WHAT'S YOUR 5 TO 9? ANTECEDENTS AND OUTCOMES OF PROFILES OF TRAJECTORIES OF DAILY RECOVERY EXPERIENCES ACROSS THE EVENING

by

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(Under the Direction of Kristen M. Shockley)

ABSTRACT

A growing body of research indicates that employees need to unwind and restore resources after work that are lost through recovery in order to maintain and improve well-being and performance. Despite recovery being described as a daily, cyclical process made up of four main recovery experiences– psychological detachment, relaxation, mastery, and control– that occur in conjunction with one another, it has not been empirically investigated as such. To illuminate the temporal dynamics of combinations of recovery experiences and the recovery process, I investigate profiles of daily recovery experience trajectories across the evening. Further, I investigate how job demands and resources relate to these profiles, and how profile membership predicts next-day work and well-being outcomes. My results provide insight into how the recovery process unfolds daily, what work experiences change this process, and how differing recovery processes relates to next-day outcomes.

INDEX WORDS: Work recovery, Well-being, Occupational health, Latent profile analysis, Experience sampling methods

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DEDICATION

My thesis is dedicated to my parents, Lori Grant and Scott Grant. Thank you so much for everything. Words can hardly describe my thanks and appreciation to you. You have been my source of inspiration, support, and guidance.

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CHAPTER 1

GENERAL INTRODUCTION

Recent trends suggest that now more than ever, workers are faced with increasing work demands due to boundaryless work and high time pressure, requiring them to work longer hours (Anttila et al., 2021). These trends are problematic because long periods of sustained effort at work deplete individuals' psychological and energetic resources, leading to strain which harms well-being and performance (Meijman & Mulder, 1998). In order to avoid negative outcomes associated with chronic strain, individuals can recover lost resources by engaging in restorative and recuperating activities during nonwork times, such as after work or on weekends (Meijman & Mulder, 1998; Sonnentag, 2001). This process, called recovery, is defined as the unwinding and restoration processes where individuals reduce strain levels from stressors and demands at work to their prestressor levels and restore lost psychological resources (Craig & Cooper, 1992; Meijman & Mulder, 1998). Synthesizing the field of recovery research, Sonnentag and Fritz (2007) explicated that four basic psychological experiences underlie recovery activities: psychological detachment (not thinking about work during nonwork time); mastery (taking part in challenging and engaging hobbies); control (having control over how one spends leisure time); and relaxation (experiencing low physical and/or mental activation) (Sonnentag & Fritz, 2007). Higher levels of these four experiences are linked to positive outcomes, including increased well-being, positive workplace behaviors, and job performance (Binnewies et al., 2009; Chawla et al., 2020; Sonnentag, 2003; Steed et al., 2019). Thus, understanding the recovery process can provide insights for both well-being and work-related outcomes.

Based on the core tenet of the Effort Recovery Model (ERM; Meijman & Mulder, 1998) that recovery is a cyclical, dynamic process of resource depletion and replenishment occurring at the daily level, several recent studies have incorporated a day-level approach using experience sampling methods (ESM) to study recovery (Sonnentag et al., 2017). While previous ESM work has provided valuable knowledge of predictors and outcomes of recovery at the daily level, there are still important gaps in this knowledge base. Specifically, previous ESM research has only focused on static, end states of daily recovery. That is, in the vast majority of recovery ESM studies, recovery experiences are measured only 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 day; Chawla et al., 2020; Sonnentag et al., 2008). Measuring recovery in this static way does not allow for the examination of how recovery experiences fluctuate across a recovery period, such as a free evening after work.

Not accounting for how recovery experiences fluctuate temporally across a recovery period is problematic for three reasons. First, measuring experiences once does not align with how recovery experiences actually occur for individuals during a nonwork period. These experiences are not static but are more dynamic in nature. For example, psychological detachment can increase right as one leaves work, decrease when one checks work emails at home, and then increase again as one progresses through the evening. The patterns of these dynamic ebbs and flows are not being captured when recovery experiences are measured once daily in an end state, resulting in a mismatch between how recovery occurs and how it has previously been measured.

