidence from the EMBARC study. *Psychological medicine*, *49*(7), 1118-1127.

West, C. P., Dyrbye, L. N., Erwin, P. J., & Shanafelt, T. D. (2016). Interventions to prevent and reduce physician burnout: A systematic review and meta-analysis. *The Lancet*, *388*(10057), 2272–2281. https://doi.org/10.1016/S0140-6736(16)31279-X

Woo, T., Ho, R., Tang, A., & Tam, W. (2020). Global prevalence of burnout symptoms among nurses: A systematic review and meta-analysis. *Journal of psychiatric research*, *123*, 9-20. https://doi.org/10.1016/j.jpsychires.2019.12.015

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review*, *26*(2), 179–201. https://doi.org/10.5465/amr.2001.4378011

Appendices

Appendix A

Ethical Approval Letter

The University Of Sheffield.

Downloaded: 08/06/2025
Approved: 21/02/2024

Aaminah Aqeel
Registration number: 220238018
Psychology
Programme: Doctorate in Clinical Psychology

Dear Aaminah

PROJECT TITLE: Do NHS staff with different occupational burnout profiles respond differently to a Job Crafting intervention?
APPLICATION: Reference Number 058364

This letter confirms that you have signed a University Research Ethics Committee-approved self-declaration to confirm that your research will involve only existing research, clinical or other data that has been robustly anonymised. You have judged it to be unlikely that this project would cause offence to those who originally provided the data, should they become aware of it.

As such, on behalf of the University Research Ethics Committee, I can confirm that your project can go ahead on the basis of this self-declaration.

If during the course of the project you need to deviate significantly from the above-approved documentation please inform me since full ethical review may be required.

Yours sincerely

Department Of Psychology Research Ethics Committee
Departmental Ethics Administrator

Appendix B

TRIPOD Checklist

TRIPOD+AI

Version: 11-January-2024

Section/Topic	Item	Development / evaluation[1]	Checklist item	Reported on page
TITLE				
Title	1	D;E	Identify the study as developing or evaluating the performance of a multivariable prediction model, the target population, and the outcome to be predicted	Page 76
ABSTRACT				
Abstract	2	D;E	See TRIPOD+AI for Abstracts checklist	Page 77-79
INTRODUCTION				
Background	3a	D;E	Explain the healthcare context (including whether diagnostic or prognostic) and rationale for developing or evaluating the prediction model, including references to existing models	Page 80-81
	3b	D;E	Describe the target population and the intended purpose of the prediction model in the context of the care pathway, including its intended users (e.g., healthcare professionals, patients, public)	Page 80-83
	3c	D;E	Describe any known health inequalities between sociodemographic groups	N/A
Objectives	4	D;E	Specify the study objectives, including whether the study describes the development or validation of a prediction model (or both)	Page 84
METHODS				
Data	5a	D;E	Describe the sources of data separately for the development and evaluation datasets (e.g., randomised trial, cohort, routine care or registry data), the rationale for using these data, and representativeness of the data	Page 85-88
	5b	D;E	Specify the dates of the collected participant data, including start and end of participant accrual; and, if applicable, end of follow-up	Page 86
Participants	6a	D;E	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including the number and location of centres	Page 85-86
	6b	D;E	Describe the eligibility criteria for study participants	Page 86-87
	6c	D;E	Give details of any treatments received, and how they were handled during model development or evaluation, if relevant	Page 88-89
Data preparation	7	D;E	Describe any data pre-processing and quality checking, including whether this was similar across relevant sociodemographic groups	Page 95
Outcome	8a	D;E	Clearly define the outcome that is being predicted and the time horizon, including how and when assessed, the rationale for choosing this outcome, and whether the method of outcome assessment is consistent across sociodemographic groups	Page 89-91
	8b	D;E	If outcome assessment requires subjective interpretation, describe the qualifications and demographic characteristics of the outcome assessors	N/A
	8c	D;E	Report any actions to blind assessment of the outcome to be predicted	N/A
Predictors	9a	D	Describe the choice of initial predictors (e.g., literature, previous models, all available predictors) and any pre-selection of predictors before model building	Page 95-97
	9b	D;E	Clearly define all predictors, including how and when they were measured (and any actions to blind assessment of predictors for the outcome and other predictors)	Page 95-97 Appendix C
	9c	D;E	If predictor measurement requires subjective interpretation, describe the qualifications and demographic characteristics of the predictor assessors	N/A
Sample size	10	D;E	Explain how the study size was arrived at (separately for development and evaluation), and justify that the study size was sufficient to answer the research question. Include details of any sample size calculation	Page 94
Missing data	11	D;E	Describe how missing data were handled. Provide reasons for omitting any data	Page 95
Analytical methods	12a	D	Describe how the data were used (e.g., for development and evaluation of model performance) in the analysis, including whether the data were partitioned, considering any sample size requirements	Page 95-97
	12b	D	Depending on the type of model, describe how predictors were handled in the analyses (functional form, rescaling, transformation, or any standardisation).	Page 95-97
	12c	D	Specify the type of model, rationale[2], all model-building steps, including any hyperparameter tuning, and method for internal validation	Page 95-97
	12d	D;E	Describe if and how any heterogeneity in estimates of model parameter values and model performance was handled and quantified across clusters (e.g., hospitals, countries). See TRIPOD-Cluster for additional considerations[3]	Page 95-97
	12e	D;E	Specify all measures and plots used (and their rationale) to evaluate model performance (e.g., discrimination, calibration, clinical utility) and, if relevant, to compare multiple models	Page 95-97
	12f	E	Describe any model updating (e.g., recalibration) arising from the model evaluation, either overall or for particular sociodemographic groups or settings	N/A
	12g	E	For model evaluation, describe how the model predictions were calculated (e.g., formula, code, object, application programming interface)	Page 95-97
Class imbalance	13	D;E	If class imbalance methods were used, state why and how this was done, and any subsequent methods to recalibrate the model or the model predictions	N/A
Fairness	14	D;E	Describe any approaches that were used to address model fairness and their rationale	N/A
Model output	15	D	Specify the output of the prediction model (e.g., probabilities, classification). Provide details and rationale for any classification and how the thresholds were identified	Page 95-97

