Received: 14 May 2025 | Accepted: 22 April 2026

DOI: 10.1111/joop.70119

RESEARCH ARTICLE

the british psychological society
promoting excellence in psychology

Evaluating training-related changes in profiles of recovery experiences

Lisa Peuckmann | **Malte Friese** | **Dorota Reis**

Department of Psychology, Saarland University, Saarbrücken, Germany

Correspondence
Lisa Peuckmann, Department of Psychology, Saarland University, Campus A2.4, Saarbrücken 66123, Germany.
Email: lisa.peuckmann@uni-saarland.de

Funding information
Deutsche Forschungsgemeinschaft

Abstract

Recovery from work is associated with better work performance and employee well-being. Thus, it is important to investigate whether and how recovery training affects the multiple distinct recovery experiences (i.e., psychological detachment, relaxation, control and mastery). However, typical variable-centred approaches cannot detect training effects on the co-occurrence of multiple recovery experiences. By contrast, person-centred approaches, which focus on how individuals encounter different combinations (i.e., profiles) of recovery experiences, show promise for evaluating recovery training. We used data from a randomized controlled trial (N=393) to examine the impact of recovery training by investigating (1) how the number and shapes of profiles changed, (2) whether individuals transitioned between profiles of recovery experiences and (3) whether these transitions were associated with changes in well-being outcomes (i.e., sleep quality and perceived stress). Recovery profiles changed in structure from pre- to post-training, and participants who received training, in particular, transitioned to a profile with improved recovery experiences. Adaptive transition paths were partly associated with enhanced sleep quality and reduced stress. We found nuanced training effects among people and recovery experiences, implying that recovery training in practice should be tailored to person-specific assessments of all recovery experiences to identify deficient yet malleable experiences.

KEYWORDS

latent profile analysis, latent transition analysis, recovery, training

Practitioner points

- Person-centred methods for evaluating recovery training provide valuable insights into which groups of people and recovery experiences to include in training and which transition paths may be most promising for well-being.
- Profiles of recovery experiences changed after training, and people transitioned among profiles as a result of training.
- Adaptive transition paths were partly associated with improved well-being outcomes, namely, sleep quality and reduced perceived stress.

INTRODUCTION

Modern employees face persistent demands that can exhaust their resources and impair well-being (Bakker & Demerouti, 2007). Effective recovery from work is essential to counterbalance these effects (Headrick et al., 2022). Yet, paradoxically, people who would benefit most from recovery tend to engage less in recovery-enhancing activities, a phenomenon known as the recovery paradox (Sonnentag, 2018). Recovery training that actively equips individuals with skills to enhance their recovery (e.g., Hahn et al., 2011) is a promising avenue for addressing this paradox. However, to advance research on recovery training, two issues need to be addressed. First, training evaluations have predominantly relied on variable-centred approaches that examine average changes in isolated recovery experiences, thereby overlooking how patterns of co-occurring recovery experiences shift in response to training. A person-centred approach can address this gap by identifying profiles of recovery experiences and tracking transitions between these profiles over time. Second, it remains unclear whether and how recovery profiles change among individuals who actively seek out recovery training, a group that is particularly relevant from a practical standpoint.

In the present research, we combine a person-centred approach (latent transition analysis, LTA) with data from a randomized controlled trial (RCT) to examine training-related changes in recovery profiles among individuals who self-selected into training. Specifically, we investigate (1) whether the structure of recovery profiles changes from pre- to post-training, (2) whether individuals transition between profiles and (3) whether these transitions are associated with changes in well-being (i.e., perceived stress and sleep quality).

A person-centered perspective on recovery

To provide the necessary background for our research questions, we first review the conceptual foundations of recovery and the person-centred perspective, and then turn to the evaluation of recovery training. Recovery from work is a restoration process that alters strain indicators after job stressors (Sonnentag et al., 2017). Four experiences are commonly conceptualized as underlying recovery processes (Sonnentag et al., 2022; Sonnentag & Fritz, 2007). These experiences refer to the psychological states people are in during nonwork time. The experience of *psychological detachment* denotes the subjective experience of leaving work behind, effectively 'unplugging' from work during nonwork time (Sonnentag & Fritz, 2007). *Relaxation* refers to a state of low physiological arousal, for example, while lying down reading. The experience of *control* refers to the perceived autonomy to decide how to allocate one's nonwork time. *Mastery* experiences arise from engaging in challenging pursuits outside of work associated with a sense of accomplishment or growth, such as achieving athletic goals. All four recovery experiences are conceptualized as indicators of the overall recovery construct and are positively correlated (Sonnentag & Fritz, 2007), yet are conceptually and empirically distinguishable at both the individual (Sonnentag & Fritz, 2007) and daily level (Bakker et al., 2015).

Empirical research on recovery experiences predominantly relies on variable-centred approaches that examine recovery experiences in isolation or as an aggregate (e.g., Ebert et al., 2015; Halbesleben et al., 2013; ten Brummelhuis & Bakker, 2012; Wang & Hanges, 2011). These approaches identify presumably universal relationships among individuals (Woo et al., 2024) but cannot determine whether recovery experiences co-occur in systematic patterns or whether such patterns differ across people. Complementarily, a person-centred perspective can identify subpopulations based on differences in the co-occurrence of recovery experiences (Morin et al., 2011; Wang & Hanges, 2011; Woo et al., 2024). Using latent profile analysis (LPA), one can estimate profiles that differentiate people into groups showing qualitative or quantitative differences in combinations of recovery experiences.

Studies applying a person-centred approach to recovery identified distinct profiles of recovery experiences and observed differential well-being across profiles (e.g., Bennett et al., 2016; Chawla et al., 2020). These contributions collectively emphasize that recovery from work is not universal. Instead, individuals vary in how their recovery experiences cluster and how these patterns relate to health and functioning. Despite the importance of these studies, their conclusions are subject to several limitations. Existing research provides limited insight into which recovery profiles characterize relevant populations, whether training alters these profiles, and whether such changes carry positive implications for well-being. We identify three specific areas in which the present research contributes to the recovery literature.

First, it remains to be learned how psychological detachment, relaxation, control and mastery co-occur in profiles. Overcoming this limitation advances recovery research beyond prior work, which included indicators beyond the canonical four recovery experiences. As a result, the previously derived profiles reflect variance in constructs conceptually distinct from the core recovery experiences. For instance, Bennett et al. (2016) used problem-solving pondering in addition to the recovery experiences. They identified four profiles that differed in the extent of psychological detachment, relaxation and, crucially, problem-solving pondering, but shared comparable moderate levels of control and mastery. For example, one latent group of people showed low levels of psychological detachment and relaxation, but rather high levels of problem-solving pondering. The 'Leaving Work Behind' profile showed the opposite pattern, associated with lower emotional exhaustion and somatic complaints. Gabriel et al. (2019) also included problem-solving pondering alongside the recovery experiences and partially replicated the profiles by Bennett et al. (2016) among working students. They again found differential associations with outcomes, such that 'Leaving Work Behind' was associated with lower somatic complaints compared with profiles with higher problem-solving pondering. While these studies provide valuable insight into how recovery-related cognitions and experiences cluster, the inclusion of non-recovery indicators limits our ability to characterize profiles defined by the four core recovery experiences. To address this, we focus exclusively on profiles of psychological detachment, relaxation, control and mastery.

Second, in recovery training evaluation research, we have yet to identify which profiles characterize the specific target population of people who self-enrol in recovery training. It is valuable to know which profiles characterize full-time employees (Bennett et al., 2016) and working students (Gabriel et al., 2019) who do not explicitly struggle with recovery, but the profiles may not translate to a population in need of recovery training. The recovery paradox (Sonnentag, 2018) suggests that individuals who perceive a need for recovery support may show particularly impaired recovery patterns, making them an especially informative population for person-centred research. Individuals who actively seek out recovery training likely do so because they perceive their current recovery as insufficient. Identifying recovery profiles in this self-selected population is therefore important for understanding the starting conditions from which training-related changes unfold.

Third, in person-centred training evaluation, we are inherently interested in whether latent profiles can change over time or remain stable. However, longitudinal person-centred research on recovery remains scarce and methodologically limited. Siltaloppi et al. (2011) examined 1-year changes in the four recovery experiences. They found the largest profile with overall high recovery experiences at both measurement occasions and four smaller profiles. However, their approach relied on an LPA that included both time points simultaneously rather than on an LTA. This approach does not separate the estimation of profiles across measurement occasions, thereby constraining inferences about true within-person transitions. Consequently, the stability and malleability of recovery profiles over time remain insufficiently understood. Chawla et al. (2020) extended the person-centred perspective to daily recovery experiences, showing that short-term shifts in profile membership can occur in response to fluctuations in job demands and resources. They identified five profiles of daily recovery experiences, with the largest profile characterized by moderate detachment, relaxation and control but low mastery. Membership in profiles with high levels of multiple or all recovery experiences was associated with lower exhaustion and better sleep quality. Grant et al. (2026) provided additional evidence that recovery experiences change in the short term by examining evening recovery trajectories. Importantly, they showed heterogeneity across people in how recovery experiences developed over the evening, uncovering multiple profiles of trajectories of the four recovery experiences. The profiles differentiated among people starting to recover early in the evening, those showing delayed recovery with increasing levels of detachment, relaxation and control across the evening, and those experiencing a particularly delayed detachment. These short-term findings are valuable for demonstrating that recovery profiles are not fixed traits but underlie situational variability. Insight into how more fundamental and sustained changes, such as those resulting from training, shape individuals' recovery patterns over extended periods is still needed. Critically, no prior person-centred study has examined whether recovery profiles change with training. This limits our understanding of whether targeted interventions can shift individuals towards more adaptive recovery patterns.

Hence, in the present research, we examine how the four recovery experiences co-occur in distinct patterns for people who self-selected into training and how these patterns change over a sustained period in response to training. We thereby provide a valuable extension to the existing person-centred recovery literature and set the stage for a deeper consideration of recovery as trainable experiences.

