Journal of Applied Psychology

What's Your 5 to 9? Antecedents and Outcomes of Profiles of Daily Recovery Experience Trajectories Across the Evening

Ryan S. Grant, Kristen M. Shockley, Fadel K. Matta, and Malissa A. Clark

Online First Publication, February 12, 2026. https://dx.doi.org/10.1037/apl0001354

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

https://doi.org/10.1037/apl0001354

What's Your 5 to 9? Antecedents and Outcomes of Profiles of Daily Recovery Experience Trajectories Across the Evening

Ryan S. Grant[1], Kristen M. Shockley[2], Fadel K. Matta[3], and Malissa A. Clark[4]

[1] Department of Psychological Science, University of North Carolina at Charlotte

[2] Department of Management and Entrepreneurship, Auburn University

[3] Department of Management, Terry College of Business, University of Georgia

[4] Department of Psychology, University of Georgia

Every day at work employees are faced with resource depleting demands, necessitating recovery after work to avoid health and well-being detriments. Recovery theory and empirical results suggest that the four main recovery experiences that underlie employee recovery—psychological detachment, relaxation, mastery, and control—can occur concurrently. At the same time, each of these recovery experiences are dynamic and change across the evening. However, previous recovery research has not investigated and empirically examined both notions at the same time. Using a combined person-centered, dynamic approach across two experience sampling studies, we examine daily profiles of trajectories of all four recovery experiences across an entire evening after work. We also examine how daily job demands and resources relate to these profiles, and how profile membership relates to next-day work and well-being outcomes. Results revealed three profiles of recovery experience trajectory combinations that were predicted by job demands and resources. Results also revealed that having psychological detachment, relaxation, and control experiences early and often across the evening results in the most optimal daily recovery process for next-day well-being. This work represents an important stride forward as it is the first to examine *how* the recovery process unfolds, along with providing practical recommendations for how employees should best recover daily.

Keywords: recovery, recovery experiences, well-being, experience sampling methods, latent profile analysis

Recovery from work—the process of unwinding and recuperating from daily work stress (Sonnentag et al., 2022)—is a critical part of worker well-being. Over the past few decades, researchers have formed a strong theoretical understanding of recovery. In terms of the content, Sonnentag and Fritz (2007) put forth that four basic psychological experiences underlie recovery activities: relaxation (experiencing low physical and/or mental activation), psychological detachment (not thinking about work during nonwork time), mastery (taking part in challenging and engaging hobbies), and control (having control over how one spends leisure time). In terms of form, workers can experience different *combinations* of levels of all four recovery experiences at the same time (e.g., high on one while low on two) and different combinations of experiences relate uniquely to antecedents and outcomes (Chawla et al., 2020; Sonnentag & Fritz, 2007). Recovery is also theorized to occur through a *dynamic process* of continuous change, ebbing and flowing across a recovery period, such as an evening after work (Meijman & Mulder, 1998; Zijlstra et al., 2014).

Despite recovery being theorized as a dynamic process, we know very little about the recovery process itself. This is due to a majority of the recovery studies that use experience sampling methods in the recovery literature only measuring recovery experiences once; either before bed or upon waking the following morning, with this one measurement point capturing average recovery for that entire recovery period (i.e., that evening; Chawla et al., 2020; Sonnentag et al., 2008). This does not align with recovery theories which suggest that recovery experiences ebb and flow across an evening. For example, Zijlstra et al. (2014) noted that recovery theories like the effort recovery model (ERM) and allostatic load theory (McEwen, 1998) "refer to

Bryan D. Edwards served as action editor.

Ryan S. Grant https://orcid.org/0009-0003-1192-2393

The syntax for this research and additional online materials can be found in a data repository on the Open Science Framework (https://osf.io/djen2/?view_only=ecce8222082843c39070fae1a6f24c6f). The authors have no known conflicts of interest to disclose. This study was partially funded by the National Institute of Occupational Safety and Health and Pilot Research Project through the Sunshine Education and Research Center at the University of South Florida (Award Number 5 T42OH008438-18-00), awarded to Ryan S. Grant. This study was supported by Centers for Disease Control and Prevention. The authors also thank the Harbert College of Business at Auburn University for funding Study 2. The authors also thank Lia O'Malley for her efforts in aiding the data collection for Study 1.

Ryan S. Grant played a lead role in conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing–original draft, and writing–review and editing. Kristen M. Shockley played a supporting role in conceptualization, funding acquisition, methodology, supervision, and writing–review and editing. Fadel K. Matta played a supporting role in formal analysis, methodology, software, and writing–review and editing. Malissa A. Clark played a supporting role in methodology and writing–review and editing.

Correspondence concerning this article should be addressed to Ryan S. Grant, Department of Psychological Science, University of North Carolina at Charlotte, 9105 University Road, Charlotte, NC 28223, United States. Email: rgrant32@charlotte.edu

(psychophysiological) 'states' that change, which implies that a 'process' is involved" (p. 245). Given recovery experiences are the underlying mechanism through which recovery occurs (Sonnentag & Fritz, 2007), they are a part of this process and should exhibit continuous change as well. Recovery theory and recent empirical work (Arnold et al., 2023) thus suggest that measurement that aligns with this conceptualization of recovery as a dynamic process should assess recovery frequently, allowing for the examination of change trajectories across time. However, once-daily summary assessments ignore this variation, obscuring the dynamic ebbs and flows and unique trajectories that characterize the recovery process. From a theoretical standpoint, distinct patterns across time likely do not relate to outcomes in the same way. That is, recovery theory suggests that we would not expect, for example, a person who has a medium, constant level of detachment across an entire evening to experience similar strain as a person who has detachment that starts high and decreases across the evening (Meijman & Mulder, 1998).

Further, not only are recovery experiences theorized to be dynamic, but they also have unique effects based on their co-occurrence (Bennett et al., 2016). However, previous research has only examined each approach in isolation. Specifically, researchers have examined how they co-occur (i.e., Chawla et al., 2020, who computed latent profile analyses of the four recovery experiences based on evening reports of the average level of each experience across the day). Such assessments are useful insofar as they illuminate which combinations of the recovery experiences—in terms of their average levels for an entire evening—are most beneficial for recovery (e.g., being high or moderately high on all four is optimal vs. a compensatory approach where one only needs to be high on one or two experiences). However, this profile approach is limited in that only using one-time assessments that ask people to think about their average level of recovery across an evening masks the trajectories that show the ebb and flow of recovery experiences. Indeed, Arnold et al. (2023) provides evidence that the four recovery experiences significantly vary across an evening. They examined each recovery experience in isolation with a variable-centered approach. The trends for some experiences were unique from others (e.g., detachment vs. mastery), but all showed significant and substantive fluctuation across an evening. Taken together, empirical evidence aligns with theoretical guidance (Meijman & Mulder, 1998; Zijlstra et al., 2014) to show that recovery experiences (a) follow meaningful daily trajectories and (b) form meaningful profiles in terms of how they tend to cluster together on a daily level.

To date, the literature lacks theoretical approaches and empirical investigations that combine these two approaches. This is problematic in that our ability to understand optimal recovery experiences is only as accurate as the theoretical phenomena we consider and the accuracy of our measurement approach. Without a theoretical and empirical approach that considers the dynamic nature of recovery as well as the co-occurrence of experiences, it is difficult to achieve a basic understanding of the complex temporal patterns of daily recovery. Reflecting this sentiment, Sonnentag et al. (2017) noted in their seminal review that "we know surprisingly little about how the recovery process unfolds over time" (p. 374). Furthermore, making additional theoretical progress on the daily change process of recovery is hindered if we do not first know the basics regarding how this process occurs (Mitchell & James, 2001; Shipp & Cole, 2015). Finally, we cannot gain an accurate understanding of how antecedents impact the recovery process, nor how the recovery process impacts important outcomes, if we are not capturing it in the way it actually occurs.

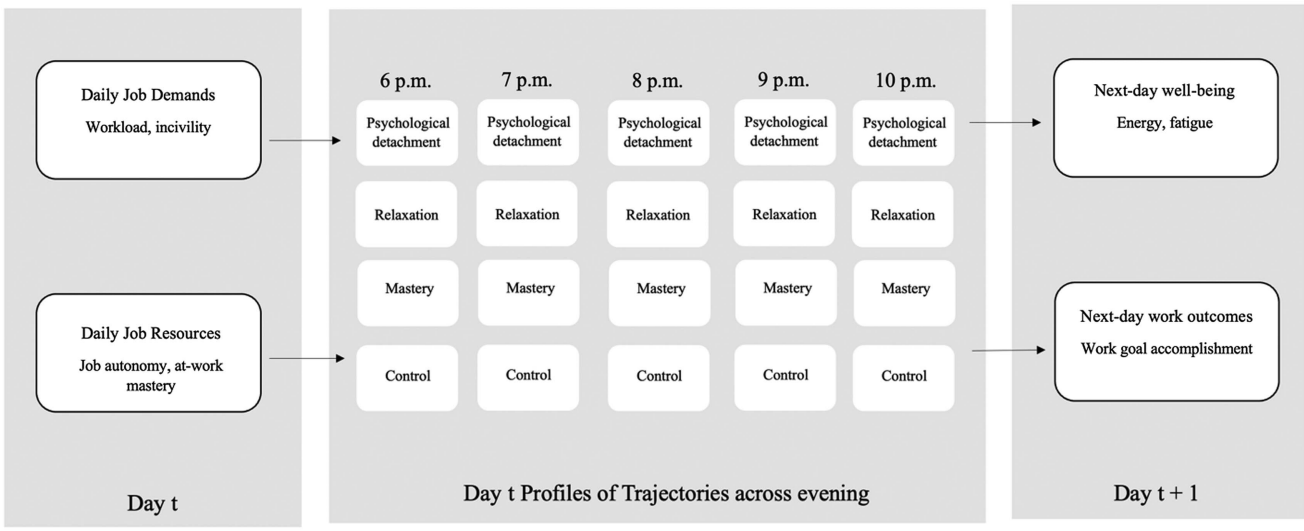
Beyond the basic theoretical implications, combining these approaches is also necessary to help reconcile conflicting findings regarding what optimal recovery processes look like. Chawla et al.'s (2020) person-centered results suggest that the most beneficial next-day recovery outcomes come from a higher daily level of all four experiences in combination. Thus, one could conclude that having all experiences in conjunction at any point in the evening is beneficial (i.e., more is better at any time), as long as this results in a high average for the evening. Using the trajectory approach across an evening, Arnold et al. (2023) found that controlling for mean levels, the psychological detachment trajectory predicted next afternoon positive affective states, such that a steeper positive slope resulted in more favorable recovery. None of the other three recovery experiences—neither their average levels nor their slopes—were predictive of next-day outcomes. In contrast to the conclusions from Chawla et al., the results of Arnold et al.'s study could lead one to draw the conclusion that only psychological detachment is meaningful and the timing of its occurrence matters beyond the mean level.

In essence, these distinct approaches provide different stories regarding what optimal recovery processes look like, which is problematic insofar as discovering what beneficial recovery processes look like is arguably the central purpose of research on daily recovery (Sonnentag, 2001; Sonnentag et al., 2017, 2022). Both approaches have their benefits. The theoretical value of a person-centered approach is that it allows for the identification of distinct subgroups that may show a distinct pattern from what is found when taking a variable-centered approach, which by definition masks these differences through averages (Wang & Hanges, 2011). The theoretical value of a variable-centered approach is that it considers recovery in a nuanced way across an evening, captures recovery as it actually unfolds, and avoids issues related to psychological processes involved in averaging values across a day (e.g., reporting only the peak or most recent experiences; Fredrickson & Kahneman, 1993). However, only when these two approaches are combined together can we unpack the way each recovery experience unfolds over time in conjunction with the way each of the other recovery experiences simultaneously unfold over time.

With this in mind, the purpose of the present study was to combine dynamic and person-centered approaches to examine the existence of *daily profiles of trajectories of change in the four recovery experiences* (i.e., relaxation, mastery, control, psychological detachment) across evenings after work. In Study 1, we adopt an experience sampling design where participants report all four recovery experiences five times across the entire evening for five consecutive workdays to examine the existence of daily trajectory profiles across all four recovery experiences. In Study 2, we replicate the profiles found in Study 1 using a distinct methodology (the evening reconstruction method; Arnold et al., 2023; Kahneman et al., 2004), capturing all four recovery experiences at five points across the evening for 10 consecutive workdays. In addition to discovering the prototypical trajectories of recovery experiences across an evening, it is also important to understand the correlates of these trajectories. To this end, in Study 2, we also examine both predictors (workload, incivility, autonomy, at-work mastery) and next-day outcomes (work goal accomplishment, energy, fatigue) related to these trajectory profiles. See Figure 1 for the study's theoretical model.

While our focus is on uncovering profiles of trajectories, average levels of recovery experiences are inherently embedded in our

Figure 1
Theoretical Model



Note. Recovery experiences are measured for 5 hr after one ended work, starting 1 hr after the time one ended work. This figure represents the timing of surveys for someone who ended work at 5 p.m. For those who ended work at 4 p.m., these surveys would begin at 5 p.m. and finish at 9 p.m.

modeling approach. Each evening recovery experience trajectory is defined by an intercept (i.e., starting point) and a slope (i.e., rate of change), and together these values shape the overall mean level of recovery across the evening. For example, a medium intercept with flat trajectory and a low intercept with an increasing trajectory may produce similar values at the end of the evening or even the same mean value across the evening, but they represent distinct temporal recovery patterns. By modeling trajectories, we not only account for average levels but also capture the dynamic process through which recovery experiences unfold across the evening. This offers a more nuanced and theoretically aligned examination of the recovery process.

Along with the theoretical benefits of incorporating the role of temporal patterns of recovery experiences in the recovery process, there are also practical benefits. By discovering optimal temporal patterns, our work provides more specific prescriptive recommendations that can be given to both organizations and individuals on *when* and *how* recovery experiences should occur in order to improve recovery and subsequent outcomes. Additionally, the profiles of trajectories approach could provide us with expanded and more specific knowledge of how antecedents in terms of individuals' work experiences impact the evening recovery process, which can have implications for job design.

General Theoretical Framework for Recovery

Recovery from work is defined as the unwinding and restoration processes where individuals reduce strain levels from stressors and demands at work to their prestress levels and restore lost psychological and energetic resources (Craig & Cooper, 1992; Meijman & Mulder, 1998). According to the ERM (Meijman & Mulder, 1998), one must spend effort at work to meet job demands. In turn, this effort results in load reactions, which are manifested in the form of physiological and psychological strain. For recovery to occur, job demands and their negative load effects must cease. Thus, the ERM suggests a more passive mechanism for recovery to occur through the cessation of job demands, activities, and thoughts. On the other hand, conservation of resources (COR; Hobfoll, 1989) theory suggests a more active mechanism of recovery. COR theory posits that exposure to job demands depletes individuals' energetic and psychological resources. In order to maintain well-being and perform at work, individuals must engage in recovery to restore lost resources and gain new resources (e.g., energy; Sonnentag & Fritz, 2007).