Second, relying on an individuals' recollections of their recovery experiences earlier that night or the previous evening also may result in only receiving "peak and end" information

(Fredrickson & Kahneman, 1993). When recalling their experiences over a specified period of time, individuals are more likely to remember how they felt at the most intense point of the experience or at its end, rather than remembering, or accurately aggregating, their recovery experiences across the entire evening (Fredrickson & Kahneman, 1993). In the context of recovery experiences, this means that they are likely not recalling their recovery experiences across the entire evening, but rather one snapshot, such as when they were most relaxed or only how they felt right before bed. Ultimately, one-time daily measurements are limited in their ability to capture information detailing the dynamism of the recovery process.

Third, due to this static method of measurement, we do not know what the ideal patterns of recovery experiences over the course of a nonwork period look like. That is, because a majority of daily level research only measures recovery as one snapshot across the nonwork period, it is difficult to garner which recovery experiences and their patterns are most beneficial. For example, is it just the mean level of recovery across an evening that is most important for predicting outcomes? Or do dynamic changes and variability over the evening in recovery experiences across the evening exert unique influences on outcomes above and beyond the influence of static, mean levels of recovery experiences?

To better illustrate this point, consider an instance where two individuals both have the same score on a measure of psychological detachment for a nonwork period, a 3 on a 5-point scale. The static viewpoint common in the recovery literature would interpret this as both individuals having detached the same amount that evening. But what if one individual psychologically detached a high amount in the first half of the evening but not the second half, and the other individual did the opposite, only detaching a high amount in the later part of the evening before bed? While they both score a 3 on the scale, it does not appear that they are experiencing recovery in the same way. That is, their recovery process of arriving at this end state of a 3 on psychological detachment is different. Adopting a more temporal perspective would shed light on how this recovery process is unfolding differently for individuals. Previous research in the recovery literature has not addressed this question due to a lack of a dynamic perspective. An empirical examination of the dynamic nature of recovery experiences is therefore needed. Not only can it provide us with a general descriptive understanding of how recovery experiences fluctuate over short time periods as phenomena, but also it can provide us with a better understanding of how results and conclusions regarding outcomes of the recovery process (well-being, work performance) change when focusing on dynamic versus static assessments of recovery experiences.

With this in mind, the purpose of the proposed study is 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 order to illuminate the temporal dynamics of recovery experiences, I adopt an ESM design that more precisely measures employee recovery experiences, where participants report these experiences six times across the entire evening for five consecutive working days. I use multilevel latent profile analysis (MLPA) in combination with Bayes slope estimates produced in hierarchical linear models to capture quadratic recovery experience change trajectories across the evening. This analytical approach allowed me to use both a longitudinal method for examining within-person change within a person-centered approach to illuminate whether profiles exist in the data of daily trajectories of recovery. Along with identifying profiles with differing trajectories of change, MLPA also allows for the prediction of membership in these daily trajectory profiles and how these differing trajectories in each subgroup relate to outcomes.

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, I will examine both predictors and outcomes related to these trajectories. In terms of predictors, I will examine two daily job demands that may inhibit whether individuals have recovery experiences: workload and unfinished tasks. I will also test the predictive role of two job resources, job control and felt appreciation at work, to examine whether it promotes recovery experiences. Further, I will test how these profiles of trajectories relate to important next-day well-being (sleep, fatigue, and emotional exhaustion) and work outcomes (work engagement, task performance and organizational citizenship behavior). Figure 1 provides an illustration of the proposed study model.

Theoretical and Practical Contributions

The findings of the proposed study have academic implications, as they would shed light on the prototypical profiles of recovery experiences across an evening, how job demands and resources predict these profiles, and which profiles relate positively or negatively to important outcomes. Building on previous work, this study would also add to the growing evidence that it is how all four recovery experiences are used in combination, not just one or two, that matters most (Bennett et al., 2016; Chawla et al., 2020). These findings could also help explain the relative importance of particular types of recovery for next-day outcomes. Uncovering the ebb and flow of recovery experiences daily for employees opens up avenues for future research related to the recovery process that underlies the relationship between recovery and its outcomes. From a practical standpoint, understanding which profiles of recovery trajectories are most and least beneficial, allows practitioners to provide evidence-based guidance on optimal recovery practices. For example, if we find that psychological detachment results in better outcomes for individuals with a pattern high on psychological detachment right after work ends as compared to those with a pattern where detachment increases sharply before bed, this could signal that we need to develop interventions that target increasing detachment earlier rather than later in the recovery period. By discovering optimal patterns, more specific recommendations could be given to both organizations and individuals in order to improve recovery processes and subsequent outcomes that are important to individuals and organizations alike.