Recovery training evaluation

Researchers developed various training approaches targeting recovery during work breaks (e.g., De Bloom et al., 2017) or outside of work (e.g., Virtanen et al., 2021). Variable-centred evaluations of these interventions typically examine average changes in singular recovery experiences. For example, in a RCT, Ebert et al. (2015) targeted all four recovery experiences among teachers with sleep problems with an online recovery training program. They found the largest effects on detachment (d=1.72) and relaxation (d=.94), with somewhat smaller though still substantial effects on mastery (d=.67) and control (d=.76). These findings suggest that recovery experiences may be differentially malleable, implying that not all recovery experiences respond equally to training. However, variable-centred evaluation cannot reveal whether there are subgroups of participants who particularly benefit from training on some but not other recovery experiences, and other subgroups who may show a different pattern of training success across the recovery experiences. Understanding differences between people and recovery experiences is crucial, as the recovery paradox (Sonnentag, 2018) indicates that individuals who perceive a need for recovery improvement may be impaired across multiple recovery processes, requiring training that addresses the complex interdependencies among recovery experiences.

A person-centred perspective on training evaluations examines how training influences patterns of co-occurring recovery experiences rather than isolated experiences. Because the data-analytic strategy impacts the conclusions drawn about training effectiveness (e.g., Lischetzke et al., 2015), a person-centred approach can reveal previously underexplored types of training effects. First, training may affect the number and shape of profiles in the sample, for example, by reducing heterogeneity such that profiles with low levels of one or more recovery experiences disappear. Nevertheless, this does not imply people must improve homogeneously. Second, training may cause participants to transition to different profiles, and these transitions may differ systematically across participants. We would expect such heterogeneity in change processes given that life circumstances (e.g., family responsibilities) constrain some recovery experiences more than others (Virtanen et al., 2020), leading to different transition paths depending on which experiences are most amenable to change. Third, a person-centred approach can reveal trade-offs among recovery experiences in response to training: while training may reinforce some experiences simultaneously, others may compete for limited time and resources. Estimated profiles and transitions from pre- to post-training, therefore, capture patterns in which people differ in their (changes to) distinct recovery experiences. Variable-centred meta-analytic evidence already points to such heterogeneity, as Karabinski et al. (2021) found that detachment benefited more from training among individuals with initial health- or recovery-related impairments.

Meta-analytic evidence further suggests that a range of training contents effectively improve recovery experiences, including boundary management, emotion regulation, sleep strategies, mindfulness, problem-focused coping and structured recovery activities (Karabinski et al., 2021; see also Crain et al., 2017; Creswell, 2017; Ebert et al., 2016; Goldberg, 2022; Querstret et al., 2016; Reinke & Ohly, 2024; Thiart et al., 2015). Although this meta-analytic evidence primarily concerns detachment, primary studies indicate that other recovery experiences benefit from similar content (Ebert et al., 2015; Hahn et al., 2011; Verbeek et al., 2019). Yet, specific training contents may influence some, but not all, recovery experiences, and variable-centred studies cannot determine patterns and trade-offs among them.

The current study included two training programs that incorporated content previously shown to be effective. The first training drew on mindfulness-based stress reduction (MBSR; Kabat-Zinn, 1982, 2006) and mindfulness-based cognitive therapy (MBCT; Segal et al., 2002; see also Siegel, 2010). The second training used cognitive-behavioural techniques based on the Detachment-Relaxation, Autonomy, Mastery, Meaning and Affiliation (DRAMMA) model (Newman et al., 2014). Both programs target diverse psychological mechanisms underlying recovery. They are therefore well-suited to influencing multiple recovery experiences (e.g., mindfulness fosters psychological detachment, body scans induce relaxation, boundary management increases control and leisure activities promote mastery). A person-centred approach offers the unique opportunity to determine which heterogeneous (transitions between) patterns of recovery experiences occur in response to such training. A remaining question is which outcomes are most suitable for capturing the effects of such transitions.

Relating person-centred recovery training effects to outcomes

In general, recovery experiences are linked to personal and work outcomes, reflecting their importance for individuals and organizations (Sonnentag et al., 2022). The four experiences are consistently positively associated with well-being, positive affect and sleep quality, and negatively with work–family conflict, negative affect and stress in meta-analytic evidence (Headrick et al., 2022). Nevertheless, they also show differential associations with outcomes. For example, relaxation, control and mastery are positively linked to job performance, whereas psychological detachment is not (Headrick et al., 2022).

In this study, we focused on perceived stress and sleep quality as outcomes because they directly measure two core functions of recovery: restoring depleted resources and reversing the overall stress process. Perceived stress represents the negative consequences that recovery is intended to mitigate, whereas sleep quality captures perceived physiological outcomes of recovery processes that counter perseverative cognitions otherwise associated with sleep problems (e.g., rumination; Berset et al., 2011). Both perceived stress and sleep quality have been positively affected in previous recovery training studies utilizing variable-centred approaches (e.g., Hahn et al., 2011).

Prior evidence shows that reductions in perceived stress and improvements in sleep quality are associated with broader downstream benefits in subjective and physiological well-being. For example, a study showed that the negative impact of perceived stress on subjective well-being was reduced when sleep quality was incorporated as a mediator (Weinberg et al., 2016), and another study evidenced that improvements in perceived stress and sleep quality were associated with reduced cardiometabolic risks (Eliasson et al., 2010). These outcomes thereby provide a parsimonious test of training efficacy while laying the groundwork for future studies to track a broader spectrum of outcomes that may be responsive to specific profile transitions.

Importantly, we expected perceived stress and sleep quality to be sensitive to training effects reflected in transitions between recovery experience profiles. Even changes in some, but not all, recovery experiences (e.g., improved detachment and relaxation with stable control and mastery) may positively affect perceived stress and sleep quality, because, meta-analytically, all recovery experiences are favourably linked to these outcomes (Headrick et al., 2022). Again, the person-centred approach is well-suited to reveal nuances in how patterns of change are associated with outcomes, adding substantial knowledge to the recovery training literature.

The present research

In the present research, we utilized data from an RCT with online training over 6 weeks and a waitlist control group to extend previous research on recovery profiles and training. We measured recovery experiences, perceived stress and sleep quality before and after training. Our sample comprises individuals who voluntarily enrolled in recovery training, providing a particularly informative context for studying profile changes associated with training. These individuals actively sought support for their recovery, suggesting they perceived their current recovery as insufficient, a population for whom recovery training is most relevant from a practical standpoint.

We combine this applied context with a person-centred approach (LTA), allowing us to address questions that previous research could not answer. Specifically, prior person-centred studies on recovery were limited by the inclusion of indicators beyond the four canonical recovery experiences (e.g., Bennett et al., 2016; Gabriel et al., 2019), the absence of populations with an explicit need for recovery improvement, and the lack of training manipulations in longitudinal person-centred designs (e.g., Chawla et al., 2020; Grant et al., 2026; Siltaloppi et al., 2011). Our research addresses these limitations by focusing exclusively on the four recovery experiences in a self-selected training sample, within an RCT.

We summarize our main objectives in the following three research questions. We aimed to assess (1) whether the occurring recovery profiles in the sample remained stable or were susceptible to change from pre- to post-training, (2) to what extent individuals transitioned between recovery profiles from pre- to post-training (i.e., whether training participation had people move to more adaptive profiles) and (3) whether and how transition paths from pre- to post-training were related to changes in perceived stress and sleep quality.

Our research makes both methodological and theoretical contributions to the literature on recovery and training evaluation. Methodologically, combining the exploratory person-centred approach (e.g., Morin et al., 2018) with training data offers a new way to validate training effectiveness. The combination of person-centred methods and training evaluation involves methodological considerations, such as the idea that violations of measurement invariance may imply meaningful change rather than a methodological problem as would be the case in variable-centred evaluations. Theoretically, our findings encourage a shift in perspective regarding the evaluation of recovery training. While variable-centred approaches dominate the field, they are limited in that they cannot surface, let alone answer, theoretical questions about *for whom* (i.e., based on specific patterns of pre-training recovery experiences) and *in which ways* (i.e., how these patterns evolve or how individuals transition between patterns in response to training) recovery training works. By adopting a person-centred lens, we demonstrate that individuals and their recovery experiences respond to training in systematically different ways, challenging the implicit assumption of universal change. This perspective paves the way for theorizing about the dispositional and contextual factors that shape diverse training responses. Our findings thus provide initial evidence on which groups of people define the target population for voluntary training participation, how individuals and recovery experiences respond differently to training, and how heterogeneous training effects are linked to well-being.

METHOD

We used data from a larger project (Reis et al., 2021, 2024). The RCT was preregistered as a clinical trial (https://drks.de/search/en/trial/DRKS00024933) and approved by an ethics committee, but the analyses reported in this article were not preregistered and are exploratory. We describe the overall sampling plan, focusing on aspects relevant to this article. We report any data exclusions, all manipulations and all measures relevant to the present purposes. We provide Supplementary Online Materials (SOM), including additional results, a codebook, the code and the data needed to reproduce our analyses on the OSF: https://osf.io/32rhy.

Participants and procedure

The RCT included 393 participants who completed the intake questionnaire. On average, participants were 40.56 years old ($SD = 10.94$), 75.57% were female, 23.92% were male, and two individuals did not disclose their gender. Participants reported a range of professions, with 25.45% employed in healthcare and education services, 14.76% in administration, 7.89% in STEM fields and IT and 6.62% as scientific staff, with further participants engaged in other occupations. On average, participants had working contracts of 35.66 h per week ($SD = 7.82$) and reported working 5.51 h of overtime per week ($SD = 8.18$).

We recruited participants by announcing the study as training promoting recovery from work via various media channels and by potential disseminators (e.g., workplace health management divisions). Inclusion criteria for participation were age over 18, core working hours between 6:45 a.m. and 5:30 p.m.,[1] a smartphone with internet access, and no current psychotherapy. Upon study enrolment via a custom website, participants were sent the intake questionnaire on their preferred starting date. The questionnaire began with eligibility criteria and informed consent, followed by demographic information, measures of relatively stable characteristics, including recovery experiences and well-being, and work-related questions. We will refer to the intake questionnaire as the pre-training or first measurement occasion.

The study included two self-guided online training programs because one aim of the larger research project leading to the data collection was to examine the equivalence of the two training approaches. We randomized participants to one of the two training groups or to a waitlist control group that participated in all assessment phases. In a previous publication based on the data from this trial, using a Bayes factor equivalence testing procedure (Linde et al., 2021; van Ravenzwaaij et al., 2019), we established that both training approaches had equivalent effects on detachment (Reis et al., 2024).[2] Here, we combined data from two training approaches and, thus, refer to a single training group ($n_{\text{training}} = 261$) and a single control group ($n_{\text{control}} = 132$).