TRIPOD+AI

Version: 11-January-2024

Training versus evaluation	16	D;E	Identify any differences between the development and evaluation data in healthcare setting, eligibility criteria, outcome, and predictors	N/A
Ethical approval	17	D;E	Name the institutional research board or ethics committee that approved the study and describe the participant-informed consent or the ethics committee waiver of informed consent	Page 85
OPEN SCIENCE				
Funding	18a	D;E	Give the source of funding and the role of the funders for the present study	Page ii
Conflicts of interest	18b	D;E	Declare any conflicts of interest and financial disclosures for all authors	Page ii
Protocol	18c	D;E	Indicate where the study protocol can be accessed or state that a protocol was not prepared	N/A
Registration	18d	D;E	Provide registration information for the study, including register name and registration number, or state that the study was not registered	N/A
Data sharing	18e	D;E	Provide details of the availability of the study data	Page ii
Code sharing	18f	D;E	Provide details of the availability of the analytical code[4]	Page ii
PATIENT & PUBLIC INVOLVEMENT				
Patient & Public Involvement	19	D;E	Provide details of any patient and public involvement during the design, conduct, reporting, interpretation, or dissemination of the study or state no involvement.	Page 85
RESULTS				
Participants	20a	D;E	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	Page 91-92
	20b	D;E	Report the characteristics overall and, where applicable, for each data source or setting, including the key dates, key predictors (including demographics), treatments received, sample size, number of outcome events, follow-up time, and amount of missing data. A table may be helpful. Report any differences across key demographic groups.	Page 92-93
	20c	E	For model evaluation, show a comparison with the development data of the distribution of important predictors (demographics, predictors, and outcome).	N/A
Model development	21	D;E	Specify the number of participants and outcome events in each analysis (e.g., for model development, hyperparameter tuning, model evaluation)	Page 91-92
Model specification	22	D	Provide details of the full prediction model (e.g., formula, code, object, application programming interface) to allow predictions in new individuals and to enable third-party evaluation and implementation, including any restrictions to access or re-use (e.g., freely available, proprietary)[5]	Page 99-103
Model performance	23a	D;E	Report model performance estimates with confidence intervals, including for any key subgroups (e.g., sociodemographic). Consider plots to aid presentation.	Page 102-103
	23b	D;E	If examined, report results of any heterogeneity in model performance across clusters. See TRIPOD Cluster for additional details[3].	N/A
Model updating	24	E	Report the results from any model updating, including the updated model and subsequent performance	N/A
DISCUSSION				
Interpretation	25	D;E	Give an overall interpretation of the main results, including issues of fairness in the context of the objectives and previous studies	Page 109-113
Limitations	26	D;E	Discuss any limitations of the study (such as a non-representative sample, sample size, overfitting, missing data) and their effects on any biases, statistical uncertainty, and generalizability	Page 115-116
Usability of the model in the context of current care	27a	D	Describe how poor quality or unavailable input data (e.g., predictor values) should be assessed and handled when implementing the prediction model	N/A
	27b	D	Specify whether users will be required to interact in the handling of the input data or use of the model, and what level of expertise is required of users	N/A
	27c	D;E	Discuss any next steps for future research, with a specific view to applicability and generalizability of the model	Page 116-117