An additional key concept central to the recovery process is that four main recovery experiences (psychological detachment, relaxation, mastery, and control) represent the psychological experiences that underlie all recovery activities. That is, although the nature of recovery activities varies (e.g., playing a sport vs. socializing with friends), the underlying psychological attributes that contribute to feeling recovered by virtue of reducing strain symptoms and restoring energetic resources are the same (Headrick et al., 2022; Sonnentag & Fritz, 2007). All four recovery experiences have been positively related to well-being in many studies and are regarded as the key mechanism through which recovery occurs (Headrick et al., 2022; Sonnentag et al., 2022; Steed et al., 2021).

Furthermore, as noted above, definitions of recovery emphasize that recovery is a dynamic process. This process occurs on a daily basis as the demands of work require individuals to expend energetic resources and lead to strain symptoms, and job demands must cease and lost resources must be replenished through recovery (Hülsheger, 2016; Meijman & Mulder, 1998; Zijlstra et al., 2014). Given that recovery experiences are a key part of the recovery process, this implies that they are also dynamic in nature and exhibit continuous change over time. Overall, recovery experiences (a) can occur in combination together as any recovery activity can be represented by multiple recovery experiences during the evening (Chawla et al., 2020) and (b) are dynamic as they are a part of the recovery process (Arnold et al., 2023).

Study 1: Uncovering Daily Profiles of Trajectories of Recovery Experiences

Despite evidence that recovery experiences are dynamic and likely change across the evening, there is not strong evidence to suggest precisely what these profiles are a priori. As such, following previous person-centered research studies (e.g., Chawla et al., 2020; Shockley et al., 2022), we do not make predictions about profiles but instead engage in "thought exercises" about which profiles may emerge, drawing from related research.

Chawla et al. (2020) asked participants in the morning to recall their daily level of each of the four recovery experiences from the evening before and found evidence for five distinct within-person profiles. However, applying Chawla et al.'s findings to the present context presents some challenges. Because the profiles obtained are based on participants' reports of their aggregate experiences across an evening, we do not know if a medium level represents a stable medium level across the evening or a trajectory with a large slope, where the average level was somewhere in the middle. Even with profiles where all recovery experiences were low, we cannot assume this represents universally low levels across an evening, as there is evidence for recall bias when people aggregate experiences, such that they rely on the most recent memories (Beal, 2015). In this context, a person might be solely relying on how they felt at the end of the evening versus truly assessing their experiences across the evening. Thus, while Chawla et al. serves as a meaningful background to suggest that profiles of recovery experiences do exist and they vary daily, it is difficult to use these findings to make inferences about trajectory profiles.

Moreover, we also attempt to draw from research that does take a trajectory approach but neglects the person-centered analyses. Arnold et al. (2023) found that psychological detachment, relaxation, and control each showed a gradual, linear increasing trajectory across the evening and that mastery experiences showed an inverted-U shaped trajectory. Because these analyses were variable-centered, they only show the average daily trend across people, masking any distinct subgroups that may show a meaningfully distinct pattern (Wang & Hanges, 2011). It is theoretically possible that there are no distinct subgroups with unique co-variation patterns of the recovery experiences and that the average is truly representative, but Chawla et al.'s (2020) findings make that seem unlikely. Thus, the trajectories found in Arnold et al. could speculatively be one potential trajectory profile (assuming that the average is truly representative of some subgroup of people), though we anticipate finding additional trajectories.

Moving beyond previous research, we draw from theoretical ideas concerning the nature of certain recovery experiences. Specifically, mastery is unique from the other experiences in that it arises from activities that require effortful self-regulation (Sonnentag & Fritz, 2007). In contrast, psychological detachment and relaxation are more passive experiences. Given the sustained effort and energy required to experience mastery, some individuals may not engage in effortful mastery experiences at all (i.e., a trajectory that starts low and remains low) or they may experience mastery for shorter lengths of time. In contrast, another profile could emerge where psychological detachment, relaxation, and control show a gradual increase across the evening, paired with a flatter trajectory for mastery that starts at a low level. This speculation is in line with the stressor-detachment model (Sonnentag & Fritz, 2015), which suggests that experiencing job demands and work stress increases psychophysiological activation and can prolong feelings of tension, negative affect, and rumination after work (Bennett et al., 2016; Steed et al., 2021). This prolonged activation can make it difficult for individuals to relax and psychologically detach immediately after work, also leading to decreased control. Additionally, this increased fatigue may make it difficult to find energy for mastery (Sonnentag, 2018).

Along with profiles where recovery experiences change together like those proposed above, another profile may emerge where recovery experiences do not ebb and flow together in highly similar patterns. For example, Sonnentag and Fritz (2007) argued that relaxation arises from activities that require few social demands and require little physical or intellectual effort. This contrasts with mastery experiences, which require either or both physical and intellectual effortful self-regulation. An additional contrast is control experiences with all the other experiences. Control is an external resource (Sonnentag & Fritz, 2007), which may not necessarily be experienced at the same time with the other experiences.

A final profile may emerge consisting of delayed, sharp increases in psychological detachment, relaxation, and control that coincide with an increase in mastery experiences. Definitions of recovery as a dynamic process suggest that individuals need to actively regulate their psychological state for recovery to occur (Zijlstra et al., 2014). Rather than letting the effects of high job demands (e.g., tension, rumination) continue to linger, individuals can initiate the recovery process through recovery activities that result in mastery experiences. In line with the ERM, this mastery experience can cease work activation and load reactions, allowing the recovery process to begin (Meijman & Mulder, 1998). These mastery experiences in turn could promote increases in the other three recovery experiences the rest of the evening.

Given the potential of multiple trajectory profiles, we propose the following:

> *Research Question 1:* Are there distinct profiles of trajectories of the four recovery experiences across an evening?

Transparency and Openness

For both studies, we describe our sampling plan, data exclusions, and measures used in the study (see the Open Science Framework repository below for complete list of measures and items, instructions, and scale anchors) in the main text. We followed the *Journal of Applied Psychology* methodological reporting checklist. This study's design and its analysis were not preregistered. Code for analyses is available at https://tinyurl.com/dvhep2hy; data are available upon reasonable request. We used R Version 6.1 (R Core Team, 2023) to run Bayes slopes analyses using *lme4* (Version 1.1-34; Bates et al., 2015), *lavaan* (Version 0.6-16; Rosseel, 2012) for multilevel confirmatory factor analysis models, and multilevelTools (Version 0.1.1; Wiley, 2024) for multilevel reliabilities. Multilevel latent profile analyses (MLPA) were conducted using Mplus 8.9 (Muthén & Muthén, 2017). The University of Georgia Institutional Review Board (Protocol #00007226; Project title: "Antecedents and Outcomes of Daily Profiles of Trajectories of Recovery Experiences") approved both Studies 1 and 2.

Study 1: Method

Participants and Procedure

We recruited working adults using personal and professional networks. To be eligible, participants had to work at least 35 hr per

week in the United States on a daytime shift, have a bedtime that is typically more than 5 hr after the time they typically stop working, not work a second job, and not be self-employed. The final sample consisted of 167 participants.[1] They were 75.4% female and 86.2% White, 64.7% were married/living with a partner, 24% were parents, and the average age was 34.31. They worked on average 41.77 hr weekly and were highly educated, with 90.4% holding a bachelor's degree or higher, and worked in 16 unique industries.

Participants completed a baseline survey before the study began with demographic and work timing information. The daily surveys began on a Monday. For each survey, participants received a unique link via email and a text message reminder letting them know that the link had been sent to their email. The five evening surveys measuring recovery experiences (i.e., psychological detachment, relaxation, mastery, control; see Table 1 for measure details) began 1 hr after the end of their workday and continued for the next 4 hr. We catered the timing to each participant by asking what time they typically ended their workday in the baseline survey and sent it 1 hr after that indicated time. For example, a participant who indicated ending work at 3 p.m. received the first survey at 4 p.m., the next at 5 p.m., then 6 p.m., 7 p.m., and the final survey at 8 p.m. These were all shifted back 1 hr for a person who ended work at 4 p.m., and 2 hr for 5 p.m., and so forth. Surveys closed out 45 min after being sent. Participants could earn up to $90 for participation.

Analytic Approach

Computing Recovery Experience Trajectories

We used the five evening ratings of the four recovery experiences to estimate daily linear change trajectories. Based on prior work examining change trajectories (e.g., Chen et al., 2011; Dust et al., 2022; Frank et al., 2022), we used the Bayes slope estimate produced in hierarchical linear models (also referred to as random coefficient models; Bliese & Ployhart, 2002) to capture linear recovery experience change trajectories across the evening. More specifically, for each recovery experience we specified a random intercept, random slope linear model (Dust et al., 2022). In these models, the first hour of the evening equals zero, and the fifth hour equals four, and we regressed each recovery experience against this hourly time term. We also freely estimated the covariance between the intercept and slope for each experience, allowing for the intercept and slope to vary across days. This produces an intercept and linear slope coefficient for each recovery experience spanning from the first hour to the fifth hour of the evening for each individual for each day of the study. These daily slopes and intercepts were then used as input into MLPA to estimate profiles.[2]

Calculating Bayes slope estimates changes the data from a three-level structure, with hourly recovery experiences at level one, days at level two, and persons at level three, to a two-level model, with recovery experience trajectories now at the day level (level one), nested within persons (level two). Given that our focus is on daily profiles of trajectories, all analyses occur at the daily level of analysis (level one, which may naturally vary within and across individuals) while accounting for between-person nesting.

Research Question Testing

Given the nested nature of the data, we conducted MLPA (see Chawla et al., 2020; Shockley et al., 2022). We also conducted a multilevel confirmatory factor analysis to evaluate a four-factor measurement model, which exhibited excellent fit, $\chi^2(102) = 548.86$, $p < .01$, CFI = 0.99, TLI = 0.99, RMSEA = 0.04, SRMR = .04. We allowed the means of the profile indicators to be freely estimated in the model, but the variances were fixed, which is recommended when convergence issues emerge when variances are freely estimated (e.g., Bauer & Curran, 2003; Chawla et al., 2020; Gabriel et al., 2018; Morin et al., 2016; Shockley et al., 2022). Based on latent profile analysis and MLPA best practice recommendations (Hirschi & Valero, 2017; Spurk et al., 2020; Vermunt & Magidson, 2002), we screened the data for extreme outliers using the Mahalanobis distance[3] of the recovery experience intercept and linear slope profile indicators, as "extreme outliers might affect the estimation of the final profiles solution and lead to extreme profiles with only a few cases" (Spurk et al., 2020, p. 9). This analysis resulted in 11 cases being removed for a final sample of 795 daily observations to be used in MLPA analyses.[4]

Because MLPA is an inductive approach, the number of profiles cannot be determined a priori. Based on this, we initially specified a two-profile solution and increased the number of latent profiles until there was no further improvements in model fit (Nylund et al., 2007). We report the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the consistent AIC (CAIC),

[1] In total, 172 employees passed the eligibility survey and consented to participate in the study. Two respondents were removed from analyses after additional evidence emerged indicating that they had provided false information for compensation (i.e., their IP address location did not match the locations they listed as their address for compensation and the names provided for compensation did not match the names on their email addresses). Two additional participants completed the baseline survey but then did not complete any of the daily surveys and another participant only completed two of the possible 35 daily surveys, reducing the final usable sample size to 167.

[2] Bayes slopes estimates reflect a weighted combination of the day's observed trajectory and the overall sample trajectory, using a shrinkage process where more reliable daily estimates are drawn more from the individual's data and noisier estimates are pulled toward the sample average. This approach yields more stable and interpretable estimates for each day while preserving meaningful day-level variation in how recovery experiences unfold (Chen et al., 2011). Thus, the random effects (daily trajectories) represent each day's deviation from the sample average, weighted by the reliability of that day's data, allowing us to model dynamic recovery patterns without full variance decomposition. Our estimates are intended to reflect daily-level features of recovery patterns, which may naturally vary within and across individuals. Indeed, we were not interested in—and our interpretation would be muddied—by splitting trajectories into within and between components that separate deviations from a person's average daily trajectory on a particular day from person-to-person differences in average daily trajectories. Thus, we did not partition variance into within-person (i.e., transient within-person deviations from an individual's average trajectory) and between-person (e.g., stable between-person trajectories) components but rather focused on *daily-level patterns of recovery trajectories.* As such, we focus on absolute (uncentered) intercepts and slopes that reflect the full recovery experience trajectory on a given day, rather than estimating variance components.

[3] In line with previous recommendations (Aggarwal, 2016; Tabachnick & Fidell, 2007), we used the chi-square statistic values provided by the Mahalanobis distance analysis to calculate p values for each case in the data and used a cutoff value of $p < .001$. Cases in our data with p values less than this cutoff were determined to be extreme outliers and subsequently removed.

[4] The profiles and their indicator values did not show any substantive differences when estimated with and without the 11 outlier cases in Study 1.