The study spanned 8 weeks, beginning with a pre-training measurement, followed by a week of experience sampling, 6 weeks of training for the training group, and concluding with another week of experience sampling and a post-training measurement. We chose the training period duration to enable the induction of macro-level (pre-to-post) change, for which meta-analytic evidence from occupational health contexts suggests that moderately long training periods of five to 8 weeks of online training are more effective than shorter periods (e.g., ≤4 weeks, Heber et al., 2017; or ≤2 weeks, Karabinski et al., 2021) and longer periods (e.g., ≥9 weeks, Heber et al., 2017). Accordingly, we

[1] In line with this criterion, 90% of participants indicated that they typically start their workday between 6:00 a.m. and 9 a.m. ($M = $ 7:47 a.m., $SD = 54$ min) and end their workday between 2:30 p.m. and 7:00 p.m. ($M = $ 4:45 p.m., $SD = 91$ min).

[2] For the present research, we analogously conducted supplementary analyses testing the changes in the other recovery experiences for equivalence across the two types of training and established equivalence of the pre- to post-training change in observed means across the two types of training for relaxation ($BF_{01} = 12.38$), control ($BF_{01} = 4.81$), and mastery ($BF_{01} = 17.82$) as well. Nevertheless, descriptive statistics for both training groups can be accessed in SOM1.1.

released one new online module per week across 6 weeks to deliver sufficient dosage without overburdening participants. Throughout the training period, participants received short experience sampling questionnaires with varying sampling intensity. For details on the procedure and training content for each week, see Figure 1. Participants received monetary rewards contingent on their participation and entered a voucher lottery, where the chances of winning increased with questionnaire compliance. Furthermore, participants received written individual feedback at the end of the study, comparing their summarized responses to those of the whole sample. One week after the end

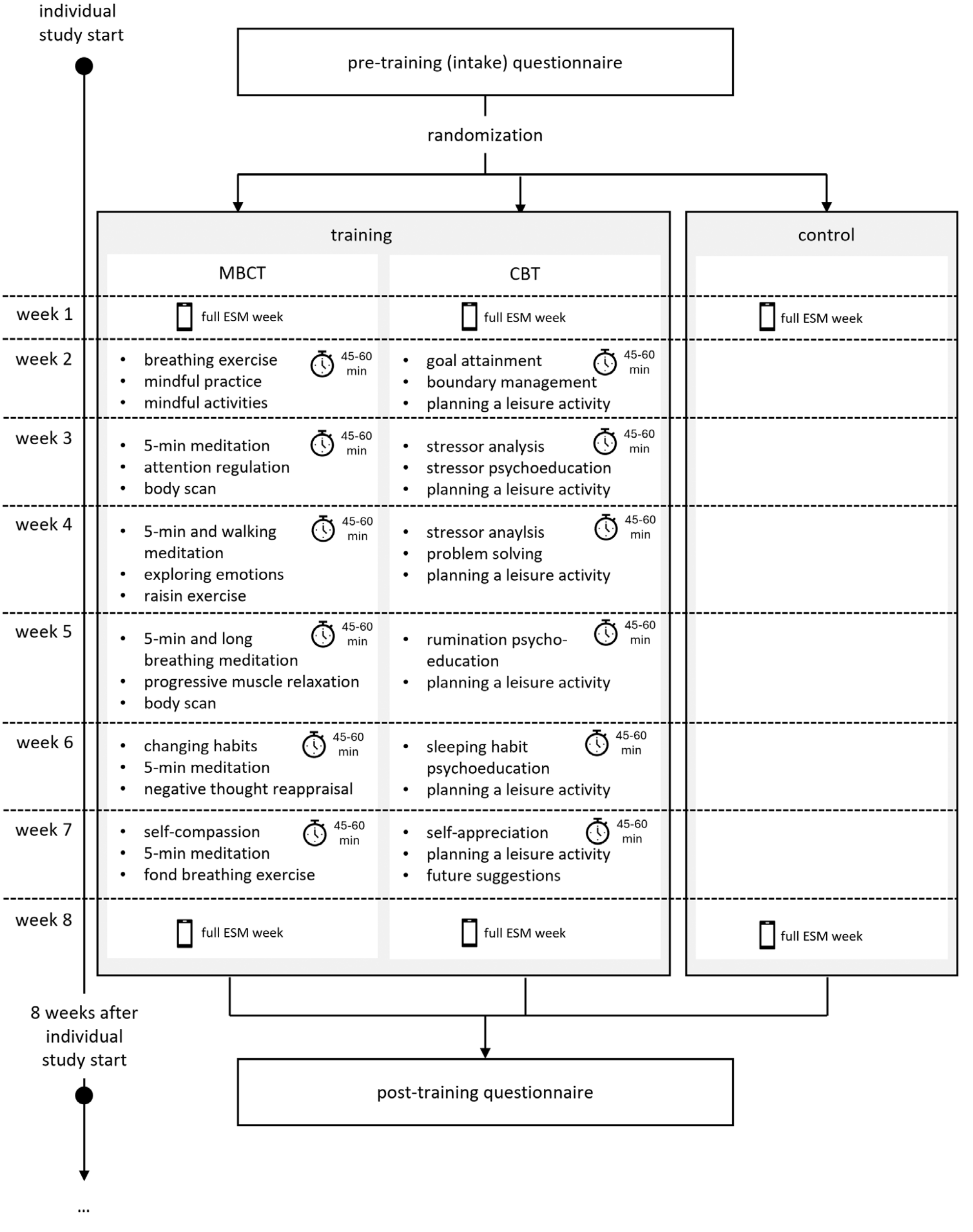

FIGURE 1 Flowchart for the data collection and training procedure, content and intended time frame. We included a detailed rationale for exemplary training content and sequencing in SOM2.1. CBT, Cognitive Behavioural Therapy; ESM, Experience Sampling Method; MBCT, Mindfulness-Based Cognitive Therapy.

of the training period, participants were prompted to fill out the post-training questionnaire, which we will refer to as the post-training or second measurement occasion. It included recovery experience indicators, well-being outcomes, and a proxy variable measuring training compliance, asking whether participants had completed the week six module.

Overall, 393 people participated in the first measurement occasion and 247 in the second (i.e., 62.85% of the sample remained, 69.70% of the control group and 59.39% of the training group).

Measures

Latent profile indicators: Recovery experiences

We measured the recovery experiences of psychological detachment, relaxation, control and mastery pre- and post-training using four items each (Recovery Experience Questionnaire; Sonnentag & Fritz, 2007). We intended to measure the recovery experiences as relatively stable using the time frame 'in the last 2 weeks'. Participants responded on a Likert scale ranging from 1 (*does not apply at all*) to 7 (*fully applies*). We report example items and reliabilities for the respective recovery experiences in Table 1 alongside descriptive statistics (for a list of all items, see SOM2.0).

Outcomes

We measured sleep quality with seven items from the Standardized Sleep Inventory (Görtelmeyer, 2011). Responses were given on a 7-point scale ranging from 1 (*never*) to 7 (*very often*). We used four items adapted from Cohen et al.'s (1983) Perceived Stress Scale (Reis et al., 2019) to assess perceived stress, ranging from 1 (*never*) to 5 (*very often*). We present descriptive statistics, example items and reliabilities in Table 1.

Analytic strategy

We followed the recommendations and adapted the code by Nylund-Gibson et al. (2023) to conduct the steps of an LTA comparing qualitative and quantitative differences in recovery experiences before and after the training phase. We conducted all analyses in R (Version 4.3.3, R Core Team, 2024) or Mplus (Version 8.8, Muthén & Muthén, 2022) via MplusAutomation (Hallquist & Wiley, 2018). We used robust maximum likelihood estimation for the LTA while accounting for missing data using full information maximum likelihood (FIML) estimation. Furthermore, to maximize sample size, we estimated all models using the combined data (i.e., training and control groups together). We later included the condition (training vs. control) as a covariate in the LTA to explore differences in latent profile membership and transition probabilities between conditions. Figure 2 visualizes an overview of the modelling steps.

Latent transition analysis

As a preparatory step, we enumerated the profiles before the LTA. We conducted separate LPAs for the pre- and post-training measurement occasions to identify how many and which profiles characterized the recovery experiences, respectively. For details on the decision-making process and more detailed results of this analysis, please refer to SOM1.2.

Measurement invariance across time

After the profile enumeration, we inspected whether the estimated recovery experience means of the profiles at the pre- and post-training measurement occasions were invariant across time (i.e.,

TABLE 1 Descriptive statistics, reliabilities and correlations for the latent profile indicators and outcomes from the pre- and post-training measurement occasions.

Scale	*M*	*SD*	ω_t	1	2	3	4	5	6	7	8	9	10
Pre-training profile indicators													
1. Psychological detachment (e.g., *I didn't think about work at all.*)	2.72	1.37	.87										
2. Relaxation (e.g., *I did relaxing things.*)	3.53	1.38	.87	.49***									
3. Control (e.g., *I felt like I could decide for myself what to do.*)	4.03	1.31	.82	.37***	.64***								
4. Mastery (e.g., *I sought out intellectual challenges.*)	3.66	1.39	.78	.20**	.33***	.35***							
Post-training profile indicators													
5. Psychological detachment	4.13	1.64	.92	.48***	.19*	.15	.13						
6. Relaxation	4.70	1.45	.90	.16	.46***	.29***	.21*	.43***					
7. Control	4.90	1.30	.90	.21*	.38***	.44***	.22**	.44***	.68***				
8. Mastery	3.97	1.51	.90	.25**	.36***	.22**	.50***	.38***	.45***	.45***			
Outcomes (pre-training in the first row and post-training in the second row)													
9. Sleep quality (e.g., *undisturbed*)	3.69	1.13	.88	.30***	.33***	.33***	.23***	.23**	.25**	.35***	.16		−.20*
	4.27	1.19	.90	.23**	.19*	.17	.16	.42***	.35***	.42***	.24**	.55***	−.39***
10. Perceived stress (e.g., *How often have you felt that you were unable to control the important things in your life?*)	2.93	.78	.73	−.30***	−.38***	−.41***	−.27***	−.17*	−.18*	−.26***	−.18*	−.35***	
	2.55	.78	.77	−.25**	−.22**	−.21*	−.18*	−.47***	−.37***	−.44***	−.32***	−.19*	.42***

Note: Column ω_t contains McDonald's omega total estimates of internal consistency. For outcomes, we included below the diagonal the correlations of pre-training sleep quality and above the diagonal the correlations of post-training sleep quality with perceived stress pre- and post-training, respectively. *p<.05; **p<.01; ***p<.001.