Appendix C
OLBI measure

oldenburg burnout inventory

name: *date:*

Instructions: Below you find a series of statements with which you may agree or disagree. Using the scale, please indicate the degree of your agreement by selecting the number that corresponds with each statement.

		strongly agree	*agree*	*disagree*	*strongly disagree*
1.	I always find new and interesting aspects in my work *(D)*	*1*	*2*	*3*	*4*
2.	There are days when I feel tired before I arrive at work *(E.R.)*	*1*	*2*	*3*	*4*
3.	It happens more and more often that I talk about my work in a negative way *(D.R)*	*1*	*2*	*3*	*4*
4.	After work, I tend to need more time than in the past in order to relax and feel better *(E.R)*	*1*	*2*	*3*	*4*
5.	I can tolerate the pressure of my work very well *(E)*	*1*	*2*	*3*	*4*
6.	Lately, I tend to think less at work and do my job almost mechanically *(D.R)*	*1*	*2*	*3*	*4*
7.	I find my work to be a positive challenge *(D)*	*1*	*2*	*3*	*4*
8.	During my work, I often feel emotionally drained *(E.R.)*	*1*	*2*	*3*	*4*
9.	Over time, one can become disconnected from this type of work *(D.R)*	*1*	*2*	*3*	*4*
10.	After working, I have enough energy for my leisure activities *(E)*	*1*	*2*	*3*	*4*
11.	Sometimes I feel sickened by my work tasks *(D.R)*	*1*	*2*	*3*	*4*
12.	After my work, I usually feel worn out and weary *(E.R)*	*1*	*2*	*3*	*4*
13.	This is the only type of work that I can imagine myself doing *(D)*	*1*	*2*	*3*	*4*
14.	Usually, I can manage the amount of my work well *(E)*	*1*	*2*	*3*	*4*
15.	I feel more and more engaged in my work *(D)*	*1*	*2*	*3*	*4*
16.	When I work, I usually feel energized *(E)*	*1*	*2*	*3*	*4*

Note: Disengagement items are 1, 3(R), 6(R), 7, 9(R), 11(R), 13, 15. Exhaustion items are 2(R), 4(R), 5, 8(R), 10, 12(R), 14, 16. (R) means reversed item when the scores should be such that higher scores indicate more burnout.

disengagement sub-total: ***exhaustion sub-total:*** ***full scale total:***

Delgadillo et al (2018) reported "Therapists are identified as having low, medium or high OLBI-D scores, based on scores above or below 1 standard deviation of the mean (M = 2.15, SD = 0.52; ≤1.62 = low, 1.63 to 2.67 = medium, ≥2.68 = high)."

Appendix *D*

Full logistic regression coefficients for all predictors.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	SOM_cluster			9.352	11	.589			
	SOM_cluster(1)	-.274	2.939	.009	1	.926	.761	.002	241.260
	SOM_cluster(2)	2.310	2.892	.638	1	.424	10.076	.035	2914.610
	SOM_cluster(3)	-.463	2.533	.033	1	.855	.629	.004	90.132
	SOM_cluster(4)	-1.107	3.025	.134	1	.715	.331	.001	124.343
	SOM_cluster(5)	1.268	2.717	.218	1	.641	3.552	.017	729.808
	SOM_cluster(6)	1.967	2.916	.455	1	.500	7.150	.024	2169.823
	SOM_cluster(7)	1.098	2.661	.170	1	.680	2.998	.016	551.673
	SOM_cluster(8)	-18.616	20768.995	.000	1	.999	.000	.000	.
	SOM_cluster(9)	3.943	2.564	2.364	1	.124	51.559	.339	7850.425
	SOM_cluster(10)	-17.564	7343.676	.000	1	.998	.000	.000	.
	SOM_cluster(11)	-32.390	14204.025	.000	1	.998	.000	.000	.
	OLBI_total_wk0_imputed_v7	.322	.153	4.425	1	.035	1.380	1.022	1.864
	age_v7	-.068	.044	2.363	1	.124	.935	.857	1.019
	Gender(1)	-19.221	9249.069	.000	1	.998	.000	.000	.
	Ethnicity			.455	12	1.000			
	Ethnicity(1)	.870	3.236	.072	1	.788	2.388	.004	1358.147
	Ethnicity(2)	-4.580	41243.425	.000	1	1.000	.010	.000	.
	Ethnicity(3)	-.723	2.316	.097	1	.755	.485	.005	45.466
	Ethnicity(4)	26.578	42984.804	.000	1	1.000	348933481600.039	.000	.
	Ethnicity(5)	-1.019	2.044	.248	1	.618	.361	.007	19.841
	Ethnicity(6)	-21.689	52745.935	.000	1	1.000	.000	.000	.