Profiles of Trajectories of Recovery Experiences

Although the theoretical and empirical reasons detailed above provide evidence that recovery experiences likely fluctuate across a recovery period resulting in unique profiles of trajectories, it is impossible to specify exact profiles a priori (see Shockley et al., 2022; Chawla et al., 2020; Gabriel et al., 2018 for similar scenarios. Only one study, Chawla et al. (2020), has examined profiles of all four recovery experiences, which were measured once before sleeping across 5 days. In person-centered research scenarios like this, it is instead recommended to not make formal predictions but instead engage in "thought exercises" on how the recovery about which patterns of trajectories may emerge and how they may relate to antecedents and outcomes (Gabriel et al., 2018; Morin et al., 2011; Shockley et al., 2020; Wang & Hanges, 2011; Woo & Allen, 2014; Zyphur, 2009). Following this recommendation, I use previous literature that has examined latent profiles of the four recovery experiences in combination to develop speculation about which profiles of trajectories may emerge.

CHAPTER 2

OVERVIEW OF THE LITERATURE

Three previous studies have examined profiles of the four recovery experiences being used in combination across different time spans, Siltaloppi et al. (2011) across an entire year, Bennett et al. (2016) at the weekly level and Chawla et al. (2020) at the daily level. Siltaloppi et al. (2011) examined profiles of the four recovery experiences at two time points 1 year apart. They had five profiles emerge: *pattern 1* (reasonably high stable levels of all four recovery experiences); *pattern 2* (high mastery and control, with low psychological detachment and relaxation); *pattern 3* (reasonably high relaxation and mastery, control that increased over time, and low detachment); *pattern 4* (all experiences except relaxation decrease over time); pattern 5 (low levels of all four recovery experiences). While these findings convey generally how employees recover over a longer time period, it is difficult to connect these findings to the present study focused on daily profiles of trajectories as yearly fluctuations are likely much different than daily fluctuations.

At the weekly level, Bennett et al. (2016) measured all four recovery experiences at two time points 2 weeks apart. Along with recovery experiences, Bennett et al. (2016) also included problem-solving pondering into their profiles, which occurs when employees continue to be engaged with work after hours thinking about ways they can improve their performance. Three profiles of recovery experiences emerged, presented in order from largest to smallest membership: *recovering ponderers* (high relaxation, high mastery, high control, high problem-solving pondering, and low psychological detachment); *leaving work behind* (high psychological detachment, relaxation, mastery, control, and low problem-solving pondering); *pondering* (high problem-solving pondering, low psychological detachment, low relaxation, moderate mastery, and moderate control).

At the daily level, Chawla et al. (2020) found that five profiles of recovery experiences emerged across the five days of the study. From largest to smallest profile membership, they were: *controlled non-mastery recovering* (moderate control, moderate psychological detachment, moderate relaxation, and very low mastery); *non-mastery recovering* (high psychological detachment, high relaxation, high control, and low mastery); *plugged in* (low levels of all four recovery experiences); *moderately unplugged* (moderate levels of all four recovery experiences); *unplugged* (high levels of all four recovery experiences). Chawla et al. (2020) also note that there was substantial variation in daily profile membership, as 90% of the sample belonged to more than one recovery profile during the week of their study. This suggests that membership in profiles of daily recovery experiences is dynamic both across the week and from day to day.
With these previous profiles from the literature in mind, one possibility is that these profiles are replicated in my study, showing that measuring recovery experiences once at the end of the non-work period is all that is needed. However, it is likely that examining profiles of trajectories of recovery experiences across an evening will result in different profiles emerging than those previously found. Speculatively, when examining profiles of recovery experiences from a more dynamic perspective, one possible profile may emerge consisting of an inverted U-shaped trajectory for mastery experiences, while the three other recovery experiences start at a high level and remain high (i.e., a flatter trajectory) as individuals engage in recovery experiences across the evening (see Figure 1). Both Bennett et al. (2016) and Chawla et al. (2020) had profiles emerge where individuals reported moderate to high levels of all four recovery experiences. It is likely that a similar profile would emerge for individuals who engage in recovery experiences