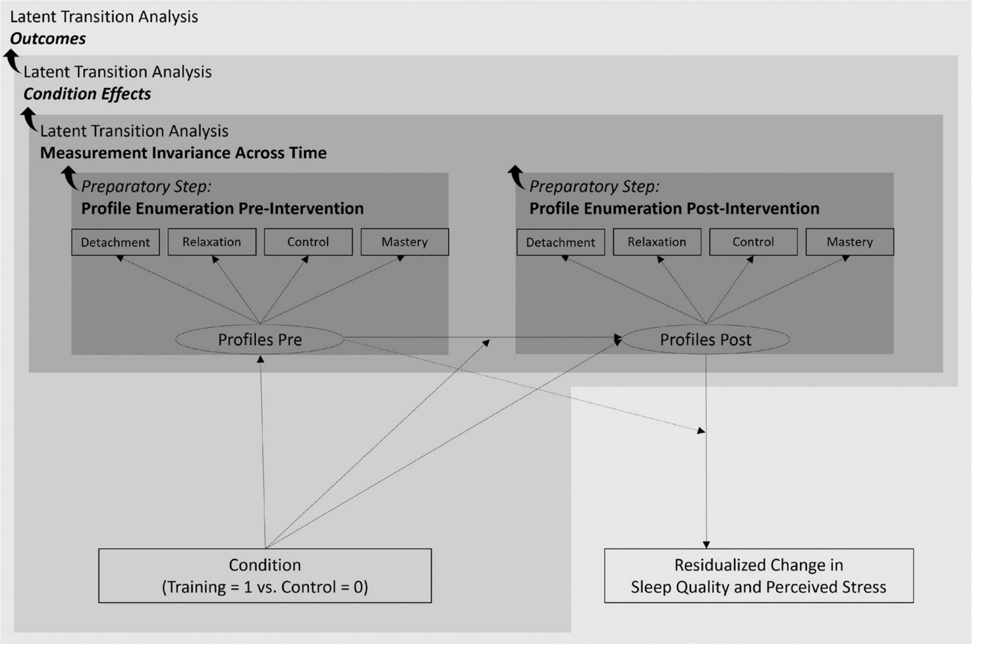

FIGURE 2 Overview of fitted models starting with the profile enumeration, separate for pre- and post-training measurement occasion, and building up to a latent transition analysis including condition as a covariate and residualized change in sleep quality and perceived stress as outcomes. Shaded areas symbolize which variables and paths were included in the modelling steps, sequentially increasing from the model fitted first (darker shaded areas inside) to last (lighter shaded area outside, i.e., the final model). To simplify the graph, we did not include paths for the direct effects of the condition as a covariate on the post-training profile indicators, but these were estimated in the *covariate noninvariant* model (see SOM1.3).

whether the same profiles occurred at both time points). To this end, we included both measurement occasions in an LTA, in which we regressed post-training profile membership on pre-training profile membership and compared models with different restrictions. We assessed whether the assumption of measurement invariance was justified for our data by comparing the fit of the invariant model with a noninvariant model using a likelihood ratio test (LRT) with the Sattorra–Bentler adjustment (Nylund et al., 2007; Nylund-Gibson et al., 2023). A nonsignificant LRT result would indicate that the more restrictive (i.e., invariant) model did not fit significantly worse than a noninvariant model and that the assumption of measurement invariance was warranted. A different number of profiles or profiles that deviated in the estimated mean structure between the first and second measurement occasions would indicate that full measurement invariance was an unwarranted assumption. Still, partial measurement invariance (i.e., restricting a subset of profiles to equality over time) might hold for a subset of similar profiles.

Condition effects

The LTA with the number of profiles and plausible restrictions regarding measurement invariance across time determined in the previous analysis steps was then expanded in a one-step approach[3] to include condition as a binary covariate (training=1 vs. control=0). We used the condition to predict profile memberships and transition probabilities. We further explored whether the same estimated profile means applied in both conditions, which, again, was a question of measurement invariance, in this case, across groups. For parsimony, we focused on results from the model (implicitly) assuming

[3]We chose a one-step approach over a three-step approach because the condition might affect the profile estimation, which (if so) could be seen as one type of training effect and should not go unnoticed.

measurement invariance across conditions (i.e., the same profiles with the same estimated indicator means occurring in the training and control groups; *covariate invariant* LTA). In SOM1.3, we elucidate whether and how the profiles varied across conditions (*covariate noninvariant* LTA) and differentiate training effects from measurement differences.

Outcomes

In a final model, we predicted well-being outcomes using different transition paths from pre- to post-training. To ensure that profile estimation was not affected by the inclusion of the outcome variables, we adopted a manual three-step approach using the Bolck, Croon and Hagenaars (BCH) weights, building on our previously established LTA model. For this step, we proceeded, in part, analogously to Lubbers et al. (2024), operationalizing the outcomes as residualized change scores (i.e., residuals from a regression of post-training values of the respective construct on pre-training values of the same construct). We z-standardized the residualized change scores to foster comparability and interpretability because the original response scales of the two outcome measures had different maxima.

RESULTS

Table 1 presents descriptive statistics for the latent profile indicators and outcomes for the pre- and post-training measurement occasions. As described earlier, after the initial profile enumeration, we fit multiple LTA models to evaluate measurement invariance across time and conditions, training effects and the prediction of outcomes. For the sake of readability, we report estimated indicator means, class membership, training effects and transition probabilities only for the final model.

To examine whether the structure of recovery profiles remained stable or was susceptible to change from pre- to post-training, we began by enumerating profiles separately for the two measurement occasions. We settled on a five-profile solution for the pre-training measurement occasion and a three-profile solution for the post-training measurement occasion based on a joint consideration of information criteria, likelihood ratio tests, Bayes Factors and substantive interpretability (for details, see SOM1.2). Figure 3 depicts the estimated means and frequencies of the profile indicators for each profile.

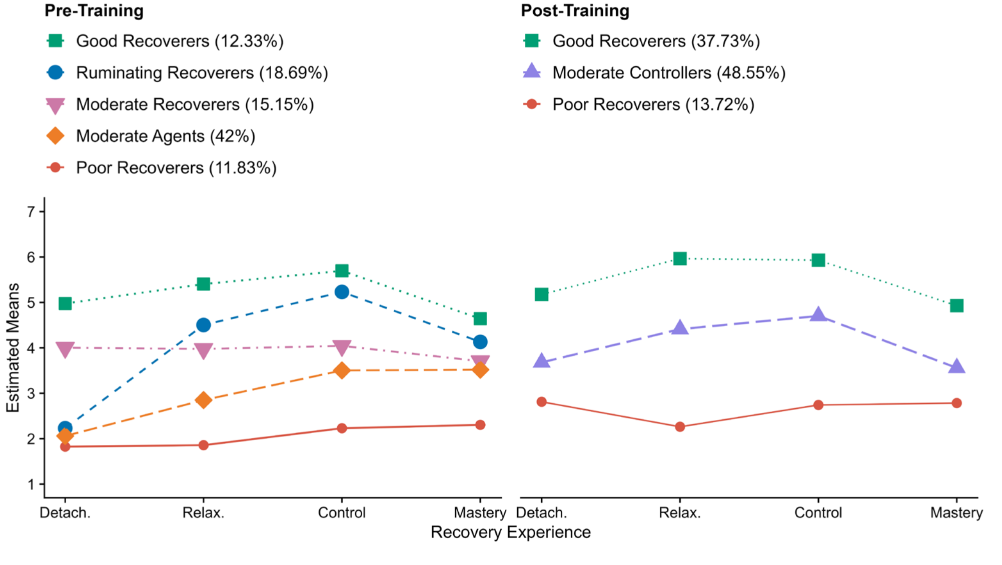

FIGURE 3 Estimated means and frequencies for the latent profiles at the pre- (left) and post-training (right) measurement occasions from the separate LPAs.

In terms of substantive interpretation, at the pre-training measurement occasion, about 40% of the sample showed mostly quantitative between-subject differences and could be divided into the *Good Recoverers*, who had high levels on all recovery experiences, the *Moderate Recoverers*, who had moderate levels, and the *Poor Recoverers*, who experienced low levels. The remaining (majority) part of the sample showed two additional profiles in which individuals employed different recovery experiences to varying degrees. Remarkably, individuals in these two profiles exhibited low levels of psychological detachment, similar to those of the *Poor Recoverers*. For the remaining recovery experiences, a group of *Ruminating Recoverers*, who had trouble detaching psychologically and thereby remained cognitively involved with their work, was able to relax moderately, perceive a substantial sense of control over their free time, and experience moderate mastery. The profile with the largest membership reflected the experiences of 42% of the sampled individuals. In addition to low psychological detachment, these individuals reported relatively low levels of relaxation but experienced moderate control and mastery. Thus, we named these individuals the *Moderate Agents*, as they did not detach or relax much but took a moderately active approach to their free time.

For the post-training measurement occasion, the reduction in the number of profiles led to a decrease in the qualitative variety of the profiles. Differences between profiles reflected mainly quantitative differences in the overall experience of recovery. About 38% of individuals could be termed *Good Recoverers* after training. Nearly half of the sample reported moderate values for all recovery experiences. Unlike the *Moderate Recoverers* from the pre-training measurement occasion, the post-training profile showed slightly higher control and slightly lower detachment levels. Control seemed especially crucial for the *Ruminating Recoverers* and the *Moderate Agents* before the training. Conversely, the profile emphasizing control at the post-training measurement occasion was associated with comparably better detachment than these two pre-training profiles. Combining the three middle profiles from the pre-training measurement occasion conveyed a different quality. Hence, we labelled the profile *Moderate Controllers*. The third profile with the lowest estimated means and the smallest membership was still composed of *Poor Recoverers*. Increased membership in the *Good Recoverers* profile yielded initial evidence of a positive training effect.