Ethnicity(7)	-.573	40858.346	.000	1	1.000	.564	.000	.
Ethnicity(8)	3.367	41243.425	.000	1	1.000	28.997	.000	.
Ethnicity(9)	-20.423	40192.970	.000	1	1.000	.000	.000	.
Ethnicity(10)	17.049	18258.018	.000	1	.999	25361763.099	.000	.
Ethnicity(11)	21.958	40192.969	.000	1	1.000	3437907904.132	.000	.
Ethnicity(12)	15.640	42628.971	.000	1	1.000	6200902.822	.000	.
Job Role			6.698	76	1.000			
Job Role(1)	-19.862	17668.586	.000	1	.999	.000	.000	.
Job Role(2)	-19.557	40192.970	.000	1	1.000	.000	.000	.
Job Role(3)	-18.553	23707.395	.000	1	.999	.000	.000	.
Job Role(4)	-19.598	40192.970	.000	1	1.000	.000	.000	.
Job Role(5)	1.872	2.422	.598	1	.439	6.503	.056	748.696
Job Role(6)	-19.233	40192.970	.000	1	1.000	.000	.000	.
Job Role(7)	-20.877	27459.038	.000	1	.999	.000	.000	.
Job Role(8)	1.069	2.023	.279	1	.597	2.913	.055	153.569
Job Role(9)	21.068	42803.800	.000	1	1.000	1411652132.736	.000	.
Job Role(10)	-2.141	41243.425	.000	1	1.000	.118	.000	.
Job Role(11)	-21.181	40192.970	.000	1	1.000	.000	.000	.
Job Role(12)	-17.086	20770.547	.000	1	.999	.000	.000	.
Job Role(13)	-16.491	25444.322	.000	1	.999	.000	.000	.
Job Role(14)	1.155	40858.346	.000	1	1.000	3.175	.000	.
Job Role(15)	-22.127	12110.874	.000	1	.999	.000	.000	.
Job Role(16)	-20.477	16761.188	.000	1	.999	.000	.000	.
Job Role(17)	4.242	2.660	2.544	1	.111	69.534	.379	12767.801
Job Role(18)	27.717	935310.855	.000	1	1.000	1089434468540.046	.000	.
Job Role(19)	-20.103	40192.970	.000	1	1.000	.000	.000	.
Job Role(20)	23.732	40192.969	.000	1	1.000	20255435867.973	.000	.
Job Role(21)	-17.825	24127.370	.000	1	.999	.000	.000	.