Table 1
Studies 1 and 2 Measures

Variable	Study and time period	Citation	Number of items	Response scale	Sample item and scale reliability
Energy	Study 2 morning	Sheridan and Ambrose (2022)	3	1 = *strongly disagree* to 5 = *strongly agree*	"Right now, I feel energetic." (ω = .89)
Fatigue	Study 2 morning	Adapted to momentary level from McNair et al. (1971)	4	1 = *strongly disagree* to 5 = *strongly agree*	Participants rated their agreement with adjectives. Examples: "tired," "exhausted." (ω = .90)
Work goal accomplishment	Study 2 afternoon	Adapted to daily level from Wanberg et al. (2010)	3	1 = *strongly disagree* to 5 = *strongly agree*	"Today, I made good progress on my work goals." (ω = .94)
Workload	Study 2 afternoon	Adapted to daily level from Spector and Jex (1998)	3	1 = *strongly disagree* to 5 = *strongly agree*	"Today, I had a lot of work to do." (ω = .84)
Incivility	Study 2 afternoon	Adapted to daily level from Lim and Cortina (2005)	4	1 = *never* to 5 = *a great deal*	Today, how often were you in a situation where any of your coworkers or superiors … "Put you down or were condescending to you." (ω = .73)
Job autonomy	Study 2 afternoon	Adapted to daily level from Morgeson and Humphrey (2006)	3	1 = *strongly disagree* to 5 = *strongly agree*	"Today, my job gave me considerable opportunity for independence and freedom in how I do my work." (ω = .85)
At-work mastery	Study 2 afternoon	Adapted to daily level from Van den Broeck et al. (2010)	4	1 = *strongly disagree* to 5 = *strongly agree*	"Today, I felt competent at my job." (ω = .84)
Recovery experiences	Studies 1 and 2 evening	Adapted to hourly level from Sonnentag and Fritz (2007)	12 (three for each recovery experience)	1 = *not at all* to 5 = *very much* except for the first psychological detachment item, see additional online materials	"During the past hour/This evening from 5–6 p.m."; Psychological detachment: "I was not thinking about work at all" ($\omega_{Study\ 1}$ = .91; $\omega_{Study\ 2}$ = .95), relaxation: "I was kicking back and relaxing" ($\omega_{Study\ 1}$ = .98; $\omega_{Study\ 2}$ = .98), mastery: "I was doing something that challenges me" ($\omega_{Study\ 1}$ = .81; $\omega_{Study\ 2}$ = .86), control: "I felt that I could decide for myself what to do" ($\omega_{Study\ 1}$ = .97; $\omega_{Study\ 2}$ = .98)

Note. For hourly recovery experiences in Study 2, the stem of the item after "This evening from" changed based on which hour the participant needed to think back to for five consecutive hours. For the 4 p.m. group, the hourly intervals are 4–5 p.m., 5–6 p.m., 6–7 p.m., 7–8 p.m., and 8–9 p.m. For the 5 p.m. group, the hourly intervals are 5–6 p.m., 6–7 p.m., 7–8 p.m., 8–9 p.m., and 9–10 p.m.

the sample-adjusted BIC (SSA-BIC), the adjusted version of the Lo, Mendell, and Rubin likelihood ratio test (Lo et al., 2001), and entropy.[5] Information criteria (AIC, BIC, CAIC, SSA-BIC) evaluate model fit by balancing goodness of fit with model complexity, applying a penalty to the model fit value for each estimated parameter to discourage overfitting. Lower values suggest a better-fitting and more parsimonious model (Nylund et al., 2007). These criteria are used to compare models with varying numbers of profiles. The adjusted Lo–Mendell–Rubin test assesses whether adding one profile significantly improves fit, based on a *p* value. For example, a significant Lo–Mendell–Rubin when moving from four to five profiles suggests the five-profile model fits better. Entropy is a measure of how accurately individuals are assigned to profiles, with values ranging from 0 to 1 and a value of 1 signifying that individuals are perfectly assigned to profiles (Morin & Marsh, 2015).

Simulation studies suggest that the BIC, CAIC, and SSA-BIC are the most accurate fit statistics for choosing a final profile solution, especially when entropy values are high (≥.80; Diallo et al., 2017a, 2017b; Peugh & Fan, 2013, 2015). Lower BIC, CAIC, and SSA-BIC values indicate better model fit. However, these values often continue to decrease as more profiles are added, favoring increasingly complex models. This can lead to overfitting, where additional profiles are minor variations of existing ones without added theoretical value. To address this, researchers recommend using a visual elbow plot of each fit value to identify the point where the slope flattens (Morin & Marsh, 2015) to find a meaningful balance between fit and parsimony (Howard et al., 2016; Petras & Masyn, 2010). After identifying this point based on BIC, CAIC, and SSA-BIC, adjacent profile (one lower and one higher) solutions are compared with assess theoretical parsimony, interpretability (Howard et al., 2016; Shockley et al., 2022; Spoelma et al., 2023) as well as empirical distinctiveness and lack of theoretical redundancy (ensuring that the same profile was not theoretically represented twice; e.g., Howard et al., 2016). Since we lacked existing theory on recovery experience profile trajectories, we prioritized parsimony.

[5] We note that it is common to report the bootstrap likelihood ratio test (BLRT) as recommended by Nylund et al. (2007). However, the BLRT is not available in Mplus 8.9 using the MIXTURE COMPLEX command that is required to run MLPA (for previous studies using similar MLPA approaches, see Chawla et al., 2020; Diefendorff et al., 2019; Shockley et al., 2022).

Study 1: Results and Discussion

Descriptive statistics and correlations are in Table 2 and multilevel reliability omega estimates based on Geldhof et al. (2014) are available in Table 1. Profile enumeration results are presented in Table 3. The information criteria fit statistics continued to decrease without reaching a clear minimum value, so we relied on the elbow plot (see additional online materials), which showed a leveling off around three profiles. Thus, we examined the three-profile solution as well as the adjacent two- and four-profile solutions. Although the four-profile solution showed slightly better fit per the BIC, CAIC, and SSA-BIC, it included a theoretically redundant profile with a trajectory pattern that closely resembled one in the three-profile solution. Specifically, the redundant profile split the *steady control*, *delayed detachment/relaxation* profile into two profiles that slightly differed in their detachment intercept and slope. Thus, the three-profile solution was more parsimonious. The two-profile model missed a theoretically meaningful and had poorer fit than the three-profile solution, leading us to retain a three-profile solution. Table 4 displays the descriptive information associated with each trajectory profile of recovery experiences, and each trajectory profile is also plotted in Figure 2.

The trajectory profile with the largest membership (43.7% of days) reflected evenings where relaxation began at low levels and increased to a moderate level, psychological detachment began at a moderate level and gradually increased to a moderately high level across the evening, control that began at a high level and remained at this level consistently across the evening, and low levels of mastery that remained unchanged across the evening; we labeled this profile *steady control*, *delayed detachment/relaxation*. The second trajectory profile (32.5% of days) consisted of low mastery across the evening paired with psychological detachment, relaxation, and

Table 2

Descriptive Statistics and Correlations for Studies 1 and 2

Variable	Study 1 *M*	Study 1 *SD*	1	2	3	4	5	6	7	8
1. Psychological detachment intercept	3.29	0.99	—	−.76*	.51*	−.22*	−.06	.08*	.52*	−.39*
2. Psychological detachment slope	0.28	0.18	−.69*	—	−.32*	.43*	.09*	−.07*	−.30*	.46*
3. Relaxation intercept	2.40	0.84	.47*	−.30*	—	−.45*	−.09*	.11*	.61*	−.39*
4. Relaxation slope	0.40	0.18	−.17*	.41*	−.47*	—	.08*	−.13*	−.17*	.49*
5. Mastery intercept	1.52	0.32	.04	−.08*	−.13*	−.02	—	−.17*	.04	−.01
6. Mastery slope	−0.01	0.09	−.01	−.02	.05	−.16*	−.29*	—	.04	.01
7. Control intercept	3.56	1.02	.43*	−.27*	.57*	−.19*	.01	.06	—	−.69*
8. Control slope	0.20	0.16	−.35*	.37*	−.45*	.46*	−.05	−.08*	−.78*	—
9. Workload										
10. Incivility										
11. Job autonomy										
12. At-work mastery										
13. Next-day energy										
14. Next-day fatigue										
15. Next-day work goal accomplishment										
Within-person variation Study 1 (%)			61.30	80.79	69.82	81.83	70.41	91.50	50.73	70.69
Within-person variation Study 2 (%)			54.71	70.76	63.61	76.03	58.40	67.07	42.61	64.41

Variable	9	10	11	12	13	14	15	Study 2 *M*	Study 2 *SD*
1. Psychological detachment intercept	−.19*	−.08	−.02	.01	.06	−.03	−.04	3.22	1.12
2. Psychological detachment slope	.12*	.06	.06	.01	−.04	.01	.02	0.32	0.24
3. Relaxation intercept	−.15*	−.08*	−.04	.02	.03	.01	−.01	2.16	0.78
4. Relaxation slope	.06	.03	.05	.02	.02	−.04	.00	0.47	0.17
5. Mastery intercept	.02	.04	.01	.00	.05	−.02	.09*	1.54	0.37
6. Mastery slope	−.01	−.03	−.05	−.01	.07*	−.04	−.03	0.01	0.10
7. Control intercept	−.13*	−.04	−.02	.06	.01	.01	.00	3.13	1.16
8. Control slope	.11*	.03	.05	−.02	−.02	.01	−.03	0.27	0.20
9. Workload	—	.07*	−.03	.16*	−.11*	.06	.06	3.10	1.11
10. Incivility		—	−.06	−.11*	−.04	.04	.05	1.18	0.45
11. Job autonomy			—	.17*	.00	−.02	.01	4.29	0.74
12. At-work mastery				—	.07*	−.10*	−.04	3.83	0.88
13. Next-day energy					—	−.76*	.17*	3.35	1.10
14. Next-day fatigue						—	−.13*	2.65	1.22
15. Next-day work goal accomplishment							—	3.90	0.97
Within-person variation Study 1 (%)									
Within-person variation Study 2 (%)	55.45	42.02	55.79	53.24	58.57	52.85	67.14		

Note. Correlations below the diagonal are for Study 1 (Level 1 $n = 795$). Correlations above the diagonal are for Study 2 (Level 1 $n = 1{,}323$ for recovery experiences; antecedents [workload, incivility, job autonomy, and at-work mastery] Level 1 $n = 1{,}315$; lagged next-day outcomes [energy, fatigue, and work goal accomplishment] Level 1 $n = 1{,}220$). The bottom rows report the percentage of within-person variance for each variable in Studies 1 and 2, calculated using intraclass correlations.

* $p < .05$.

Table 3
Latent Profile Enumeration Fit Statistics for Studies 1 and 2

# of profiles	LL	FP	AIC	BIC	SSA-BIC	CAIC	LMR (p)	Entropy
Study 1								
2	−1,344.142	25	2,738.284	2,855.242	2,775.854	2,753.284	.00	.84
3	−1,168.414	34	2,404.827	2,563.891	2,455.922	2,438.827	.00	.81
4	−1,062.601	43	2,211.202	2,412.371	2,275.822	2,254.202	.42	.81
5	−960.860	52	2,025.721	2,268.995	2,103.866	2,077.721	.19	.81
6	−872.698	61	1,867.396	2,152.774	1,959.066	1,928.396	.28	.83
Study 2								
2	−3,187.159	25	6,424.318	6,554.009	6,474.595	6,449.318	.04	.84
3	−2,925.216	34	5,918.432	6,094.812	5,986.809	5,952.432	.07	.87
4	−2,591.488	43	5,268.976	5,492.046	5,355.454	5,311.976	.28	.84
5	−2,389.952	52	4,883.904	5,153.662	4,988.482	4,935.904	.22	.85
6	−2,236.120	61	4,594.241	4,910.688	4,716.919	4,655.241	.28	.83

Note. CAIC is calculated by adding the number of free parameters to the BIC value. LL = log-likelihood; FP = free parameters; AIC = Akaike information criteria; BIC = Bayesian information criteria; SSA-BIC = sample-size-adjusted BIC; CAIC = consistent AIC; LMR = Lo et al. (2001) test.

control beginning at low levels that sharply increased and reached moderate to moderately high levels toward the latter part of the evening. We labeled this trajectory profile *delayed recovery*. The third trajectory profile (23.8% of days) included moderately high levels of detachment, control, and relaxation that showed a slight increase across the evening. Mastery was consistently low. We labeled this profile *early steady recovery*.

To answer Research Question 1, distinct daily profiles of recovery experience trajectories across the evening do exist that are both quantitatively and qualitatively distinct. Notably, individuals engage in little mastery, as the same trajectory appears across profiles. It may be that fatiguing and depleting demands at work prevent individuals from having mastery experiences, as these experiences require effortful self-regulation (Sonnentag, 2018, Sonnentag & Fritz, 2007). It appears that the key differentiator in recovery trajectories is at what point individuals begin their recovery process during the evening, as most days end with individuals reaching moderate or moderately high levels of detachment, relaxation, and control.

Table 4
Descriptive Information for Daily Latent Recovery Trajectory Profiles for Studies 1 and 2

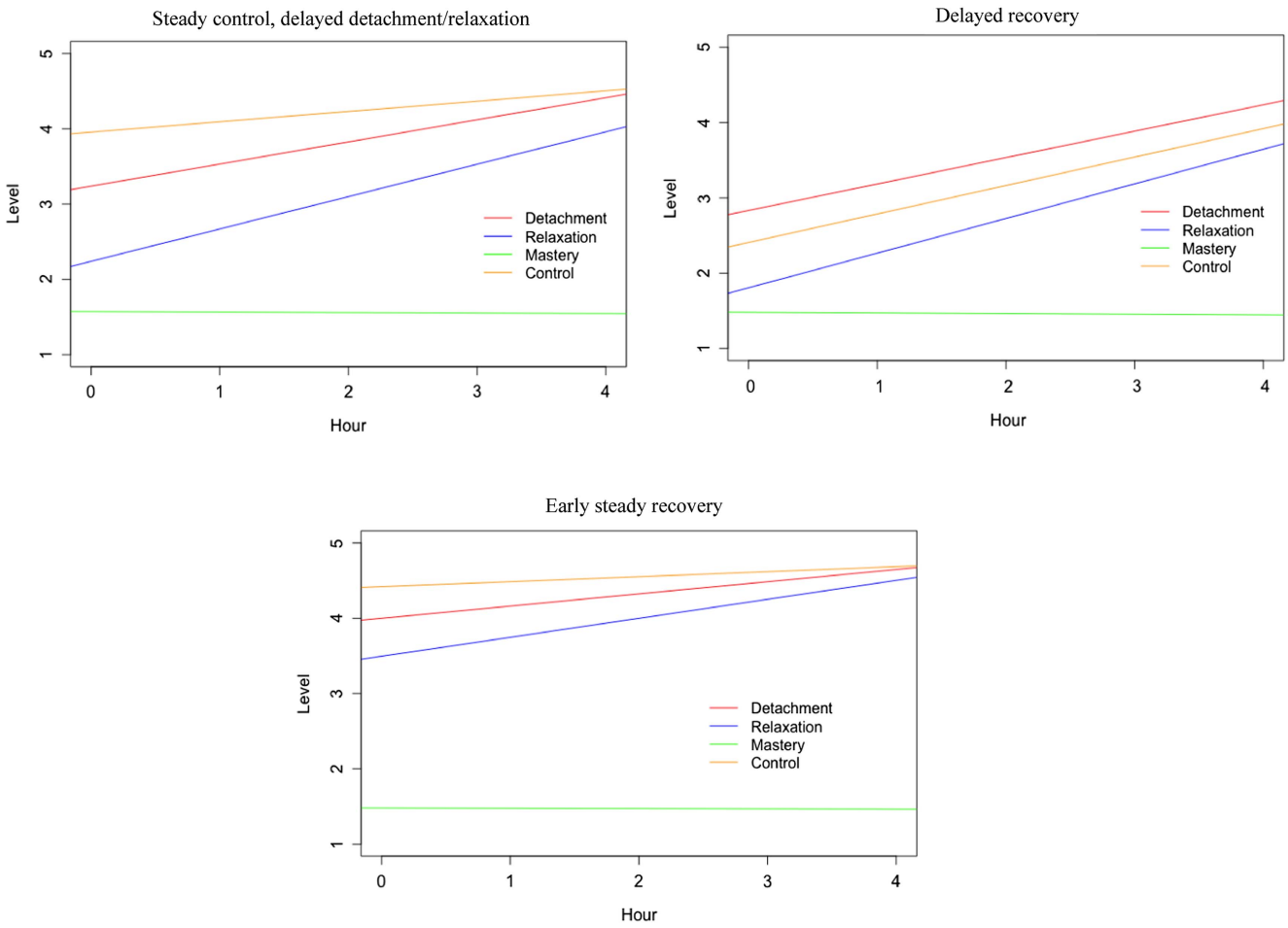
		Psychological detachment intercept		Psychological detachment slope		Relaxation intercept		Relaxation slope	
Profile	Percent of days	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI
Study 1									
Steady control, delayed detachment/ relaxation	43.7	3.24	[3.07, 3.41]	0.29	[0.26, 0.33]	2.24	[2.13, 2.35]	0.43	[0.40, 0.46]
Delayed recovery	32.5	2.83	[2.63, 3.04]	0.35	[0.32, 0.39]	1.81	[1.70, 1.92]	0.46	[0.43, 0.49]
Early steady recovery	23.8	4.00	[3.86, 4.14]	0.16	[0.14, 0.19]	3.50	[3.34, 3.65]	0.25	[0.22, 0.28]
Study 2									
Delayed recovery	49.0	2.30	[2.22, 2.37]	0.49	[0.46, 0.53]	1.78	[1.68, 1.89]	0.51	[0.49, 0.56]
Early steady recovery	38.9	4.09	[3.90, 4.29]	0.15	[0.12, 0.18]	2.78	[2.68, 2.90]	0.39	[0.37, 0.41]
Steady detachment, delayed control/ relaxation	12.1	4.14	[3.90, 4.38]	0.14	[0.11, 0.17]	1.74	[1.63, 1.82]	0.53	[0.47, 0.60]