Latent transition analysis

Measurement invariance across time

To further understand the extent to which the profile structure changed, we subsequently included both measurement occasions in an LTA with five profiles at the first measurement occasion and three profiles at the second. The different number of profiles contradicted the notion of full measurement invariance across time. Nevertheless, a visual inspection of the profiles in Figure 3 revealed structural similarities between the pre- and post-training measurement occasions. Three profiles primarily differentiated individuals quantitatively (i.e., good, moderate and poor recovery). The LRT comparing a maximally invariant LTA model (i.e., we constrained means for three profiles to be equal across time) with an LTA with freely estimated means reflected a significantly worse fit of the maximally invariant LTA model, $\chi^2(12)=22.36$, $p=.034$. By contrast, the LRT comparing a partially invariant LTA model (i.e., we constrained means for two profiles to be equal across time) with an LTA with freely estimated means was not significant, $\chi^2(8)=11.24$, $p=.188$. Consequently, we assumed partial measurement invariance with two equivalent profiles across time. In the final model, the estimated means for both the *Good Recoverers* and the *Poor Recoverers* could be restricted to be equal across measurement occasions. The means for the *Moderate Controllers* at the post-training measurement occasion did not sufficiently resemble any of the other pre-training profiles (i.e., they could not be statistically constrained to any of the pre-training profiles' means, see Table 2).

TABLE 2 Estimated means and variances for the latent profiles in the final model.

Measurement occasion	Profile	Detach.	Relax.	Control	Mastery
Pre-training					
		Estimated means			
	Good Recoverers	5.18	5.89	5.88	4.91
	Ruminating Recoverers	2.36	5.09	5.22	4.09
	Moderate Recoverers	4.30	4.31	4.59	3.96
	Moderate Agents	2.19	3.27	3.96	3.79
	Poor Recoverers	2.10	2.12	2.77	2.81
		Estimated variances			
		.79	.50	.81	1.61
Post-training					
		Estimated means			
	Good Recoverers	5.18	5.89	5.88	4.91
	Moderate Controllers	3.65	4.40	4.69	3.50
	Poor Recoverers	2.10	2.12	2.77	2.81
		Estimated variances			
		1.91	.69	.65	1.60

Note: We constrained variances to be equal across all profiles; hence, we report them only once per measurement occasion and recovery experience.

Condition effects

To explore how profile memberships and transitions between profiles relate to training, we included condition as a covariate, assuming partial measurement invariance across time, as established previously. The *covariate invariant* model showed that the condition did not significantly predict pre-training profile membership. The odds ratios that compared the probability that any one profile relative to the *Ruminating Recoverers* profile characterized the training group (vs. the control group) for the pre-training measurement occasion did not differ significantly from 1 (*Good Recoverers*: $OR = 2.86$, 95% CI [.68, 12.05], *Poor Recoverers*: $OR = 1.27$, 95% CI [.51, 3.16], *Moderate Recoverers*: $OR = 2.79$, 95% CI [.83, 9.36], and *Moderate Agents*: $OR = 1.56$, 95% CI [.43, 5.70]). Odds ratios of 1 indicate an equal likelihood that the training and control groups would be in the respective profiles, rather than the *Ruminating Recoverers* group. These results suggest randomization success, as we would not expect differences between conditions before any training. By contrast, post-training profile membership was partly significantly predicted by the condition. Participants in the training group were nearly four times as likely to be *Good Recoverers* instead of *Moderate Controllers* than those in the control group, $OR = 3.92$, 95% CI [1.42, 10.78]. The likelihood of being *Poor Recoverers* instead of *Moderate Controllers* did not differ significantly between the conditions, $OR = .94$, 95% CI [.33, 2.63].

Regarding transition probabilities, we include a summary of transition probabilities and profile memberships, averaged across conditions, for the final model in Figure 4. For nearly any pre-training profile, participants had the highest probability of transitioning to a profile with higher recovery experiences (partly or overall).[4] Table 3 presents descriptive differences in transition probabilities between the training and control groups. To highlight a few differences, participants in the training group were

[4]Some very large or low transition probabilities were fixed to 1 or 0, respectively (a default setting in Mplus). For example, (nearly) no one transitioned from being a *Good Recoverer* to a *Poor Recoverer* or *Moderate Controller*, so the probability of remaining a *Good Recoverer* is displayed as 100%.

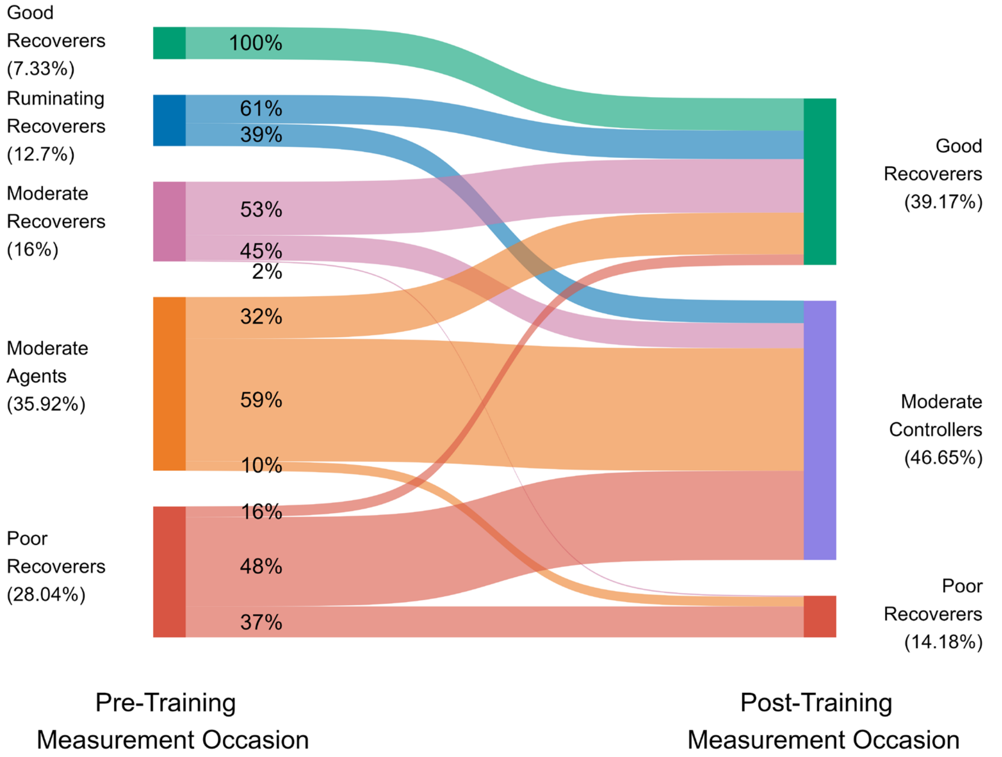

FIGURE 4 Estimated sizes of the profile clusters from the pre- and post-training measurement occasions and transition probabilities from the pre- to the post-training profile clusters. The slight differences in proportional membership between the pre- and post-training profiles in Figure 3 and this figure are due to the estimates being derived from different models using varying amounts of data. Specifically, the values in Figure 3 were based on separate LPAs, which considered either only the pre-training or only the post-training measurement occasion. By contrast, the values in this figure were derived from the final LTA model, which included both measurement occasions and the condition as a binary covariate.

TABLE 3 Transition probabilities from the pre- to the post-training profile clusters by condition.

	Good Recoverers		*Moderate Controllers Recoverers*		*Poor Recoverers*	
Post-training profiles	**Control**	**Training**	**Control**	**Training**	**Control**	**Training**
Pre-training profiles						
Good Recoverers	**1.00**	**1.00**	.00	.00	.00	.00
Ruminating Recoverers	*.39*	*.72*	.61	.28	.00	.00
Moderate Recoverers	*.31*	*.64*	.66	.35	.04	.02
Moderate Agents	*.15*	*.40*	.73	.52	.13	.08
Poor Recoverers	*.06*	*.21*	*.52*	*.46*	**.42**	**.34**

Note: Cells contain the transition probabilities from the pre-training profiles (rows) to the post-training profiles (columns) separately for the control and the training groups. **Bolded** probabilities can be interpreted as stability (i.e., showing the same profile for both measurement occasions), and *italicized* probabilities reflect an overall improvement (i.e., higher recovery experiences). Probabilities not highlighted can be viewed as transitions to a profile with (partly) decreased recovery experiences or to a profile with partly increased and partly decreased recovery experiences. Both very high and very low transition probabilities were fixed at 1 and 0 to aid model estimation (Mplus default).

more likely, descriptively, to transition from any pre-training profile to *Good Recoverer* status than those in the control group. Vice versa, the control group showed greater stability in remaining *Poor Recoverers* or continuing to exhibit moderate recovery experiences.

Outcomes

We subsequently included changes in well-being outcomes in the analysis to find out whether and how these were related to transition paths from pre- to post-training. Positive residualized change scores for sleep quality indicate an improvement (i.e., higher sleep quality at the post-training measurement occasion than, on average, predicted from sleep quality at the pre-training measurement occasion). By contrast, negative residualized change scores indicate a deterioration in sleep quality. Vice versa, negative residualized change scores for perceived stress indicate an improvement, whereas positive residualized change scores indicate that people perceived more stress. *Ruminating Recoverers* who transitioned to being *Good Recoverers* reduced their perceived stress, $M = -.63$, $SE = .24$, $p = .009$, like *Moderate Recoverers* who improved to *Good Recoverers*, $M = -.93$, $SE = .26$, $p < .001$. For the latter, there was also a significant improvement in sleep quality, $M = .65$, $SE = .25$, $p = .011$. By contrast, perceived stress levels significantly increased over time for individuals who remained *Poor Recoverers*, $M = .53$, $SE = .17$, $p = .002$. We visualized small, nonsignificant residualized change scores associated with further transition paths in SOM1.4.