	Job Role(22)	-18.104	40192.970	.000	1	1.000	.000	.000	.
	Job Role(23)	-1.077	45241.861	.000	1	1.000	.341	.000	.
	Job Role(24)	-21.508	40192.970	.000	1	1.000	.000	.000	.
	Job Role(26)	29.455	41892.120	.000	1	.999	6195474053270.594	.000	.
	Job Role(27)	1.290	1.831	.496	1	.481	3.632	.100	131.443
	Job Role(28)	1.837	1.536	1.431	1	.232	6.278	.309	127.329
	Job Role(29)	-19.995	23747.554	.000	1	.999	.000	.000	.
	Job Role(30)	-19.744	40192.970	.000	1	1.000	.000	.000	.
	Job Role(31)	17.981	42628.971	.000	1	1.000	64411079.548	.000	.
	Job Role(32)	-21.634	40192.970	.000	1	1.000	.000	.000	.
	Job Role(33)	2.104	1.988	1.120	1	.290	8.195	.167	403.085
	Job Role(34)	1.649	1.443	1.305	1	.253	5.201	.307	88.045
	Job Role(35)	-20.424	40192.970	.000	1	1.000	.000	.000	.
	Job Role(36)	-17.461	40192.970	.000	1	1.000	.000	.000	.
	Job Role(37)	-24.903	10646.735	.000	1	.998	.000	.000	.
	Job Role(38)	-19.871	8332.239	.000	1	.998	.000	.000	.
	Job Role(39)	-17.363	27427.281	.000	1	.999	.000	.000	.
	Job Role(40)	-20.809	40192.970	.000	1	1.000	.000	.000	.
	Job Role(41)	-18.318	20383.425	.000	1	.999	.000	.000	.
	Job Role(42)	3.556	5.012	.503	1	.478	35.012	.002	646615.688
	Job Role(43)	-17.405	40192.970	.000	1	1.000	.000	.000	.
	Job Role(44)	-20.357	40192.970	.000	1	1.000	.000	.000	.
	Job Role(45)	.880	45241.861	.000	1	1.000	2.411	.000	.
	Job Role(46)	-21.184	10335.039	.000	1	.998	.000	.000	.
	Job Role(47)	-20.588	40192.970	.000	1	1.000	.000	.000	.
	Job Role(48)	-19.723	23726.309	.000	1	.999	.000	.000	.
	Job Role(49)	-.691	2.021	.117	1	.732	.501	.010	26.316
	Job Role(50)	1.539	2.918	.278	1	.598	4.662	.015	1419.408

	Job Role(51)	-.901	41243.425	.000	1	1.000	.406	.000	.
	Job Role(52)	-.595	1.426	.174	1	.676	.551	.034	9.026
	Job Role(53)	-2.890	41243.425	.000	1	1.000	.056	.000	.
	Job Role(54)	-19.445	26352.327	.000	1	.999	.000	.000	.
	Job Role(55)	-19.102	40192.970	.000	1	1.000	.000	.000	.
	Job Role(56)	-2.393	41243.425	.000	1	1.000	.091	.000	.
	Job Role(57)	-18.784	40192.970	.000	1	1.000	.000	.000	.
	Job Role(58)	-18.500	23831.096	.000	1	.999	.000	.000	.
	Job Role(59)	-20.659	40192.970	.000	1	1.000	.000	.000	.
	Job Role(60)	-16.201	25198.043	.000	1	.999	.000	.000	.
	Job Role(61)	-22.103	40192.970	.000	1	1.000	.000	.000	.
	Job Role(62)	-1.707	41243.425	.000	1	1.000	.181	.000	.
	Job Role(63)	-21.505	40192.970	.000	1	1.000	.000	.000	.
	Job Role(64)	-20.158	40192.970	.000	1	1.000	.000	.000	.
	Job Role(65)	-17.884	40192.970	.000	1	1.000	.000	.000	.
	Job Role(66)	-18.988	19126.677	.000	1	.999	.000	.000	.
	Job Role(67)	-17.590	28065.641	.000	1	.999	.000	.000	.
	Job Role(68)	1.528	1.583	.932	1	.334	4.609	.207	102.513
	Job Role(69)	-23.331	40192.970	.000	1	1.000	.000	.000	.
	Job Role(70)	-17.180	23515.997	.000	1	.999	.000	.000	.
	Job Role(71)	-19.835	40192.970	.000	1	1.000	.000	.000	.
	Job Role(72)	.803	1.924	.174	1	.676	2.232	.051	96.862
	Job Role(73)	17.756	10043.908	.000	1	.999	51456461.928	.000	.
	Job Role(74)	-17.829	40192.970	.000	1	1.000	.000	.000	.
	Job Role(75)	1.497	40858.346	.000	1	1.000	4.469	.000	.
	Job Role(76)	-20.232	40192.970	.000	1	1.000	.000	.000	.
	Job Role(77)	6.154	40858.346	.000	1	1.000	470.389	.000	.
	Working_hours_v7	.101	.075	1.822	1	.177	1.106	.955	1.281

Constant	-17.190	7.747	4.924	1	.026	.000		

a. Variable(s) entered on step 1: SOM_cluster, OLBI_total_wk0_imputed_v7, age_v7, Gender, Ethnicity, Job Role, Working_hours_v7.