		Mastery intercept		Mastery slope		Control intercept		Control slope	
Profile	Percent of days	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI
Study 1									
Steady control, delayed detachment/ relaxation	43.7	1.57	[1.52, 1.62]	−0.01	[−0.02, 0.01]	3.96	[3.80, 4.12]	0.14	[0.12, 0.16]
Delayed recovery	32.5	1.48	[1.44, 1.53]	−0.01	[−0.02, 0.00]	2.41	[2.27, 2.55]	0.38	[0.35, 0.40]
Early steady recovery	23.8	1.48	[1.41, 1.55]	0.00	[−0.02, 0.01]	4.42	[4.31, 4.53]	0.07	[0.05, 0.08]
Study 2									
Delayed recovery	49.0	1.60	[1.55, 1.65]	0.01	[0.00, 0.02]	2.55	[2.37, 2.75]	0.36	[0.33, 0.39]
Early steady recovery	38.9	1.51	[1.44, 1.57]	0.00	[0.00, 0.01]	4.15	[4.01, 4.30]	0.11	[0.09, 0.12]
Steady detachment, delayed control/ relaxation	12.1	1.41	[1.32, 1.48]	0.01	[0.00, 0.02]	2.27	[1.97, 2.55]	0.42	[0.35, 0.50]

Note. CI = 95% confidence interval.

Figure 2

Latent Profiles of Trajectories of Daily Recovery Experiences Across the Evening for Study 1



Note. The *y* axis refers to participants' level of each recovery experience on a 5-point Likert scale (1 = *not at all*; 5 = *very much*). See the online article for the color version of this figure.

Study 2: Replication and Extension of Daily Profiles of Recovery Experience Trajectories

The goal of Study 2 is to see if the trajectory profiles found in Study 1 replicate (Woo et al., 2024). We also examine antecedents of the trajectory profiles (two job demands and two job resources) as well as next-day outcomes (energy, fatigue, work goal accomplishment). Further, a limitation with Study 1 was that asking participants to rate their recovery experiences each hour may have led to some reactivity issues; that is, being asked about detachment or relaxation every hour could actually make it difficult to achieve such detachment or relaxation. Likewise, those who were deep in recovery experiences may have not responded to surveys due to this immersion, creating potential bias in missing data. To overcome this limitation, in Study 2, we adopt a different method, the evening reconstruction method (Arnold et al., 2023; Kahneman et al., 2004), which asks participants to recall the events of the evening at the end of the night, thus removing the potential of reactivity effects in the moment.

Hypothesis 1: There are three distinct trajectory profiles of experiences across an evening (delayed recovery; steady control, delayed detachment/sharply increasing relaxation; early steady recovery).

Antecedents of Recovery Experience Patterns

The ERM argues that the effort required to meet job demands depletes workers' energy and resources; when jobs are more demanding this effort is higher and thus more depleting, which impacts recovery experiences (Meijman & Mulder, 1998; Sonnentag & Fritz, 2007). COR theory suggests that in order to recover from depleting job demands, one must replenish resources through recovery. When jobs provide individuals with additional resources, this should be beneficial for their recovery after work as current resources can enhance further resource gains (Halbesleben et al., 2014; Hobfoll et al., 2018; Steed et al., 2021). Both job demands and resources may take numerous forms (Humphrey et al., 2007; ten Brummelhuis & Bakker, 2012). In the present context, we chose to

focus on one demand related to overload, workload (the amount or difficulty of one's work; Bowling & Kirkendall, 2012), as well as one emotional demand, workplace incivility (low-intensity discourteous behavior that violates workplace norms of respect and has ambiguous harm intent to the target; Andersson & Pearson 1999). For resources we chose two resources that are motivational in nature, job autonomy (discretion one has in completing their work; Humphrey et al., 2007) and at-work mastery (individual's overall perception of accomplishment of work tasks and mastery of tasks at work; Van den Broeck et al., 2010). These demands/resources were chosen based on their theoretical link to recovery and likelihood of varying day-to-day (McCormick et al., 2020).

Both workload and incivility have been linked to lower levels of recovery experiences in studies of average daily and chronic experiences (Demsky et al., 2019; Kinnunen et al., 2011; Molino et al., 2015; Nicholson & Griffin, 2015; Smit & Barber, 2016). On the other hand, autonomy and at-work mastery have shown to be positively related to recovery experiences (Bennett et al., 2016; Kinnunen et al., 2011; Rodríguez-Muñoz et al., 2018). Beyond this, we expect that there will be some nuanced temporal effects when examining these relationships across the evening. The stressor-detachment model (Sonnentag & Fritz, 2015) suggests that high levels of daily job demands induce psychological and physical strain that induce negative activation (e.g., negative emotions like anxiety, physiological symptoms in the form of increased blood pressure and muscular tension) that are likely to linger even after the workday ends. High strain levels also put one in a depleted state that makes it harder to control and direct one's thoughts away from work-related cognitions (Bono et al., 2013; Ilies et al., 2010; Germeys & De Gieter, 2018). However, these strain effects should wear off over time as one gains mental distance from their work, recovers some resources, and fatigue decreases (Arnold et al., 2023). Supporting this, multiple studies (Cropley & Millward Purvis, 2003; Cropley et al., 2006) found a work rumination trajectory where rumination is highest in the early part of the evening and gradually decreases across the evening. This would coincide with trajectories of psychological detachment, relaxation, and control that start lower as one continues to think about work after hours, but increase across the evening as one's strain and subsequent rumination wear off, mimicking the *delayed recovery* trajectory profile.[6] Conversely, when daily job demands are lower, people should have smaller strain reactions, making it easier to disconnect from work earlier in the evening and begin with recovery experiences at higher levels, reflecting trajectories more in line with the *steady control, delayed detachment/relaxation*, and the *early steady recovery* trajectory profiles.

Hypothesis 2: Higher daily workload increases the likelihood of an evening trajectory pattern that belongs to the delayed recovery trajectory profile, compared with the other evening trajectory profiles.

Hypothesis 3: Higher daily incivility increases the likelihood of an evening trajectory pattern that belongs to the delayed recovery trajectory profile, compared with the other evening trajectory profiles.

Furthermore, the presence of resources should also likely impact trajectory profile membership. With regard to autonomy, when workers have greater autonomy, this provides energetic resources and reduces the strain they experience due to work (Elsass & Veiga, 1997; Kinnunen et al., 2015). In turn, this makes it easier for one to have psychological detachment, relaxation, and control experiences at higher levels right after one ends work and maintain those levels due to a reduction in work-related thoughts (higher detachment), a reduction in psychological and physiological activation due to work strain (higher relaxation), and a reduction in depletion due to prolonged strain due to mental representation of work stress (higher control).

Hypothesis 4: Higher daily job autonomy increases the likelihood of an evening trajectory pattern that belongs to the early steady recovery trajectory profile, compared with the other evening trajectory profiles.

With regard to at-work mastery, when one feels a sense of mastery and accomplishment at work, this helps individuals reach a sense of cognitive closure and a "job well done," resulting in a perception they no longer need to think about work tasks after work (Smit, 2016; Song et al., 2024). Supporting this, previous work suggests that accomplishing work tasks and goals can lead to "postfulfillment inhibition," whereby task-related thoughts are less accessible in one's memory (Marsh et al., 1998). In turn, this allows individuals to immediately mentally disconnect from work. Using the same reasoning above for job autonomy, this more immediate mental disconnection facilitates having psychological detachment, relaxation, and control at higher levels earlier in the evening.

Hypothesis 5: Higher daily at-work mastery increases the likelihood of an evening trajectory pattern that belongs to the early steady recovery trajectory profile, compared with the other evening trajectory profiles.

Profiles of Trajectories in Relation to Next-Day Well-Being and Work Outcomes

Recovery experiences are theorized to improve and maintain well-being as well as promote work outcomes (cf, Sonnentag et al., 2022), which has been supported by meta-analyses (Bennett et al., 2018; Headrick et al., 2022; Steed et al., 2021). To align outcomes with our two guiding theoretical perspectives, we chose energy (COR) and fatigue (ERM) to represent well-being. The ERM (Meijman & Mulder, 1998) suggests that for recovery to occur one must cease exposure to job demands which in turn reduces load reactions, with the main load reaction discussed by this model being fatigue. The COR theory perspective (Hobfoll, 1989) suggests that individuals must recover lost resources; the recovery process revolves around the depletion and restoration of energy (Meijman & Mulder, 1998; Zijlstra et al., 2014). Work goal accomplishment was also selected as an outcome because meta-analytic evidence and recovery theory indicate that recovery experiences, through the cessation of job demands and resource restoration, enhance performance (Headrick et al., 2022; Steed et al., 2021).

[6] Note that although in many cases, there is reason to suspect a link between antecedents and mastery as a specific recovery experience, we do not discuss mastery, as it was not differentiated in any of our trajectory profiles (i.e., it was consistently low in each trajectory profile).

Energy is conceptualized as a resource, such that when people perceive they have more energy, this increases their eagerness and capability of using those resources toward desired goals (Quinn & Dutton, 2005; Quinn et al., 2012). Since resource gain is key to restoring well-being under COR theory, having recovery experiences earlier not only prevents prolonged resource depletion due to job demands, but also allows for the accumulation of more energy throughout the evening. This line of thinking is supported by COR theory, which suggests that resource gains follow an upward, exponential trend (Halbesleben et al., 2014). That is, on days where individuals belong to either the *steady control*, *delayed detachment/relaxation* trajectory profile, or the *delayed recovery* trajectory profile, they spend more time with resources being consumed by work-related thoughts and less time accumulating resources compared with those in the *early steady recovery* trajectory profile. Based on this, we hypothesize:

> *Hypothesis 6:* On evenings where individuals belong to the early steady recovery trajectory profile, they will have higher next-day energy compared with the other evening trajectory profiles.

Belonging to the *early steady recovery* trajectory profile will also be more advantageous for reducing next-day fatigue compared with the other profiles. As mentioned earlier, the ERM suggests that for recovery to occur, exposure to job demands must cease. As a result, the ERM suggests that when adequate recovery occurs, fatigue is reduced, which allows for energy to be restored (Meijman & Mulder, 1998; Zijlstra et al., 2014). When one does not cease the negative effects of work demands earlier in the evening and begin the recovery process earlier, the ERM suggests this allows psychophysiological activation due to work demands to continue to accumulate and contribute to fatigue (Meijman & Mulder, 1998). In turn, individuals with this pattern of trajectories that do not increase until midway into the evening would be in a less recovered, suboptimal state the next day at work. Rather, the ERM suggests a more optimal pattern would be one that stops the buildup of fatigue as early as possible in the evening. Thus, we hypothesize that

> *Hypothesis 7:* On evenings where individuals belong to the early steady recovery trajectory profile, they will have lower next-day fatigue compared with the other evening trajectory profiles.

By better reducing fatigue and restoring energy, we propose that individuals in the *early steady recovery* trajectory profile will also achieve higher next-day work goal accomplishment compared with the other profiles. First, individuals belonging to this daily profile have more energy at their disposal to put toward accomplishing work goals the next day. Second, as fatigue represents a reduced capacity to work and take on effortful challenges (Meijman & Mulder, 1998; Zijlstra et al., 2014), experiencing less fatigue will also allow individuals to perform better at work the next day (Ford et al., 2011). Recovery theory and empirical results also suggest that recovery experiences reduce negative emotions (e.g., frustration, anxiety), helping restore and promote positive emotions and mood states (e.g., calm, joy; Sonnentag & Fritz, 2007; Young et al., 2024). According to broaden and build theory, experiencing positive emotions broadens one's "action-thought" repertoires, which expands an individual's possible range of thoughts and actions that can come to mind (Fredrickson & Branigan, 2005). This broadened mindset can, in turn, enhance creativity, problem solving, decision making, efficiency, and integrative thoughts (cf, Vacharkulksemsuk & Fredrickson, 2013), all of which contribute to effective work performance and work goal accomplishment. Supporting this notion, positive emotions have been linked to improved work performance and proactive behavior (Lin et al., 2016; Ouyang et al., 2019; Wright et al., 2007). In sum, the combination of increased positive emotions and energy, along with reduced fatigue, equips individuals to perform better and accomplish work goals effectively.

> *Hypothesis 8:* On evenings where individuals belong to the early steady recovery profile, they will have higher next-day work goal accomplishment compared with the other evening trajectory profiles.