Subsequently, we report exploratory pairwise comparisons of individuals who improved to *Good Recoverers* or *Moderate Controllers*, respectively, to assess whether their residualized change in sleep quality and perceived stress differed from those of individuals who started at and remained at a good or moderate level of recovery experiences, respectively. Furthermore, we explored whether deteriorating from the pre- to post-training measurement occasion concerning the level of recovery experiences was associated with different residualized changes in the outcomes than improving recovery experiences. In terms of significant comparisons between paths, *Ruminating Recoverers* who transitioned to *Good Recoverers* improved their sleep quality more, $\Delta_z = 1.33$, 95% CI [.14, 2.53], and reduced their perceived stress more, $\Delta_z = -1.75$, 95% CI [−3.14, −.36], than initial *Ruminating Recoverers* who were *Moderate Controllers* on the post-training measurement occasion. Individuals who improved from *Moderate* to *Good Recoverers* had a higher (i.e., more positive) residualized change score for sleep quality, $\Delta_z = 1.04$, 95% CI [.49, 1.60], than individuals who transitioned from the *Moderate* to the *Poor Recoverers* profile. Furthermore, *Ruminating* and *Moderate Recoverers* who turned into *Good Recoverers* reduced their stress more than *Good Recoverers* who remained *Good Recoverers*, $\Delta_z = -1.12$, 95% CI [−1.96, −.29], and $\Delta_z = -.83$, 95% CI [−1.61, −.06], respectively. These results indicate that transitions to profiles with improved recovery experiences were partly associated with improved sleep quality and perceived stress.

DISCUSSION

Harnessing data from a large-scale RCT, we investigated potential changes in recovery experience profiles as a function of participation in recovery training, the impact of training participation on recovery profile memberships and transitions, and the implications of different transition paths for changes in well-being. Our key findings can be summarized as follows: (1) Five and three profiles of recovery experiences on the pre- and post-training measurement occasions reflected between-person differences in the levels (quantity) and partly the combination (quality) of recovery experiences, with a change in the profile structures from the pre- to the post-training measurement occasion. We interpret this result as reflecting genuine structural change because profiles dissolving from pre- to post-training came with expected improvements in detachment. Additionally, the pre-training profile structure represented a specific population in need of training, implying that the profile composition should change during training. Furthermore, (2) most participants improved by transitioning to a profile with higher recovery experiences from the pre- to the post-training measurement occasion, even some from the untrained control condition. However, the probability of reporting high levels of recovery experiences at the post-training measurement occasion and the descriptive probabilities of improving one's recovery experiences profile were higher for the training group. This result reflects a training effect in the intended direction. Concerning well-being, (3) individuals who improved their recovery experiences partly also benefited in terms of improved sleep quality and decreased perceived stress levels more than individuals who remained in the same profile of recovery experiences (even those in moderate to good profiles) and more than individuals who moved into a worse profile. This distinction between transition paths enhances understanding of the link among recovery, training and well-being.

Previous research has shown that people report different profiles of recovery experiences (Bennett et al., 2016; Gabriel et al., 2019). Our findings also support the existence of multiple profiles reflecting different types of joint occurrences of recovery experiences, again demonstrating the importance of person-centred approaches to complement variable-centred approaches for understanding how people recover from work. The profiles derived from our data show similarities to previously obtained profiles of recovery experiences. Profiles similar to the *Ruminating Recoverers* profile and the *Good Recoverers* profile also occurred in Bennett et al. (2016) and Gabriel et al. (2019). A *Moderate Recoverers* profile also reflected parts of the sample in Gabriel et al. (2019) and Chawla et al. (2020), and a profile similar to the *Moderate Agents* profile, which had the largest membership on our pre-training measurement occasion, was obtained in Bennett et al. (2016). So, our findings overlap with the previously reported types of recoverers in working populations. In contrast to previous studies, multiple profiles on our pre-training measurement occasion shared low levels of psychological detachment. This finding is likely due to a self-selection effect intentionally provoked by advertising our study using terms such as 'switching off from work'. Thus, the study was particularly attractive to people with low psychological detachment and those who struggled with recovery from work in general. The latter group was particularly evident in the *Poor Recoverers* profile in our study. This profile did not exist in previous studies on recovery experience profiles, which did not include training and, therefore, targeted different populations. Plausibly, improvements in the malleable experience of psychological detachment led to a reduction in the number of profiles post-training because two profiles with low levels vanished.[5]

We expanded upon previous research on the profile structure of recovery experiences by examining stability versus change over an 8-week interval, and included training for parts of the sample. We showed how recovery training can affect profile membership and profile transitions. Regarding stability versus change, the overall profile structure changed to a reduced number of more homogeneous profiles from pre- to post-training. Most participants transitioned to a profile with improved recovery experiences, and the training group showed a particularly pronounced improvement tendency. This finding shows that profiles of recovery experiences are not static but change over time, and that training fosters recovery (i.e., increased membership in more adaptive profiles and higher probabilities of improvement in the training group). Whereas the training group improved their recovery more, the control group also demonstrated adaptive transitions across time. We believe this finding may be explained by potential measurement reactivity to the assessments with varying sampling intensity during the training period in all conditions (i.e., including the control group). Frequent assessments in daily life may, for example, increase subjective emotional awareness (Eisele et al., 2023). It is also possible that participants in our waitlist control group, who chose to participate in the training study because they felt the need to improve their recovery experiences, might have been inclined to reflect on their recovery from work, thereby experiencing a pseudo-training effect.

Theoretical contributions

Our findings open three avenues for recovery theory. First, we identified heterogeneous groups of people who voluntarily enrolled in recovery training, which invites theorizing about what distinguishes them. One pattern in particular puzzled us: people who already scored high on all recovery experiences (*Good Recoverers*) still signed up. A plausible explanation is that this group is driven by perfectionistic strivings, that is, self-focused pursuits of improvement (Reis & Prestele, 2020; Stoeber & Otto, 2006). Future research should test whether dispositional factors such as perfectionism predict self-selection into recovery training. Second, recovery experience patterns changed with training, but detachment changed the most, regardless of the pre-training profile. This asymmetric malleability may reflect the rigidity of life circumstances

[5]This is not simply due to systematic dropout. Frequencies of participants from the five pre-training profiles remaining at the post-training measurement occasion did not significantly deviate from an expected distribution in the case of even dropout among pre-training profiles, $\chi^2(4)=1.35$, $p=.852$. This also held when looking at the training, $\chi^2(4)=0.34$, $p=.987$, and at the control group separately, $\chi^2(4)=2.40$, $p=.663$.

(e.g., family obligations) that constrain improvement in control, relaxation and mastery more than in detachment (Virtanen et al., 2020). Third, adaptive transition paths predicted greater gains in well-being than stable profiles or declines in recovery experiences. This pattern points to a dynamic view of recovery: upward movement in recovery experiences may itself function as a resource, such that positive change predicts well-being gains beyond what already high levels of recovery experiences can confer. Taken together, these findings set a theoretical agenda for recovery research that takes heterogeneity in training response, asymmetric malleability across experiences and the value of positive change seriously.

Methodological implications

Evaluating training using person-centred approaches, compared with variable-centred approaches, also has methodological implications. That is, measurement invariance between pre- and post-training profiles is required in variable-centred but may not be a desirable outcome in person-centred training research. In variable-centred approaches, measurement invariance across time is a prerequisite, as training-related change in the focal construct can be interpreted only after ensuring that the construct is measured equivalently across the measurement occasions under comparison (Fokkema et al., 2013; Seddig & Leitgöb, 2018). By contrast, person-centred approaches are not concerned with measuring constructs, but the measurement model (and thereby what is tested for [in]variance) reflects groups of people. Whereas we would not assume that training should alter the measurement of an investigated construct (i.e., a variable-centred approach), it is plausible that training changes the experiences of subgroups of people, reflected in profiles (i.e., a person-centred approach). For example, we observed *Ruminating Recoverers* before but not after the training. In large parts, initial *Ruminating Recoverers* improved their psychological detachment and were *Good Recoverers* post-training. Restricting the number of profiles and the estimated profile indicator means to equality across time would have concealed this training effect and likely would have resulted in a poor model fit. Therefore, the violation of measurement invariance between the pre- and post-training measurement occasions can (maybe counterintuitively) be viewed as a strength in our case and in person-centred (as opposed to variable-centred) approaches more broadly. Since the training aims to change the composition of latent profiles but not the underlying construct's meaning, changes in the number, size and shape of profiles can reflect meaningful intervention effects rather than measurement flaws.

Another perspective could be to view the profiles as universal and constant across the population. That is, the profile structure would not be a target for training. However, the individuals recruited for training research may reflect a population that needs training (e.g., people struggling with recovery), whether through self-selection or researchers' inclusion criteria. Should these participants become more similar to the general population (e.g., people with varying abilities to recover from work) after being trained, the hope of achieving measurement invariance would be at odds with detecting training effects in a person-centred approach.

Practical implications

Besides methodological implications, our study has practical implications. The distinct profiles of recovery experiences reflect the variety of ways in which people recover from work. Still, even among individuals interested in improving their recovery, most already exhibited moderate mastery and had at least moderate control over their free time. Considering the differential malleability of recovery experiences, there were also the least quantitative differences in mastery levels between the profiles, both before and after the training. Transitions between profiles were thus associated with numerically smaller changes in mastery compared with other recovery experiences. This finding aligns with variable-centred training evaluations, which show smaller or less sustainable effects on mastery than on other recovery experiences (Ebert et al., 2015; Hahn et al., 2011). By contrast, many people struggled to switch off from work: In our sample, more than 72% of participants reported low detachment on the pre-training measurement occasion. Nevertheless, detachment seems malleable, as reflected by changes in the profile structure, which show a reduction in the number of profiles with low levels of detachment.

Our findings suggest that practitioners who implement training in their organizations should assess all recovery experiences before designing a training program. This approach will enable them to identify groups of people with deficient yet malleable recovery experiences related to well-being or performance, enabling tailored training. Previous research has used person-centred approaches to identify groups of people and types of resources that could be targeted for training to achieve a healthy, high-performing workforce, for example, in the domain of job and off-job crafting (Ho et al., 2024). Our research shows that individuals who lack psychological detachment can train their recovery effectively. Hence, it could be worthwhile to apply CBT-based approaches that address rumination as a process rather than its content (e.g., rumination-focused cognitive-behavioural therapy, RFCBT; Watkins, 2016). Further, organization-based training could promote a team culture that facilitates recovery from work. For example, supervisors should communicate their support and appreciation for employees' recovery after work (Bennett et al., 2016) and their (non-)expectations regarding post-work availability.