Study 2: Method

Participants and Procedure

Study 2 was a unique sample from Study 1 recruited via the same method and using the same eligibility criteria. Our sample consisted of 157 participants[7] who were 70.1% female and 79.9% white, 69.5% were married/living with a partner, and 37% were parents. They had an average age of 34.22, worked on average 39.9 hr weekly, and were highly educated, with 92.2% holding a bachelor's degree or higher, and working in 16 unique industries. They were compensated up to $60 for participating.

Participants completed an eligibility and baseline survey before the study began and then three surveys per day (morning, afternoon, evening) for 10 consecutive working days (two workweeks, Monday–Friday). Each survey link was emailed to participants and accompanied by a text message reminder to check their email for the link. The morning surveys measuring well-being outcomes (i.e., energy and fatigue) were sent at 7:30 a.m. local time and had to be completed by 10:30 a.m. For the afternoon surveys measuring job demands, job resources, and work outcomes (i.e., workload, incivility, job autonomy, at-work mastery, work goal accomplishment), these were sent at a unique time for each participant depending on when they indicated in the baseline survey that their typical workday ended. The afternoon surveys were sent 15 min before the time they indicated as the end of their workday and the survey stayed open for 2 hr and 15 min. The evening survey measuring recovery experiences using the evening reconstruction method was sent 4 hr and 45 min after the time they indicated they end work and they were instructed to complete it before they went to sleep.

During the evening survey, we utilized the evening reconstruction method (Arnold et al., 2023) based on the original day reconstruction method (Kahneman et al., 2004). Participants practiced the procedure and were given detailed instructions on how to complete

[7] In total, 160 employees passed the eligibility survey and consented to participate in the study. Two respondents were removed from analyses after additional evidence emerged indicating that they had provided false information for compensation (i.e., their IP address location did not match the locations they listed as their address for compensation and the names provided for compensation did not match the names on their email addresses). One additional participant was removed due to careless responding (providing the same response to all items), reducing the final usable sample size to 157 participants.

the evening reconstruction in the baseline survey. These instructions and examples of the daily evening reconstruction can be found in the additional online materials. First, for each hour after work (e.g., if they ended work at 4 p.m., 4–5 p.m., 5–6 p.m., 6–7 p.m., 7–8 p.m., 8–9 p.m.; if they ended work at 5 p.m., 5–6 p.m., 6–7 p.m., 7–8 p.m., 8–9 p.m., 9–10 p.m.), participants were asked to recall what activities they were engaged in during that particular hour. Next, they rated their recovery experiences for each hour, and we used survey logic to impute the activity (activities) they stated engaging in during that particular hour as a reminder prompt. They repeated this process for all four experiences for 5 hr across the evening. This allowed us to obtain 5 hr of recovery experience data, which allowed for the calculation of Bayes trajectories to be used in profile analyses.

All measures used in Study 2 and their multilevel reliability estimates are reported in Table 1. The full list of items and instructions are in the additional online materials. We used the same outlier analysis in Study 1, which resulted in 25 cases being removed for a final sample size of 1,323 daily observations to be used in the MLPA analyses.[8]

Analytic Approach

The same analytic approach for MLPA used in Study 1 was used in Study 2 to determine the number of profiles (Hypothesis 1). We also conducted a multilevel confirmatory factor analysis to evaluate our measurement model, which exhibited excellent fit both for the model with only antecedents and outcomes: $\chi^2(310) = 885.27$, $p < .01$, CFI = 0.97, TLI = 0.96, RMSEA = 0.04, SRMR = .03, and the model with recovery experiences: $\chi^2(102) = 881.23$, $p < .01$, CFI = 0.99, TLI = 0.99, RMSEA = 0.04, SRMR = .03. These were run in separate models because the recovery experiences are a three-level model (multiple per day per person) and the antecedents and outcomes are a two-level model (days nested in people).

To test Hypotheses 2–5, we used the R3STEP method in Mplus (Asparouhov & Muthén, 2014a). The R3STEP method uses multinomial logistic regression to assess whether an increase in an antecedent increases the likelihood that an individual belongs to one profile compared with another profile. To test Hypotheses 6–8, we used the Bolck–Croon–Hagenaars (BCH; Bolck et al., 2004) method in Mplus (Asparouhov & Muthén, 2014b; Bakk & Vermunt, 2016). The BCH analysis indicates whether one profile is significantly different from other profiles on each outcome. The benefit of the BCH analysis is that it avoids shifts in profile membership in the final stage of the three-step approach and uses a weighted multiple group analysis to calculate outcomes results (Asparouhov & Muthén, 2014b). To empirically examine how recovery experience trajectories predict next-day work and well-being outcomes, we modeled these outcomes (i.e., energy, fatigue, and work goal accomplishment) during the morning and the afternoon of the *subsequent* workday ($t + 1$), with recovery experiences being measured across the evening of day t (see Figure 1).

Study 2: Results

Descriptive statistics and correlations are in Table 2. Profile enumeration results are in Table 3 and mean values of profile indicators are shown in Table 4. All trajectory profiles are depicted visually in Figure 3. To address Hypothesis 1, we conducted the same profile enumeration process used in Study 1. The elbow plot slope flatted around four profiles, so we examined the three-, four-, and five-profile solutions. While the four-profile solution provided better fit statistics, it also included a theoretically redundant profile that split the *delayed recovery* profile into two profiles that only slightly differed in their control intercept and slope. Similarly, the five-profile solution included two theoretically redundant profiles that closely resembled the *delayed recovery* profile from the three-profile solution, with all three profiles showing low initial levels and gradual increases in the nonmastery recovery experiences. Based on this, we retained the most theoretically parsimonious three-profile solution.

Two profiles were replicated from Study 1, with the largest trajectory profile from our sample being the *delayed recovery* trajectory profile (49.0% of days), followed by the *early steady recovery* trajectory profile (38.9% of days). A new trajectory profile emerged in our second sample that had similar trajectory patterns to the *steady control, delayed detachment/relaxation* trajectory profile from Study 1, but this new trajectory profile had high and consistent psychological detachment rather than control. This new trajectory profile consisted of relaxation and control trajectories that started low and sharply increased across the evening, psychological detachment that started high and stayed high, and low levels of mastery across the evening. We named this new and smallest (12.1% of days) trajectory profile *steady detachment, delayed control/relaxation.*

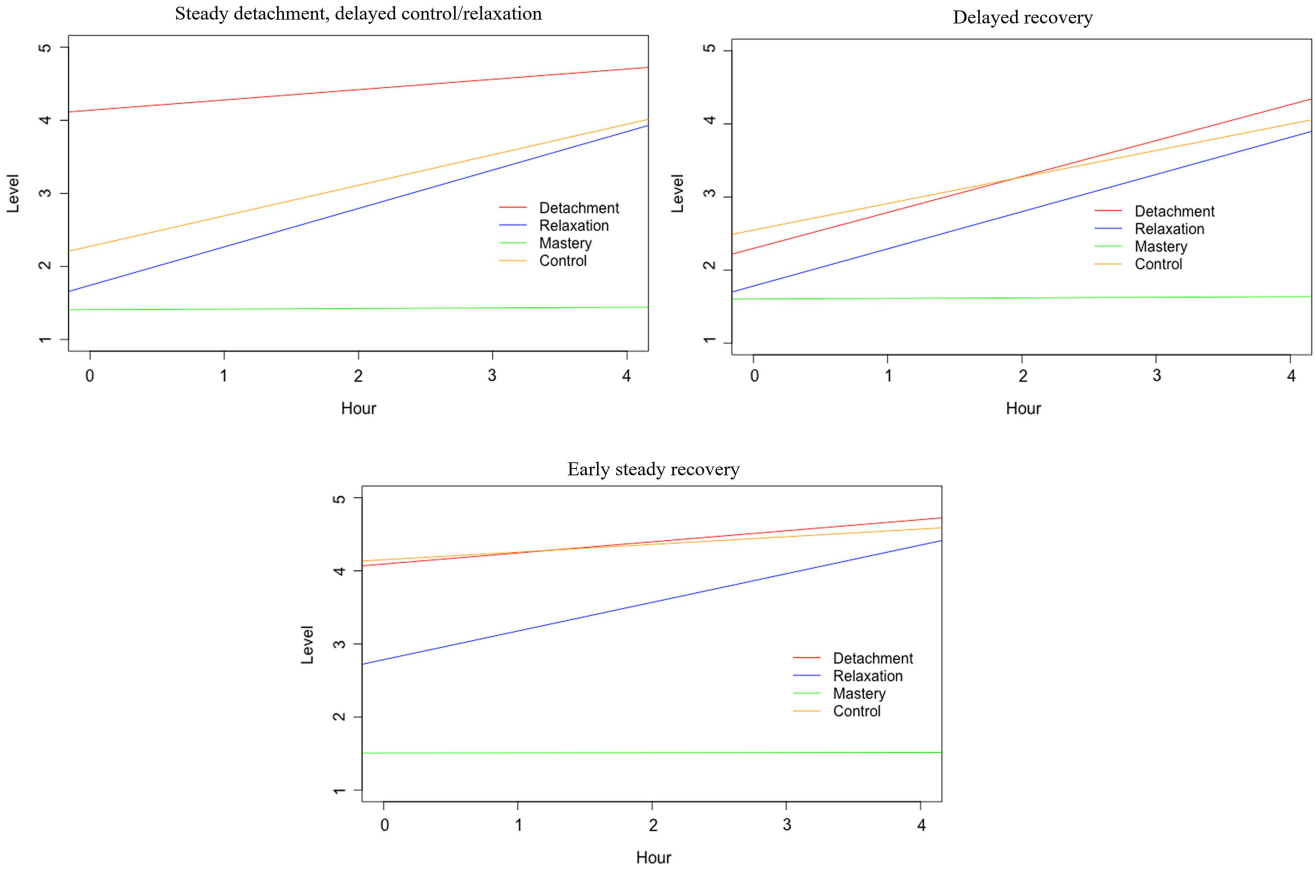
The results of the R3STEP analyses (Hypotheses 2–5) can be seen in Table 5. Hypothesis 2 predicted that people would be more likely to fall in the evening trajectory profile of *delayed recovery* compared with the other trajectory profiles when their daily workload was higher. As one's daily workload increased, this made individuals around 1.8 times more likely to belong to the *delayed recovery* trajectory profile ($OR = 1.79$, $p < .001$) in comparison to the *early steady recovery* trajectory profile. Workload did not differentiate membership between the *delayed recovery* trajectory profile and the *steady detachment, delayed control/relaxation* trajectory profile. Hypothesis 2 was thus partially supported. We also note that increasing workload made one 0.71 times less likely to belong to the *early steady recovery* trajectory profile ($OR = .71$, $p < .05$) in comparison with the *steady detachment, delayed control/relaxation* trajectory profile. Hypothesis 3 predicted that people would be more likely to fall in the evening trajectory profile of *delayed recovery* compared with the other profiles when their daily incivility was higher. This was not supported, as incivility did not differentiate membership for any of the profiles.

Hypothesis 4 predicted that on days with higher job autonomy, people would be more likely to belong to the *early steady recovery* trajectory profile compared with the other trajectory profiles. Job autonomy did not significantly relate to trajectory profile membership, providing no support for Hypothesis 4. Hypothesis 5 predicted that on days with higher at-work mastery, people would be more likely to belong to the *early steady recovery* trajectory profile compared with the other profiles. Supporting Hypothesis 5, having higher daily at-work mastery made individuals almost 1.6 times more likely to belong to the *early steady recovery* trajectory profile ($OR = 1.56$, $p < .01$) in comparison with the *delayed recovery* trajectory profile and 1.53 times more likely to belong to the *early steady recovery* trajectory profile ($OR = 1.53$, $p < .05$) in

[8] The profiles and their indicator values did not show any substantive differences when estimated with and without the 25 outlier cases in Study 2.

Figure 3

Latent Profiles of Trajectories of Daily Recovery Experiences Across the Evening for Study 2



Note. The *y* axis refers to participants' level of each recovery experience on a 5-point Likert scale (1 = *not at all*; 5 = *very much*). See the online article for the color version of this figure.

comparison with the *steady detachment, delayed control/relaxation* trajectory profile.

The results of the BCH analyses (Hypotheses 6–8) can be seen in Table 6. Hypotheses 6–8 predicted that on evenings when people belonged to the *early steady recovery* trajectory profile they would have higher next-day energy and work goal accomplishment and lower next-day fatigue compared with the other trajectory profiles. Results showed a consistent pattern for all outcomes; belonging to the *early steady recovery* trajectory profile resulted in higher next-day energy ($M = 3.53$ vs. $M = 3.23$), lower fatigue ($M = 2.40$ vs. $M = 2.81$), and higher work goal accomplishment ($M = 4.05$ vs. $M = 3.83$) than the *delayed recovery* trajectory profile. There were no significant differences in outcomes between *early steady recovery* and the *steady detachment, delayed control/relaxation* trajectory profiles. This partially supports Hypotheses 6–8.

Study 2: Discussion

Despite using a different method, we empirically replicated the three-profile solution and conceptually replicated two of the three trajectory profiles from Study 1. In addition, when examining the profiles holistically, the three trajectory profiles in Study 2 had broadly similar recovery experience trajectory trends when compared with Study 1, although there were some differences in the specific indicators. That is, we found a trajectory profile where all three nonmastery experiences start at low levels and sharply increase across the evening (*delayed recovery*), a trajectory profile where all three nonmastery experiences start high and stay high (*early steady recovery*), and a trajectory profile that is theoretically situated between the other two, where two experiences (relaxation and control) began at lower levels that sharply increased and psychological detachment started high and stayed high (*steady detachment, delayed control/relaxation*).

While these overarching patterns replicated, there were some differences in specific recovery experiences across samples. Specifically, in the *early steady recovery* trajectory profile, the relaxation trajectory in Study 2 started slightly lower and increased more over time, compared with its flatter trajectory in Study 1. The control trajectory also started at a slightly higher level and had a flatter slope in Study 1 compared with the trajectory in Study 2. Additionally, the *steady detachment, delayed control/relaxation* trajectory profile differed from the *steady control, delayed detachment/relaxation* trajectory profile from Study 1 in that psychological detachment and control were flipped, with psychological detachment starting at a high level and having a flat slope rather than control as was seen in Study 1. Further, there were differences in the experiences that did not start at high levels

Table 5
Predictor Analyses Results

Variable	Steady detachment, delayed control/relaxation versus delayed recovery			Early steady recovery versus delayed recovery			Early steady recovery versus steady detachment, delayed control/relaxation			Delayed recovery versus early steady recovery		
	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*
Workload	−0.24	0.13	0.79	−0.58	0.10	0.56**	−0.34	0.15	0.71*	0.58**	0.10	1.79
Incivility	0.01	0.31	1.01	−0.45	0.39	0.64	−0.47	0.51	0.63	0.45	0.39	1.57
Job autonomy	−0.07	0.18	0.93	0.00	0.15	1.00	0.08	0.21	1.08	−0.00	0.15	1.00
At-work mastery	0.02	0.14	1.02	0.45	0.14	1.56**	0.43	0.18	1.53*	−0.45**	0.14	0.64

Note. $N = 1{,}315$. We also calculated *OR*s for the comparison of each profile using absolute values of the coefficient from the R3STEP analysis to make the results easier to interpret. Positive coefficient values indicate that higher values on the antecedent make a person more likely to be in the first latent profile of the two latent profiles being compared; negative values indicate that higher values on the antecedent make a person more likely to be in the second latent profile compared. Job demands (i.e., workload and incivility) and job resources (i.e., autonomy and at-work mastery) are modeled during the same workday with daily profiles of trajectories of recovery experiences. Coef. = the estimate (β) from the R3STEP multinomial logistic regression analysis, which uses listwise deletion; *SE* = standard error of the coefficient.
* $p < .05$. ** $p < .01$.

(psychological detachment in Study 1 and control in Study 2). In Study 2, control began at a lower level and increased more steeply across the evening in comparison to psychological detachment in Study 1, which started at a moderate level and increased more gradually. Relaxation followed a similar pattern in both studies, starting low and gradually rising to moderate levels. Some variations in trajectory profiles across samples are to be expected, as person-centered approaches often capture different subpopulations unique to each sample (Bigelow et al., 2024; Oberski, 2016).

One possibility that could explain these different trajectory profiles across samples is differences in the straining nature of their jobs. In line with the stressor-detachment model, it could be that one sample had more straining jobs (i.e., higher job demands and lower job resources) that made it more difficult to detach earlier. Compared with the Study 2 sample, the Study 1 sample had a statistically significantly larger amount of daily workload, 3.20 versus 3.10, $t(2007) = 1.99$, $p < .05$, and lower amount of daily job autonomy, 4.01 versus 4.29, $t(2009) = 6.90$, $p < .001$. Another possibility that explains these different trajectory profiles across samples is that the sample in Study 2 had more parents than in Study 1, 37% versus 24%, $t(79) = -6.99$, $p < .001$. Speculatively, parents may be able to psychologically detach earlier in the evening, but at the same time have lower relaxation and control earlier in the evening as they engage in taxing childcare-related demands (Steed et al., 2021). In total, it appears that two most prototypical trajectory profiles are the *delayed recovery* and *early steady recovery* trajectory profiles. In addition, a smaller proportion of days can be characterized by a profile that is a hybrid of these two most common profiles, where one experience (psychological detachment or control) starts high and stays high while the other two remaining nonmastery experiences start low and increase to higher levels.

Overall, our results suggest that the optimal profile of daily recovery experience trajectories is a day consisting of starting high and staying high on detachment, relaxation, and control across the evening. This aligns with COR theory and the ERM, as it suggests that ceasing work demands and recovering resources for a longer amount of time leads to a more beneficial recovery process. In terms of predictors, we found that having a higher daily workload relates to a delay in recovery experiences such that they do not reach higher levels until later in the evening. On the contrary, higher levels of at-work mastery relates to starting recovery earlier. These results generally align with the stressor-detachment model and suggest that characteristics of one's job play a critical role in determining when employees' recovery starts.

Supplemental Analyses

Comparison to Chawla et al.'s (2020) Findings

To highlight the value of examining profiles of recovery experience trajectories, we also analyzed our data using Chawla et al.'s (2020) daily summary assessment approach. Specifically, for each

Table 6
Outcome Analyses Results

Outcome	Steady detachment, delayed control/relaxation (A)	Early steady recovery (B)	Delayed recovery (C)	χ^2
Next-day morning				
Energy	3.36	3.53^{C}	3.23^{B}	6.33*
Fatigue	2.70	2.40^{C}	2.81^{B}	9.67**
Next-day afternoon				
Work goal accomplishment	3.80	4.05^{C}	3.83	6.43*

Note. $N = 1{,}220$. The BCH procedure in Mplus uses full information maximum likelihood estimation. The values per outcome are means. The chi-square value reflects the significance of the omnibus test. The pairwise comparisons are highlighted through the superscripts, indicating profiles that are significantly different at least at $p < .05$ within each row. BCH = Bolck–Croon–Hagenaars.
* $p < .05$. ** $p < .01$.

individual and each day for the Study 2 sample, we computed the average of their 5 hr' worth of data for each recovery experience for each day (i.e., 10 days' worth of average recovery experiences nested within persons) and used this as input for MLPA. As can be seen in the additional online materials, we went through the entire profile enumeration process using the profiles of averages approach and arrived at a four-profile data fitting the data best. These four profiles closely replicated four of the five of Chawla et al.'s profiles. Consistent with Chawla et al., we found that the profile with higher average levels across all four recovery experiences in the evening was linked to the most positive outcomes compared with the other profiles.

To further compare approaches, we examined where individuals in our most beneficial profile for outcomes—the *early steady recovery* trajectory profile—would be classified using Chawla et al.'s daily average-level method. In Study 2, on 79.4% of days assigned to our *early steady recovery* profile would have been classified into an average-level profile with high average levels of psychological detachment, relaxation, and control paired with a low mastery level, which Chawla et al.'s (2020) findings deemed was not only detrimental in terms of outcomes, but also just as detrimental for work and well-being outcomes as having low levels of all recovery experiences. That is, on most days where individuals belonged to our most beneficial recovery trajectory profile in terms of outcomes, they would have also been considered to belong to a maladaptive profile using an average-level profile approach. Thus, our trajectory approach provides conclusions that directly oppose the conclusions that Chawla et al.'s approach would provide. Critically, these results demonstrate the limitations of using a profile approach based on average levels. Had we only examined recovery in the aggregate, we would have missed an important conclusion from our study that is masked by average levels—that starting recovery early in the evening is more beneficial than a trajectory that gradually increases to high levels.

Moreover, we conducted additional analyses to ensure that our results were not driven by mean levels of the four experiences rather than the actual trajectories, given that mean levels and slopes are confounded to some extent. Specifically, we conducted our outcome analyses controlling for mean levels of each recovery experience across the evening and found that the original outcome associations remained consistent. In fact, when controlling for mean levels, we found even stronger support for our hypotheses related to work goal accomplishment and fatigue; the *early steady recovery* profile had significantly higher work goal accomplishment and lower fatigue than the *steady detachment, delayed control/relaxation profile*—differences not observed in the original analyses without mean-level controls. Overall, these results provide empirical support suggesting that trajectory patterns have unique associations with outcomes even when controlling for mean levels.

Removal of Mastery

Given the lack of mastery across both samples, we also computed all profile analyses with mastery removed (see additional online materials for details) to see if our profiles and interpretations would change. We found that the same three-profile solutions emerged in both studies, with almost identical trajectory patterns for the nonmastery recovery experiences. Outcome analyses also remained consistent, indicating that removing mastery did not meaningfully alter the profiles or their implications.

General Discussion

Despite a large body of research on daily recovery, the literature still has not directly examined the daily recovery process the way it is theorized to occur using combinations of recovery experience trajectories. This prevents us from answering several vital questions in the recovery literature such as: How does the daily recovery process (dynamically and collectively across recovery experiences) unfold across the evening? What is the optimal pattern of recovery experience trajectories across the evening that leads to the best next-day well-being and work outcomes? How do job demands and job resources impact these recovery experience patterns? Across two experience sampling methods studies, we answer these questions by uncovering prototypical daily profiles of recovery experience trajectories. We empirically replicate the three-profile solution and conceptually replicated two profiles across both studies. The two conceptually replicated profiles were one where nonmastery experiences start high and stay high across the evening, and one where the nonmastery experiences start low and increase to high levels across the evening. We also found hybrids of the two replicated profiles, which differed across studies but had similar overall patterns, where one experience (control in Study 1 and psychological detachment in Study 2) started high and stayed high while the other two remaining nonmastery experiences started low and increased across the evening. Last, we examined how work experiences predict profile membership, finding that at-work mastery and workload are predictive of profile membership but autonomy and incivility are not. Our results point to the importance of employees starting their recovery process early in the evening as being best for next-day well-being and work outcomes.

Theoretical, Practical, and Methodological Implications

Our study has multiple theoretical contributions. First, our work was the first to combine the profile (Chawla et al., 2020) and trajectory (Arnold et al., 2023) approaches to provide the most accurate examination of the daily recovery process in the same way it is theorized to occur. Such examination and analysis allowed us to gain insights that would have been impossible if using a profile assessment that did not also take into account trajectories and a variable-centered trajectory approach that examined each recovery experience in isolation. As a result, our results help resolve conflicting findings and provide consensus regarding what optimal daily recovery experience patterns look like. Our findings suggest that some previous notions in the recovery literature regarding how employees should best recover may be misguided by virtue of either imprecise measurement or analysis. Specifically, our work diverged from Chawla et al. (2020) and provided two important insights that could not be extrapolated from their work.

First, our results suggest that daily mastery may not be as critical as previously thought. Chawla et al. (2020) found that profiles with higher mean levels of daily psychological detachment, relaxation, and control (but low on mastery) were just as detrimental for work and well-being outcomes as profiles that had low mean levels of all four experiences. Said otherwise, without mastery experiences, even having high levels of all the other recovery is not beneficial.

Contradictorily, our results suggest that it can still be beneficial to have low mastery experiences, as long one starts having the other three experiences earlier. We are not suggesting Chawla et al.'s approach is wrong, rather, that it only examines generally what a beneficial daily recovery profile looks like. On the contrary, our approach examines the role of time in daily recovery profiles. That is, our profiles of trajectories approach accounts for *when* one has those experiences at differing levels, and how differences in temporal patterns of recovery experiences can lead to better or worse outcomes. In doing so, our trajectory profiles provide more fine-grained theoretical understanding of the role of temporal dynamics in determining what beneficial recovery looks like.

Second, our findings offer a new perspective in the recovery literature by emphasizing the importance of *when* recovery occurs—not just how much. While prior work (e.g., Chawla et al., 2020) suggests that having higher levels of all recovery experiences is beneficial regardless of timing, our results challenge this assumption. Specifically, we find that recovery is most effective when it occurs in sustained periods—what we refer to as "bulk" recovery—early and consistently throughout the evening. In contrast, profiles characterized by delayed recovery that ramps up later (i.e., the *delayed recovery* profile) are associated with poorer outcomes, even if they reach high levels by the end of the evening. Importantly, these insights would be obscured using mean-based approaches, which condense the evening into a single value and fail to account for *when* recovery occurs. This suggests that recovery should not be something accumulated in scattered doses whenever possible, but rather something intentionally front loaded and sustained. Put simply, individuals may benefit more from treating their recovery time like a wholesale purchase—by investing in larger, earlier blocks.

This notion of the importance of early recovery also runs counter to previous work on the four recovery experience trajectories in isolation that uses a variable-centered approach. Arnold et al. (2023) found that the trajectories for psychological detachment, relaxation, and control all increased linearly across the evening, whereas mastery was curvilinear in nature, peaking in the middle of the evening. While this mimics one of our profiles (*delayed recovery*) with the exception of mastery, our findings suggest that valuable information is lost in assuming that this is the default trajectory for everyone, given that we found multiple other distinct profiles. Our results highlight the advantages of a person-centered trajectory approach, demonstrating how this approach unveils unique relationships with work and well-being outcomes. For example, Arnold et al. found that only the psychological detachment slope significantly and positively related to next-day well-being, leading to the conclusion that it does not matter how one starts recovery as long as one finishes recovery at higher levels. However, our results suggest that combinations of recovery experience trajectories that have relatively weak slopes (i.e., a flat trajectory) but start earlier (i.e., a higher intercept) result in the best outcomes. Even though the *delayed recovery* profile ended at relatively high levels of recovery, this profile had uniformly worse outcomes than the profile that started earlier. Without using our approach, results regarding what beneficial recovery trajectories look like would have been missed. By ensuring a strong fit between recovery theory and method via person-centered trajectories (Edmondson & Mcmanus, 2007), we were able to provide more theoretically specific information regarding what daily beneficial recovery looks like. When it comes to daily recovery, it appears that it is how you start, not how you finish.

Moreover, our fine-grained examination of the daily recovery process advances knowledge on two prominent recovery theoretical models: the ERM and COR. COR theory suggests that as one accumulates resources, this results in an upward exponential trend where resource gain results in increasingly larger resource accumulation (Halbesleben et al., 2014). Our results point toward this resource accumulation trend being able to occur across the evening for recovery, given that those who had recovery experiences early and often had the largest levels of next-day energy. This can be seen when more closely examining the intercept and slope values of the profiles. The *early steady recovery* profile has intercepts that were almost double those of the *delayed recovery* profile. Additionally, the *delayed recovery* profile does not reach the levels of recovery experiences that the *early steady recovery* profile has at the start of the evening until around 4 hr into the evening. Thus, although they end at similar levels, the process to get there is much different, and it appears that starting earlier allows one to accumulate more resources over the course of the evening. This provides more specific understanding of the role of resources in the recovery process, which has been criticized as being unclear in the recovery literature (Sonnentag et al., 2022). Future research should directly test this mechanism by using an empirical approach similar to the one we used here, examining how trajectories of energy or other resources coincide with trajectories of recovery experiences. Additionally, our study provided a more direct test of the ERM. The ERM suggests that in order for recovery to occur, work-related psychophysiological activation must cease, which in turn reduces fatigue and allows energy to be restored (Meijman & Mulder, 1998). Our findings generally supported this notion, with starting recovery earlier resulting in the lower fatigue, but these underlying activation mechanisms need to be tested further. Future research could examine how recovery trajectories coincide with physiological measures of strain (e.g., cortisol).