Limitations and future directions

As with any study, there are limitations to consider. First, we used only self-reports. Therefore, common method variance might have inflated the relationships between the variables (Podsakoff et al., 2003). Although recovery experiences are currently best accessed through self-report, more objective assessments of outcomes may be insightful (e.g., actigraphy for sleep quality). In this respect, it is important to note that the present data are part of a larger project and that a high participant burden may have compromised measurement validity. Similarly, we assessed training compliance using a self-report proxy variable, indicating that 63% of the training group had completed the last training module at the second measurement occasion. Unfortunately, this measure does not provide insights into variability in participation within individuals across weeks and between individuals. Second, person-centred analyses are inherently exploratory, and numerous decisions within the analyses necessarily had to be made in light of the data. Here, transparency about all analytical paths is key, guiding our reports in the manuscript and SOM.[6]

A further issue is that, while we perceive the diverse professional backgrounds in our sample as a strength, different professions may vary in their recovery experiences and potential training effects. Due to sample size constraints, we could not explore differences between professions, but a person-centred approach may reveal potential qualitative differences across professions in future research. Sonnentag et al. (2022) argue that differences between professions in recovery may be especially pronounced when work-rest cycles (e.g., shiftwork) or the extent of physical demands (e.g., blue-collar workers) differ. Our sample was quite homogeneous in these regards because of our inclusion criterion regarding core working hours during the day. We therefore attracted mainly white-collar workers as participants, as is typical for recovery research (Sonnentag et al., 2022). Additionally, our sample was predominantly female, limiting the generalizability of the results to populations with different gender distributions. Still, women are more likely to seek help regarding their mental health (Liddon et al., 2018), making them an especially relevant target group when it comes to individuals voluntarily engaging in recovery training.

[6]For transparency and to check for the robustness of our results, we further conducted a sensitivity analysis addressing the imbalanced sample sizes of the training and control group (see SOM1.5). The interpretation of the results aligns with the results reported for the full sample in this manuscript, indicating our results were not produced by the imbalanced sample sizes.

CONCLUSION

Our results corroborate the idea that employees report different profiles of concurrent recovery experiences. These profiles are a target for training, as many participants improved in their recovery from work and transitioned from less to more adaptive recovery profiles. Adaptive transitions were associated with better sleep quality and lower perceived stress, and were particularly likely among trained participants. Our research makes methodological contributions by showing how a person-centred approach is well-suited to reveal patterns and training effects that have been previously underexplored. We inspire future theoretical developments around recovery training, by showing who participates in recovery training (e.g., people struggling with psychological detachment in particular), how recovery experiences respond differentially to training (e.g., psychological detachment being especially malleable), and how heterogeneous training responses across individuals translate into improved well-being (e.g., improvements of recovery experiences linked to more favourable outcomes than maintenance or declines of levels of recovery).

AUTHOR CONTRIBUTIONS

Lisa Peuckmann: Data curation; formal analysis; visualization; writing – review and editing; writing – original draft. **Malte Friese:** Investigation; supervision; writing – original draft; writing – review and editing. **Dorota Reis:** Conceptualization; investigation; funding acquisition; methodology; resources; software; supervision; data curation; writing – original draft; writing – review and editing.

ACKNOWLEDGEMENTS

This research was funded by a grant from the German Research Foundation to Dorota Reis (RE 3938/2-1). We want to thank Alexander Hart, Saskia Kirchner, Paula Lambert, Tabea Werner, Tobias Ludwig, Kai Krautter and Paul Stasch for their indispensable help with this project. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data set is available on the OSF: https://osf.io/32rhy.

ORCID

Lisa Peuckmann https://orcid.org/0009-0001-6434-5185
Malte Friese https://orcid.org/0000-0003-0055-513X
Dorota Reis https://orcid.org/0000-0002-0027-9713

REFERENCES

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, *22*(3), 309–328. https://doi.org/10.1108/02683940710733115

Bakker, A. B., Sanz-Vergel, A. I., Rodríguez-Muñoz, A., & Oerlemans, W. G. M. (2015). The state version of the recovery experience questionnaire: A multilevel confirmatory factor analysis. *European Journal of Work and Organizational Psychology*, *24*(3), 350–359. https://doi.org/10.1080/1359432X.2014.903242

Bennett, A. A., Gabriel, A. S., Calderwood, C., Dahling, J. J., & Trougakos, J. P. (2016). Better together? Examining profiles of employee recovery experiences. *Journal of Applied Psychology*, *101*(12), 1635–1654. https://doi.org/10.1037/apl0000157

Berset, M., Elfering, A., Lüthy, S., Lüthi, S., & Semmer, N. K. (2011). Work stressors and impaired sleep: Rumination as a mediator. *Stress and Health: Journal of the International Society for the Investigation of Stress*, *27*(2), e71–e82. https://doi.org/10.1002/smi.1337

Chawla, N., MacGowan, R. L., Gabriel, A. S., & Podsakoff, N. P. (2020). Unplugging or staying connected? Examining the nature, antecedents, and consequences of profiles of daily recovery experiences. *Journal of Applied Psychology*, *105*(1), 19–39. https://doi.org/10.1037/apl0000423

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, *24*(4), 385–396. https://doi.org/10.2307/2136404

Crain, T. L., Schonert-Reichl, K. A., & Roeser, R. W. (2017). Cultivating teacher mindfulness: Effects of a randomized controlled trial on work, home, and sleep outcomes. *Journal of Occupational Health Psychology*, *22*(2), 138–152. https://doi.org/10.1037/ocp0000043

Creswell, J. D. (2017). Mindfulness trainings. *Annual Review of Psychology*, *68*(1), 491–516. https://doi.org/10.1146/annurev-psych-042716-051139

De Bloom, J., Sianoja, M., Korpela, K., Tuomisto, M., Lilja, A., Geurts, S., & Kinnunen, U. (2017). Effects of park walks and relaxation exercises during lunch breaks on recovery from job stress: Two randomized controlled trials. *Journal of Environmental Psychology*, *51*, 14–30. https://doi.org/10.1016/j.jenvp.2017.03.006

Ebert, D. D., Berking, M., Thiart, H., Riper, H., Laferton, J. A. C., Cuijpers, P., Sieland, B., & Lehr, D. (2015). Restoring depleted resources: Efficacy and mechanisms of change of an internet-based unguided recovery training for better sleep and psychological detachment from work. *Health Psychology*, *34*(Suppl), 1240–1251. https://doi.org/10.1037/hea0000277

Ebert, D. D., Lehr, D., Heber, E., Riper, H., Cuijpers, P., & Berking, M. (2016). Internet- and mobile-based stress management for employees with adherence-focused guidance: Efficacy and mechanism of change. *Scandinavian Journal of Work, Environment & Health*, *42*(5), 382–394. https://doi.org/10.5271/sjweh.3573

Eisele, G., Vachon, H., Lafit, G., Tuyaerts, D., Houben, M., Kuppens, P., Myin-Germeys, I., & Viechtbauer, W. (2023). A mixed-method investigation into measurement reactivity to the experience sampling method: The role of sampling protocol and individual characteristics. *Psychological Assessment*, *35*(1), 68–81. https://doi.org/10.1037/pas0001177

Eliasson, A. H., Kashani, M., Mayhew, M., Ude, A., Hoffman, J., & Vernalis, M. (2010). Reducing perceived stress improves sleep quality: A longitudinal outcomes study. *Chest*, *138*(4), 913A. https://doi.org/10.1378/chest.10417

Fokkema, M., Smits, N., Kelderman, H., & Cuijpers, P. (2013). Response shifts in mental health trainings: An illustration of longitudinal measurement invariance. *Psychological Assessment*, *25*(2), 520–531. https://doi.org/10.1037/a0031669

Gabriel, A. S., Calderwood, C., Bennett, A. A., Wong, E. M., Dahling, J. J., & Trougakos, J. P. (2019). Examining recovery experiences among working college students: A person-centered study. *Journal of Vocational Behavior*, *115*, 103329. https://doi.org/10.1016/j.jvb.2019.103329

Goldberg, S. B. (2022). A common factors perspective on mindfulness-based trainings. *Nature Reviews Psychology*, *1*(10), 605–619. https://doi.org/10.1038/s44159-022-00090-8

Görtelmeyer, R. (2011). *Schlaffragebogen A und B - Revidierte Fassung [Standardized Sleep Inventory for the SF-A/R and SF-B/R–revised version]*. Hogrefe.

Grant, R. S., Shockley, K. M., Matta, F. K., & Clark, M. A. (2026). What's your 5 to 9? Antecedents and outcomes of profiles of daily recovery experience trajectories across the evening. *Journal of Applied Psychology*. Advance Online Publication. https://doi.org/10.1037/apl0001354

Hahn, V. C., Binnewies, C., Sonnentag, S., & Mojza, E. J. (2011). Learning how to recover from job stress: Effects of a recovery training program on recovery, recovery-related self-efficacy, and well-being. *Journal of Occupational Health Psychology*, *16*(2), 202–216. https://doi.org/10.1037/a0022169

Halbesleben, J. R., Wheeler, A. R., & Paustian-Underdahl, S. C. (2013). The impact of furloughs on emotional exhaustion, self-rated performance, and recovery experiences. *Journal of Applied Psychology*, *98*(3), 492–503. https://doi.org/10.1037/a0032242

Hallquist, M. N., & Wiley, J. F. (2018). MplusAutomation: An R package for facilitating large-scale latent variable analyses in Mplus. *Structural Equation Modeling*, *25*, 621–638. https://doi.org/10.1080/10705511.2017.1402334

Headrick, L., Newman, D. A., Park, Y. A., & Liang, Y. (2022). Recovery experiences for work and health outcomes: A meta-analysis and recovery-engagement-exhaustion model. *Journal of Business and Psychology*, *38*, 821–864. https://doi.org/10.1007/s10869-022-09821-3

Heber, E., Ebert, D. D., Lehr, D., Cuijpers, P., Berking, M., Nobis, S., & Riper, H. (2017). The benefit of web- and computer-based interventions for stress: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *19*(2), e32. https://doi.org/10.2196/jmir.5774

Ho, K. L., Mäkikangas, A., Kerksieck, P., Morstatt, A. I., de Bloom, J., & Bauer, G. F. (2024). Job and off-job crafting profiles: Time-lagged relationships with job, home and personal resources and well-being outcomes. *Journal of Occupational and Organizational Psychology*, *97*(3), 952–976. https://doi.org/10.1111/joop.12506

Kabat-Zinn, J. (1982). An outpatient program in behavioral medicine for chronic pain patients based on the practice of mindfulness meditation: Theoretical considerations and preliminary results. *General Hospital Psychiatry*, *4*(1), 33–47. https://doi.org/10.1016/0163-8343(82)90026-3

Kabat-Zinn, J. (2006). *Gesund durch Meditation: Das große Buch der Selbstheilung*. Fischer-Taschenbuch-Verlag.