Third, we advance understanding on the temporal dynamics of the recovery process, which is essential for achieving understanding of dynamic phenomena like daily recovery (Mitchell & James, 2001; Shipp & Cole, 2015). Two patterns stand out from our profile analyses. First, it appears that when captured using a dynamic trajectory approach, individuals do not seem to be engaging in mastery experiences. Across two separate samples and a total of three workweeks worth of data, we consistently found that individuals have mastery trajectories that start at low levels and remain unchanged across the evening. Said otherwise, they are rarely having mastery experiences. We see a few possibilities that may explain this finding. One possibility is that the measure used to capture mastery experiences (Sonnentag & Fritz, 2007) is not capturing these experiences sufficiently. Through engaging in growth-oriented, challenging activities, mastery experiences are theorized to provide individuals with a sense of accomplishment and self-efficacy, which replenishes motivational and energetic resources (Headrick et al., 2022; Sonnentag & Fritz, 2007). Given our finding of a lack of mastery here, it may be that individuals are engaging in effortful recovery activities that help one gain additional resources, which may not be captured by the mastery experience items. A better approach may be to directly examine the underlying dimensions of recovery activities using the recovery activities questionnaire (Alameer et al., 2023), and examining how recovery

activities lead to resource restoration. A second possibility is that mastery is a low base-rate experience that occurs mostly on weekends rather than after work on weekdays. Given mastery requires effortful self-regulation to have these experiences (Sonnentag & Fritz, 2007), it may be that individuals just do not have the resources to engage in mastery after expending effort at work. On weekends however, job demands are largely removed, and individuals have more time and resources to put toward mastery experiences. In total, it appears that the concept of mastery and what individuals do to build up motivational and energetic resources needs to be revisited in recovery research.

The second pattern that emerged from our profiles is that it appears that many individuals are delaying their recovery process. Mimicking Arnold et al.'s (2023) findings, in 46.3% of total days across both samples, individuals belong to the *delayed recovery* profile. This indicates that about half the time, individuals are starting with recovery experiences at low levels that do not reach moderate to high levels until the end of the evening. Given our outcome analyses showed this pattern results in worse well-being and work outcomes, future research should examine factors that allow individuals to start their recovery process earlier in the evening. Rather than letting the strain of job demands continue to linger, future research can examine which particular recovery activities (e.g., playing a sport or going to happy hour) may kickstart the recovery process earlier.

Finally, in terms of antecedents, using our more fine-grained measurement protocol provides us with a better understanding of how demands and resources at work impact dynamic aspects of the recovery process. Our results indicate that having a high workload delays the recovery process from occurring until later in the evening. Conversely, having higher amount of at-work mastery was related to individuals starting their recovery earlier in the evening. These results both coincide with the predictions of the stressor-detachment model (Sonnentag & Fritz, 2015). We add temporal specificity to this model, as our results suggest that the effects of strain on thinking about work after hours appears to mainly affect recovery experiences in the early part of the evening and that these prolonged work cognitions may fade as the evening progresses. The antecedent findings also offer practical strategies for maximizing recovery. One strategy could be to prioritize bulk recovery sessions on days when one has less spillover from job demands and ample resources, allowing them to fully benefit from larger blocks of recovery time. In other words, people could "reserve" their bulk recovery for days when they can maximize the time dedicated to it. Future research could examine the effectiveness of this by seeing how individuals who proactively schedule only one or two dedicated bulk recovery days during a week compare to individuals who only have sporadic, smaller doses of recovery daily in a more reactive way differ in terms of work and well-being outcomes.

Our work also provides important practical implications. Simply speaking, knowledge that the timing of recovery matters is important for employees to know as they consider the best ways to recover. Building off the previous point regarding bulk recovery, the results imply that people should strategically schedule times to recover in bulk where they know they will be able to recover early and often. There may be certain days where this bulk recovery may be more important and more likely to happen. For example, it may be particularly useful to do this on an evening when one knows they need to perform at a high level the next day at work, like when one has to present to an important potential client. Being cognizant to fully engage in psychological detachment, relaxation, and control early and often on those nights could be especially beneficial. As another example, individuals with a spouse could choose one or multiple days per week where each partner can fully engage in recovery experiences rather than both partners just grabbing shorter periods of recovery on a day-to-day basis. If one does not have a partner, they could choose less recovery on certain days (such as when demands are high) which means bulked recovery on other days. This strategic approach to scheduling bulk recovery helps ensure that individuals reap the full benefits of dedicated recovery time.

Moving beyond individuals, our results indicate that organizations and supervisors should become highly aware of the daily workload of their employees. Although workload has been described as a challenge demand that increases motivation to complete work tasks (Cavanaugh et al., 2000; Lepine et al., 2005), our results suggest that daily workload negatively impacts the recovery process. Thus, our findings point toward the reduction of workload as possibly being a preventive measure that results in better recovery for employees. This is especially critical as it can allow organizations and managers to help their employees avoid the "recovery paradox" (Sonnentag, 2018), whereby facing high levels of job stress and strain makes one even less likely to recover that day, even though recovery is needed more that day.

Last, our study provided methodological contributions. We show how within-person Bayes slopes trajectories can be used in combination with MLPA to examine profiles of trajectories. To our knowledge, these two analyses have not been used in combination before in a published article. This method could be used in other areas of research for any phenomena that has multiple variables occurring in conjunction that change over time (e.g., the three dimensions of burnout). Moreover, our study provided evidence that two distinct approaches—an experience sampling study with multiple measurements across an evening and an experience sampling study using the day reconstruction method produced similar results. This information may be useful to future researchers as they design studies, considering the differing costs and participant burden involved in each method.

Limitations and Future Directions

Along with the strengths of the present study, it should also be interpreted within the context of its limitations. A limitation of this study is the nature of the samples, who were predominately White and highly educated. Accordingly, our samples are likely not an accurate representation of the workforce. This is a concern given that nearly all studies in the recovery literature focus on white-collar samples (Sonnentag et al., 2017, 2022). By using less generalizable samples, we may be missing out on whether recovery findings found in white-collar workers generalize to other occupational groups, who make up a larger proportion of the workforce (Bergman & Jean, 2016). A second limitation is that only two of the three profiles conceptually replicated, suggesting that the hybrid profiles may be more sample specific. Future research could test whether these hybrid profiles emerge in new samples or if the two prototypical profiles are sufficient. Finally, we note that the magnitude of mean differences in outcomes between profiles are small, and caution should be taken when interpreting our findings. Although these

differences appear small, even modest daily recovery effects can accumulate over time and meaningfully impact long-term well-being and performance (Abelson, 1985; Ford et al., 2014; Sonnentag et al., 2022). We hope this work encourages future research to examine how short-term recovery patterns shape long-term outcomes (Sonnentag et al., 2022).

A future step would be to examine dynamic recovery experiences in combination with other recovery opportunities time frames besides just evenings after work, like weekends or at-work recovery. Given that nearly all studies in the recovery literature examine these opportunities in isolation (Sonnentag et al., 2017), it would be interesting to see how recovery processes during different recovery opportunities compound and impact one another. For example, future research could examine how microbreaks and other energy management strategies used at work impact recovery experience trajectories after work. Do individuals who use at-work recovery to reduce their daily strain and manage their energy levels have more optimal recovery trajectories? Or do individuals who do not recover during the workday have more recovery experiences after work to compensate for their lack of at-work recovery? Questions like these could be better answered by research designs that measure recovery experiences across both work and nonwork time.

Conclusion

Despite the daily recovery process being conceptualized as individuals having all four recovery experiences in combination (i.e., profiles) and dynamically across the evening (i.e., trajectories), what these patterns of trajectories look like had not been examined. Using a dynamic, person-centered approach, this study examined evening profiles of recovery experience trajectories, exhibiting how recovery unfolds, antecedents of trajectory patterns, and identifying optimal recovery experience trajectory profiles for work and well-being outcomes. Our results reveal that patterns of trajectories marked by consistently high levels of detachment, relaxation, and control early and throughout the evening are most beneficial. Additionally, high workloads delay recovery, while at-work mastery results in recovery starting earlier. In unveiling the daily recovery process, this study takes an important step toward examining the dynamic nature of daily recovery experiences after work and providing prescriptive recommendations on how employees should best recover to improve and maintain both well-being and work performance.

References

Abelson, R. P. (1985). A variance explanation paradox: When a little is a lot. *Psychological Bulletin*, *97*(1), 129–133. https://doi.org/10.1037/0033-2909.97.1.129

Aggarwal, C. C. (2016). Proximity-based outlier detection. *Outlier analysis* (pp. 111–147). Springer International Publishing. https://doi.org/10.1007/978-3-319-47578-3_4

Alameer, K. M., Uitdewilligen, S., & Hülsheger, U. R. (2023). What are the active ingredients in recovery activities? Introducing a dimensional approach. *Journal of Occupational Health Psychology*, *28*(4), 239–262. https://doi.org/10.1037/ocp0000354

Andersson, L. M., & Pearson, C. M. (1999). Tit for tat? The spiraling effect of incivility in the workplace. *The Academy of Management Review*, *24*(3), 452–471. https://doi.org/10.2307/259136

Arnold, M., Casper, A., & Sonnentag, S. (2023). Daily trajectories of evening recovery experiences and their role for next-day mood. *Journal of Occupational Health Psychology*, *28*(5), 291–309. https://doi.org/10.1037/ocp0000359

Asparouhov, T., & Muthén, B. (2014a). Auxiliary variables in mixture modeling: Three-step approaches using M plus. *Structural Equation Modeling*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. (2014b). *Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model*. Mplus Web Note #21. https://www.statmodel.com/download/asparouhov_muthen_2014.pdf

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling*, *23*(1), 20–31. https://doi.org/10.1080/10705511.2014.955104

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods*, *8*(3), 338–363. https://doi.org/10.1037/1082-989X.8.3.338

Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling methods in organizational research. *Annual Review of Organizational Psychology and Organizational Behavior*, *2*(1), 383–407. https://doi.org/10.1146/annurev-orgpsych-032414-111335

Bennett, A. A., Bakker, A. B., & Field, J. G. (2018). Recovery from work-related effort: A meta-analysis. *Journal of Organizational Behavior*, *39*(3), 262–275. https://doi.org/10.1002/job.2217

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

Bergman, M. E., & Jean, V. A. (2016). Where have all the "workers" gone? A critical analysis of the unrepresentativeness of our samples relative to the labor market in the industrial–organizational psychology literature. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *9*(1), 84–113. https://doi.org/10.1017/iop.2015.70

Bigelow, B., Kautz, J., Carpenter, N. C., & Harris, T. B. (2024). A person-centered approach to behaving badly at work: An examination of workplace deviance patterns. *Journal of Applied Psychology*, *109*(11), 1742–1764. https://doi.org/10.1037/apl0001192

Bliese, P. D., & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustration. *Organizational Research Methods*, *5*(4), 362–387. https://doi.org/10.1177/1094428102237116

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*(1), 3–27. https://doi.org/10.1093/pan/mph001

Bono, J. E., Glomb, T. M., Shen, W., Kim, E., & Koch, A. J. (2013). Building positive resources: Effects of positive events and positive reflection on work stress and health. *Academy of Management Journal*, *56*(6), 1601–1627. https://doi.org/10.5465/amj.2011.0272

Bowling, N. A., & Kirkendall, C. (2012). Workload: A review of causes, consequences, and potential interventions. In J. Houdmont, S. Leka, & R. R. Sinclair (Eds.), *Contemporary occupational health psychology: Global perspectives on research and practice* (Vol. 2, pp. 221–238). Wiley Blackwell. https://doi.org/10.1002/9781119942849.ch13

Cavanaugh, M. A., Boswell, W. R., Roehling, M. V., & Boudreau, J. W. (2000). An empirical examination of self-reported work stress among U.S. managers. *Journal of Applied Psychology*, *85*(1), 65–74. https://doi.org/10.1037/0021-9010.85.1.65

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

Chen, G., Ployhart, R. E., Thomas, H. C., Anderson, N., & Bliese, P. D. (2011). The power of momentum: A new model of dynamic relationships between job satisfaction change and turnover intentions. *Academy of Management Journal*, *54*(1), 159–181. https://doi.org/10.5465/amj.2011.59215089

Craig, A., & Cooper, R. E. (1992). Symptoms of acute and chronic fatigue. In A. P. Smith & D. M. Jones (Eds.), *Handbook of human performance, Vol. 1. The physical environment; Vol. 2. Health and performance; Vol. 3. State and trait* (pp. 289–339). Academic Press. https://doi.org/10.1016/B978-0-12-650353-1.50017-4

Cropley, M., Dijk, D.-J., & Stanley, N. (2006). Job strain, work rumination, and sleep in school teachers. *European Journal of Work and Organizational Psychology*, *15*(2), 181–196. https://doi.org/10.1080/13594320500513913

Cropley, M., & Millward Purvis, L. J. (2003). Job strain and rumination about work issues during leisure time: A diary study. *European Journal of Work and Organizational Psychology*, *12*(3), 195–207. https://doi.org/10.1080/13594320344000093

Demsky, C. A., Fritz, C., Hammer, L. B., & Black, A. E. (2019). Workplace incivility and employee sleep: The role of rumination and recovery experiences. *Journal of Occupational Health Psychology*, *24*(2), 228–240. https://doi.org/10.1037/ocp0000116

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2017a). Performance of growth mixture models in the presence of time-varying covariates. *Behavior Research Methods*, *49*(5), 1951–1965. https://doi.org/10.3758/s13428-016-0823-0

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2017b). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods*, *22*(1), 166–190. https://doi.org/10.1037/met0000084

Diefendorff, J. M., Gabriel, A. S., Nolan, M. T., & Yang, J. (2019). Emotion regulation in the context of customer mistreatment and felt affect: An event-based profile approach. *Journal of Applied Psychology*, *104*(7), 965–983. https://doi.org/10.1037/apl0000389

Dust, S. B., Liu, H., Wang, S., & Reina, C. S. (2022). The effect of mindfulness and job demands on motivation and performance trajectories across the workweek: An entrainment theory perspective. *Journal of Applied Psychology*, *107*(2), 221–239. https://doi.org/10.1037/apl0000887

Edmondson, A. C., & Mcmanus, S. E. (2007). Methodological fit in management field research. *Academy of Management Review*, *32*(4), 1246–1264. https://doi.org/10.5465/amr.2007.26586086

Elsass, P. M., & Veiga, J. F. (1997). Job control and job strain: A test of three models. *Journal of Occupational Health Psychology*, *2*(3), 195–211. https://doi.org/10.1037/1076-8998.2.3.195

Ford, M. T., Cerasoli, C. P., Higgins, J. A., & Decesare, A. L. (2011). Relationships between psychological, physical, and behavioural health and work performance: A review and meta-analysis. *Work & Stress*, *25*(3), 185–204. https://doi.org/10.1080/02678373.2011.609035

Ford, M. T., Matthews, R. A., Wooldridge, J. D., Mishra, V., Kakar, U. M., & Strahan, S. R. (2014). How do occupational stressor–strain effects vary with time? A review and meta-analysis of the relevance of time lags in longitudinal studies. *Work & Stress*, *28*(1), 9–30. https://doi.org/10.1080/02678373.2013.877096

Frank, E. L., Matta, F. K., Sabey, T. B., & Rodell, J. B. (2022). What does it cost you to get there? The effects of emotional journeys on daily outcomes. *Journal of Applied Psychology*, *107*(7), 1203–1226. https://doi.org/10.1037/apl0000908