Karabinski, T., Haun, V., Nübold, A., Wendsche, J., & Wegge, J. (2021). Trainings for improving psychological detachment from work: A meta-analysis. *Journal of Occupational Health Psychology*, *26*(3), 224–242. https://doi.org/10.1037/ocp0000280

Liddon, L., Kingerlee, R., & Barry, J. A. (2018). Gender differences in preferences for psychological treatment, coping strategies, and triggers to help-seeking. *British Journal of Clinical Psychology*, *57*(1), 42–58. https://doi.org/10.1111/bjc.12147

Linde, M., Tendeiro, J. N., Selker, R., Wagenmakers, E.-J., & van Ravenzwaaij, D. (2021). Decisions about equivalence: A comparison of TOST, HDI-ROPE, and the Bayes factor. *Psychological Methods*, *28*, 740–755. https://doi.org/10.1037/met0000402

Lischetzke, T., Reis, D., & Arndt, C. (2015). Data-analytic strategies for examining the effectiveness of daily interventions. *Journal of Occupational and Organizational Psychology*, *88*(3), 587–622. https://doi.org/10.1111/joop.12104

Lubbers, J., Spinhoven, P., Cladder-Micus, M. B., Spijker, J., Speckens, A. E. M., & Geurts, D. E. M. (2024). Change in mindfulness profiles after mindfulness-based cognitive therapy for major depressive disorder. *Mindfulness*, *15*, 1682–1700. https://doi.org/10.1007/s12671-024-02390-x

Morin, A. J. S., Bujacz, A., & Gagné, M. (2018). Person-centered methodologies in the organizational sciences: Introduction to the feature topic. *Organizational Research Methods*, *21*(4), 803–813. https://doi.org/10.1177/1094428118773856

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling: A Multidisciplinary Journal*, *18*(4), 613–648. https://doi.org/10.1080/10705511.2011.607714

Muthén, L. K., & Muthén, B. O. (2022). *Mplus user's guide (1998–2017. 8th ed.)*. Muthén & Muthén. [Software].

Newman, D. B., Tay, L., & Diener, E. (2014). Leisure and subjective well-being: A model of psychological mechanisms as mediating factors. *Journal of Happiness Studies*, *15*(3), 555–578. https://doi.org/10.1007/s10902-013-9435-x

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Nylund-Gibson, K., Garber, A. C., Carter, D. B., Chan, M., Arch, D. A. N., Simon, O., Whaling, K., Tartt, E., & Lawrie, S. I. (2023). Ten frequently asked questions about latent transition analysis. *Psychological Methods*, *28*(2), 284–300. https://doi.org/10.1037/met0000486

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Querstret, D., Cropley, M., Kruger, P., & Heron, R. (2016). Assessing the effect of a cognitive behaviour therapy (CBT)-based workshop on work-related rumination, fatigue, and sleep. *European Journal of Work and Organizational Psychology*, *25*(1), 50–67. https://doi.org/10.1080/1359432X.2015.1015516

R Core Team. (2024). *R: A language and environment for statistical computing [Software]*. R Foundation for Statistical Computing. https://www.R-project.org/

Reinke, K., & Ohly, S. (2024). Examining the training design and training transfer of a boundary management training: A randomized controlled intervention study. *Journal of Occupational and Organizational Psychology*, *97*, 864–888. https://doi.org/10.1111/joop.12497

Reis, D., Hart, A., Krautter, K., Prestele, E., Lehr, D., & Friese, M. (2024). Mindfulness and cognitive-behavioral strategies for psychological detachment: Comparing effectiveness and mechanisms of change. *Journal of Occupational Health Psychology*, *29*, 258–279. https://doi.org/10.1037/ocp0000381

Reis, D., Hart, A., Lehr, D., & Friese, M. (2021). Promoting recovery in daily life: Study protocol for a randomized controlled trial. *BMC Psychology*, *9*(1), 91. https://doi.org/10.1186/s40359-021-00591-w

Reis, D., Lehr, D., Heber, E., & Ebert, D. D. (2019). The German version of the Perceived Stress Scale (PSS-10): Evaluation of dimensionality, validity, and measurement invariance with exploratory and confirmatory bifactor modeling. *Assessment*, *26*(7), 1246–1259. https://doi.org/10.1177/1073191117715731

Reis, D., & Prestele, E. (2020). The role of trait and state perfectionism in psychological detachment from daily job demands. *Stress and Health*, *36*(2), 228–245. https://doi.org/10.1002/smi.2901

Seddig, D., & Leitgöb, H. (2018). Approximate measurement invariance and longitudinal confirmatory factor analysis: Concept and application with panel data. *Survey Research Methods*, *12*(1), 29–41. https://doi.org/10.18148/srm/2018.v12i1.7210

Segal, Z. V., Williams, J. M. G., & Teasdale, J. D. (2002). *Mindfulness-based cognitive therapy for depression: A new approach to preventing relapse*. Guilford Press.

Siegel, R. D. (2010). *The mindfulness solution: Everyday practices for everyday problems*. Guilford Press.

Siltaloppi, M., Kinnunen, U., Feldt, T., & Tolvanen, A. (2011). Identifying patterns of recovery experiences and their links to psychological outcomes across one year. *International Archives of Occupational and Environmental Health*, *84*(8), 877–888. https://doi.org/10.1007/s00420-011-0672-1

Sonnentag, S. (2018). The recovery paradox: Portraying the complex interplay between job stressors, lack of recovery, and poor well-being. *Research in Organizational Behavior*, *38*, 169–185. https://doi.org/10.1016/j.riob.2018.11.002

Sonnentag, S., Cheng, B. H., & Parker, S. L. (2022). Recovery from work: Advancing the field toward the future. *Annual Review of Organizational Psychology and Organizational Behavior*, *9*(1), 33–60. https://doi.org/10.1146/annurev-orgpsych-012420-091355

Sonnentag, S., & Fritz, C. (2007). The recovery experience questionnaire: Development and validation of a measure for assessing recuperation and unwinding from work. *Journal of Occupational Health Psychology*, *12*(3), 204–221. https://doi.org/10.1037/1076-8998.12.3.204

Sonnentag, S., Venz, L., & Casper, A. (2017). Advances in recovery research: What have we learned? What should be done next? *Journal of Occupational Health Psychology*, *22*(3), 365–380. https://doi.org/10.1037/ocp0000079

Stoeber, J., & Otto, K. (2006). Positive conceptions of perfectionism: Approaches, evidence, challenges. *Personality and Social Psychology Review*, *10*(4), 295–319. https://doi.org/10.1207/s15327957pspr1004_2 ten Brummelhuis, L. L., & Bakker, A. B. (2012). Staying engaged during the week: The effect of off-job activities on next day work engagement. *Journal of Occupational Health Psychology*, *17*(4), 445–455. https://doi.org/10.1037/a0029213

Thiart, H., Lehr, D., Ebert, D. D., Berking, M., & Riper, H. (2015). Log in and breathe out: Internet-based recovery training for sleepless employees with work-related strain—Results of a randomized controlled trial. *Scandinavian Journal of Work, Environment & Health*, *41*(2), 164–174. http://www.jstor.org/stable/24466922

van Ravenzwaaij, D., Monden, R., Tendeiro, J. N., & Ioannidis, J. P. A. (2019). Bayes factors for superiority, non-inferiority, and equivalence designs. *BMC Medical Research Methodology*, *19*(1), 71. https://doi.org/10.1186/s12874-019-0699-7

Verbeek, J., Ruotsalainen, J., Laitinen, J., Korkiakangas, E., Lusa, S., Mänttäri, S., & Oksanen, T. (2019). Interventions to enhance recovery in healthy workers: A scoping review. *Occupational Medicine*, *69*(1), 54–63. https://doi.org/10.1093/occmed/kqy141

Virtanen, A., De Bloom, J., & Kinnunen, U. (2020). Relationships between recovery experiences and well-being among younger and older teachers. *International Archives of Occupational and Environmental Health*, *93*(2), 213–227. https://doi.org/10.1007/s00420-019-01475-8

Virtanen, A., Van Laethem, M., De Bloom, J., & Kinnunen, U. (2021). Drammatic breaks: Break recovery experiences as mediators between job demands and affect in the afternoon and evening. *Stress and Health*, *37*(4), 801–818. https://doi.org/10.1002/smi.3041

Wang, M., & Hanges, P. J. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods*, *14*(1), 24–31. https://doi.org/10.1177/1094428110383988

Watkins, E. R. (2016). *Rumination-focused cognitive-behavioral therapy for depression*. Guilford Publications.

Weinberg, M. K., Noble, J. M., & Hammond, T. G. (2016). Sleep well feel well: An investigation into the protective value of sleep quality on subjective well-being. *Australian Journal of Psychology*, *68*(2), 91–97. https://doi.org/10.1111/ajpy.12098

Woo, S. E., Hofmans, J., Wille, B., & Tay, L. (2024). Person-centered modeling: Techniques for studying associations between people rather than variables. *Annual Review of Organizational Psychology and Organizational Behavior*, *11*, 453–480. https://doi.org/10.1146/annurev-orgpsych-110721-045646

How to cite this article: Peuckmann, L., Friese, M., & Reis, D. (2026). Evaluating training-related changes in profiles of recovery experiences. *Journal of Occupational and Organizational Psychology*, *99*, e70119. https://doi.org/10.1111/joop.70119