Fredrickson, B. L., & Branigan, C. (2005). Positive emotions broaden the scope of attention and thought-action repertoires. *Cognition and Emotion*, *19*(3), 313–332. https://doi.org/10.1080/02699930441000238

Fredrickson, B. L., & Kahneman, D. (1993). Duration neglect in retrospective evaluations of affective episodes. *Journal of Personality and Social Psychology*, *65*(1), 45–55. https://doi.org/10.1037/0022-3514.65.1.45

Gabriel, A. S., Campbell, J. T., Djurdjevic, E., Johnson, R. E., & Rosen, C. C. (2018). Fuzzy profiles: Comparing and contrasting latent profile analysis and fuzzy set qualitative comparative analysis for person-centered research. *Organizational Research Methods*, *21*(4), 877–904. https://doi.org/10.1177/1094428117752466

Geldhof, G. J., Preacher, K. J., & Zyphur, M. J. (2014). Reliability estimation in a multilevel confirmatory factor analysis framework. *Psychological Methods*, *19*(1), 72–91. https://doi.org/10.1037/a0032138

Germeys, L., & De Gieter, S. (2018). A diary study on the role of psychological detachment in the spillover of self-control demands to employees' ego depletion and the crossover to their partner. *European Journal of Work and Organizational Psychology*, *27*(1), 140–152. https://doi.org/10.1080/1359432X.2017.1417259

Halbesleben, J. R. B., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR": Understanding the role of resources in conservation of resources theory. *Journal of Management*, *40*(5), 1334–1364. https://doi.org/10.1177/0149206314527130

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*(4), 821–864. https://doi.org/10.1007/s10869-022-09821-3

Hirschi, A., & Valero, D. (2017). Chance events and career decidedness: Latent profiles in relation to work motivation. *The Career Development Quarterly*, *65*(1), 2–15. https://doi.org/10.1002/cdq.12076

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, *44*(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Hobfoll, S. E., Halbesleben, J., Neveu, J.-P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, *5*(1), 103–128. https://doi.org/10.1146/annurev-orgpsych-032117-104640

Howard, J., Gagné, M., Morin, A. J. S., & Van Den Broeck, A. (2016). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior*, *95–96*, 74–89. https://doi.org/10.1016/j.jvb.2016.07.004

Hülsheger, U. R. (2016). From dawn till dusk: Shedding light on the recovery process by investigating daily change patterns in fatigue. *Journal of Applied Psychology*, *101*(6), 905–914. https://doi.org/10.1037/apl0000104

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology*, *92*(5), 1332–1356. https://doi.org/10.1037/0021-9010.92.5.1332

Ilies, R., Dimotakis, N., & De Pater, I. E. (2010). Psychological and physiological reactions to high workloads: Implications for well-being. *Personnel Psychology*, *63*(2), 407–436. https://doi.org/10.1111/j.1744-6570.2010.01175.x

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776–1780. https://doi.org/10.1126/science.1103572

Kinnunen, U., Feldt, T., de Bloom, J., & Korpela, K. (2015). Patterns of daily energy management at work: Relations to employee well-being and job characteristics. *International Archives of Occupational and Environmental Health*, *88*(8), 1077–1086. https://doi.org/10.1007/s00420-015-1039-9

Kinnunen, U., Feldt, T., Siltaloppi, M., & Sonnentag, S. (2011). Job demands–resources model in the context of recovery: Testing recovery experiences as mediators. *European Journal of Work and Organizational Psychology*, *20*(6), 805–832. https://doi.org/10.1080/1359432X.2010.524411

Lepine, J. A., Podsakoff, N. P., & Lepine, M. A. (2005). A meta-analytic test of the challenge stressor–hindrance stressor framework: An explanation for inconsistent relationships among stressors and performance. *Academy of Management Journal*, *48*(5), 764–775. https://doi.org/10.5465/amj.2005.18803921

Lim, S., & Cortina, L. M. (2005). Interpersonal mistreatment in the workplace: The interface and impact of general incivility and sexual harassment. *Journal*

of Applied Psychology, *90*(3), 483–496. https://doi.org/10.1037/0021-9010.90.3.483

Lin, C.-C., Kao, Y.-T., Chen, Y.-L., & Lu, S.-C. (2016). Fostering change-oriented behaviors: A broaden-and-build model. *Journal of Business and Psychology*, *31*(3), 399–414. https://doi.org/10.1007/s10869-015-9417-6

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Marsh, R. L., Hicks, J. L., & Bink, M. L. (1998). Activation of completed, uncompleted, and partially completed intentions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*(2), 350–361. https://doi.org/10.1037/0278-7393.24.2.350

McCormick, B. W., Reeves, C. J., Downes, P. E., Li, N., & Ilies, R. (2020). Scientific contributions of within-person research in management: Making the juice worth the squeeze. *Journal of Management*, *46*(2), 321–350. https://doi.org/10.1177/0149206318788435

McEwen, B. S. (1998). Stress, adaptation, and disease: Allostasis and allostatic load. In S. M. McCann, J. M. Lipton, E. M. Sternberg, G. P. Chrousos, P. W. Gold, & C. C. Smith (Eds.), *Molecular aspects, integrative systems, and clinical advances* (pp. 33–44). New York Academy of Sciences.

McNair, D. M., Lorr, M., & Droppleman, L. F. (1971). *Profile of mood states*. Multi-Health Systems.

Meijman, T. F., & Mulder, G. (1998). Psychological aspects of workload. In P. J. D. Drenth & C. J. de Wolff (Eds.), *Handbook of work and organizational psychology, Vol. 2*: *Work psychology* (pp. 5–33). Psychology Press.

Mitchell, T. R., & James, L. R. (2001). Building better theory: Time and the specification of when things happen. *Academy of Management Review*, *26*(4), 530–547. https://doi.org/10.2307/3560240

Molino, M., Cortese, C. G., Bakker, A. B., & Ghislieri, C. (2015). Do recovery experiences moderate the relationship between workload and work–family conflict? *Career Development International*, *20*(7), 686–702. https://doi.org/10.1108/CDI-01-2015-0011

Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, *91*(6), 1321–1339. https://doi.org/10.1037/0021-9010.91.6.1321

Morin, A. J. S., & Marsh, H. W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teachers' multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*(1), 39–59. https://doi.org/10.1080/10705511.2014.919825

Morin, A. J. S., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*(2), 231–254. https://doi.org/10.1177/1094428115621148

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

Nicholson, T., & Griffin, B. (2015). Here today but not gone tomorrow: Incivility affects after-work and next-day recovery. *Journal of Occupational Health Psychology*, *20*(2), 218–225. https://doi.org/10.1037/a0038376

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*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Oberski, D. (2016). Mixture models: Latent profile and latent class analysis. In J. Robertson & M. Kaptein (Eds.), *Modern statistical methods for HCI* (pp. 275–287). Springer International Publishing. https://doi.org/10.1007/978-3-319-26633-6_12

Ouyang, K., Cheng, B. H., Lam, W., & Parker, S. K. (2019). Enjoy your evening, be proactive tomorrow: How off-job experiences shape daily proactivity. *Journal of Applied Psychology*, *104*(8), 1003–1019. https://doi.org/10.1037/apl0000391

Petras, H., & Masyn, K. (2010). General growth mixture analysis with antecedents and consequences of change. In A. R. Piquero & D. Weisburd (Eds.), *Handbook of quantitative criminology* (pp. 69–100). Springer International Publishing. https://doi.org/10.1007/978-0-387-77650-7_5

Peugh, J., & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling*, *20*(4), 616–639. https://doi.org/10.1080/10705511.2013.824780

Peugh, J., & Fan, X. (2015). Enumeration index performance in generalized growth mixture models: A Monte Carlo test of Muthén's (2003) hypothesis. *Structural Equation Modeling*, *22*(1), 115–131. https://doi.org/10.1080/10705511.2014.919823

Quinn, R. W., & Dutton, J. E. (2005). Coordination as energy-in-conversation. *Academy of Management Review*, *30*(1), 36–57. https://doi.org/10.5465/amr.2005.15281422

Quinn, R. W., Spreitzer, G. M., & Lam, C. F. (2012). Building a sustainable model of human energy in organizations: Exploring the critical role of resources. *The Academy of Management Annals*, *6*(1), 337–396. https://doi.org/10.5465/19416520.2012.676762

R Core Team. (2023). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rodríguez-Muñoz, A., Sanz-Vergel, A. I., Antino, M., Demerouti, E., & Bakker, A. B. (2018). Positive experiences at work and daily recovery: Effects on couple's well-being. *Journal of Happiness Studies: An Interdisciplinary Forum on Subjective Well-Being*, *19*(5), 1395–1413. https://doi.org/10.1007/s10902-017-9880-z

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Sheridan, S., & Ambrose, M. L. (2022). My cup runneth over: A daily study of the energy benefits for supervisors who feel appreciated by their subordinates. *Journal of Management*, *48*(2), 440–471. https://doi.org/10.1177/0149206320967104

Shipp, A. J., & Cole, M. S. (2015). Time in individual-level organizational studies: What is it, how is it used, and why isn't it exploited more often? *Annual Review of Organizational Psychology and Organizational Behavior*, *2*(1), 237–260. https://doi.org/10.1146/annurev-orgpsych-032414-111245

Shockley, K. M., Gabriel, A. S., & Yuan, Z. (2022). Profiles of attribution for work–family conflict episodes and their relation to negative emotions. *Journal of Organizational Behavior*, *43*(4), 643–661. https://doi.org/10.1002/job.2597

Smit, B. W. (2016). Successfully leaving work at work: The self-regulatory underpinnings of psychological detachment. *Journal of Occupational and Organizational Psychology*, *89*(3), 493–514. https://doi.org/10.1111/joop.12137

Smit, B. W., & Barber, L. K. (2016). Psychologically detaching despite high workloads: The role of attentional processes. *Journal of Occupational Health Psychology*, *21*(4), 432–442. https://doi.org/10.1037/ocp0000019

Song, Y., Tu, M.-H., Fang, Y., & Krishnan, S. (2024). Looking forward or backward: A temporal lens to disentangle adaptive and maladaptive reactions to daily goal-performance discrepancy. *Journal of Applied Psychology*, *109*(1), 99–114. https://doi.org/10.1037/apl0001137

Sonnentag, S. (2001). Work, recovery activities, and individual well-being: A diary study. *Journal of Occupational Health Psychology*, *6*(3), 196–210. https://doi.org/10.1037/1076-8998.6.3.196

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., Binnewies, C., & Mojza, E. J. (2008). "Did you have a nice evening?" A day-level study on recovery experiences, sleep, and affect. *Journal of Applied Psychology*, *93*(3), 674–684. https://doi.org/10.1037/0021-9010.93.3.674

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., & Fritz, C. (2015). Recovery from job stress: The stressor-detachment model as an integrative framework. *Journal of Organizational Behavior*, *36*(Suppl. 1), S72–S103. https://doi.org/10.1002/job.1924

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

Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: Interpersonal Conflict at Work Scale, Organizational Constraints Scale, Quantitative Workload Inventory, and Physical Symptoms Inventory. *Journal of Occupational Health Psychology*, *3*(4), 356–367. https://doi.org/10.1037/1076-8998.3.4.356

Spoelma, T. M., Mai, K. M., & Wei, W. (2023). Understanding the effects of cheating configurations on team creative performance: A social impact theory perspective. *Personnel Psychology*, *77*(2), 595–620. https://doi.org/10.1111/peps.12563

Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior*, *120*, Article 103445. https://doi.org/10.1016/j.jvb.2020.103445

Steed, L. B., Swider, B. W., Keem, S., & Liu, J. T. (2021). Leaving work at work: A meta-analysis on employee recovery from work. *Journal of Management*, *47*(4), 867–897. https://doi.org/10.1177/0149206319864153

Tabachnick, B. G., & Fidell, L. S. (2007). Cleaning up your act: Screening data prior to analysis. *Using multivariate statistics* (5th ed., pp. 52–98). Allyn & Bacon/Pearson Education.

ten Brummelhuis, L. L., & Bakker, A. B. (2012). A resource perspective on the work–home interface: The work–home resources model. *American Psychologist*, *67*(7), 545–556. https://doi.org/10.1037/a0027974

Vacharkulksemsuk, T., & Fredrickson, B. L. (2013). Looking back and glimpsing forward: The broaden-and-build theory of positive emotions as applied to organizations. In A. B. Bakker (Ed.), *Advances in positive organizational psychology* (pp. 45–60). Emerald Group Publishing. https://doi.org/10.1108/S2046-410X(2013)0000001005

Van den Broeck, A., Vansteenkiste, M., De Witte, H., Soenens, B., & Lens, W. (2010). Capturing autonomy, competence, and relatedness at work: Construction and initial validation of the Work-Related Basic Need Satisfaction Scale. *Journal of Occupational and Organizational Psychology*, *83*(4), 981–1002. https://doi.org/10.1348/096317909X481382

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. Hagenaars & A. McCutcheon (Eds.), *Applied latent class analysis* (pp. 89–106). Cambridge University Press. https://doi.org/10.1017/CBO9780511499531.004

Wanberg, C. R., Zhu, J., & Van Hooft, E. A. J. (2010). The job search grind: Perceived progress, self-reactions, and self-regulation of search effort. *Academy of Management Journal*, *53*(4), 788–807. https://doi.org/10.5465/amj.2010.52814599

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

Wiley, J. (2024). *multilevelTools: Multilevel and mixed effects model diagnostics and effect sizes* (R package Version 0.2.0). https://joshuawiley.com/multilevelTools

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*(1), 453–480. https://doi.org/10.1146/annurev-orgpsych-110721-045646

Wright, T. A., Cropanzano, R., & Bonett, D. G. (2007). The moderating role of employee positive well being on the relation between job satisfaction and job performance. *Journal of Occupational Health Psychology*, *12*(2), 93–104. https://doi.org/10.1037/1076-8998.12.2.93

Young, H. R., Scott, B. A., Ferris, D. L., Lee, H. W., Awasty, N., & Johnson, R. E. (2024). Distances and directions: An emotional journey into the recovery process. *Journal of Applied Psychology*, *109*(1), 115–134. https://doi.org/10.1037/apl0001122

Zijlstra, F. R. H., Cropley, M., & Rydstedt, L. W. (2014). From recovery to regulation: An attempt to reconceptualize 'recovery from work'. *Stress and Health*, *30*(3), 244–252. https://doi.org/10.1002/smi.2604

Received January 18, 2024
Revision received November 19, 2025
Accepted November 21, 2025 ■