across the evening, except when it comes to mastery experiences. Due to static measurement, previous studies likely missed the inverted U-shape of the mastery trajectory. Mastery may have this inverted U-shaped trajectory as mastery is likely to only be experienced for a short amount of time. For example, an individual may exercise for only an hour, or go to a piano lesson for only thirty minutes after work. Indeed, the American Time Use Survey (Bureau of Labor Statistics, 2021) shows that when individuals in the U.S. engage in activities that would be classified as mastery experiences after hours, they only do so for an hour and thirty minutes on average, while they engage in relaxation for around four hours. This data on how individuals use their time after work suggests that it is unlikely that a profile emerges consisting of mastery experiences being high across the entire evening, as previous static profile research has shown. Instead, for individuals who engage in all four recovery experiences across an evening, this profile would likely consist of high starting points and flat trajectories of psychological detachment, relaxation, and control, while mastery would have an inverted U-shaped trajectory. Contrary to this high recovery profile, a profile may emerge where individuals start low on recovery experiences and remain low (i.e., a flatter trajectory). This profile may emerge because some individuals may not engage in recovery experiences at all across the evening due to experiences at work that day or time demands being placed on them by their work. Chawla et al. (2020) found that experiencing high job demands that day in the form of role ambiguity and time pressure made individuals less likely to belong to profiles consisting of using multiple recovery experiences together (i.e., non-mastery recovering or unplugged). These daily findings align with results seen across the recovery literature, deemed the recovery paradox (Sonnentag et al., 2017). The ERM suggests that days consisting of high job demands should increase individuals' need for recovery, and in turn lead to them being more likely to have recovery experiences (Meijman

& Mulder, 1998). However, empirical data suggest that the opposite actually occurs, with demands being negatively related to recovery experiences (Mojza et al., 2010; Sonnentag & Bayer, 2005; Volmer et al., 2012). Thus, this recovery paradox occurs because on days when individuals should have high need for recovery due to demands, they actually engage in less recovery experiences. Based on this, it is likely that on days of high demands and stress at work that all four recovery experiences will be impaired in the evening. In terms of trajectories, this would result in a pattern where all four experiences would begin low that evening and remain relatively low (flat trajectories). Along with experiences that day, it may also be that individuals may have a large workload that requires them to continue working after hours. Previous work suggests that weekly work hours is negatively related to both psychological detachment and relaxation (Kinnunen et al., 2011). In sum, it is likely that a profile emerges consisting of low start points and flat trajectories for the four recovery experiences across an evening for individuals who only recover little or not at all.

Along with recovery experience profiles that consist of relatively flat trajectories across the evening, it is likely that there are profiles with a U-shaped trajectory for multiple or all recovery experiences. Over the past ten years or so, the use of information and communication technology (ICT) such as smartphones and laptops after hours has become a common part of organizational life for most employees (Wajcman & Rose, 2011). Many employees now use ICT to communicate with their supervisor and coworkers or continue working on tasks after hours. The use of ICT also makes it so that employees can be almost constantly connected to work as their supervisor or coworkers communicate with them electronically after work. Receiving a text message or e-mail after hours may cause individuals to start thinking about a work task, or spur them into action and start working on it. Braukmann et al. (2018) found that receiving and reply to work e-mails after hours was negatively related to psychological detachment. They also found that working after hours was negatively related to relaxation. These findings could also be applied to the other recovery experiences. For example, an individual may be relaxing and not be thinking about work, but may receive an email from their supervisor. In turn, this could lead to them working on a task for an hour or so, decreasing both relaxation and psychological detachment. It may also decrease their perceptions of control, as they feel their supervisor dictates what they do with their time after hours. Working on a task may also prevent them from engaging in mastery experiences. However, they may only engage in work tasks or work-related rumination for a portion of the evening, and may engage in recovery experiences again, causing their trajectories to increase. Or, their recovery trajectories may not increase again or may only increase a minimal amount if the individual continues to complete work tasks or think about work for a longer period of time. In sum, a profile may emerge where some, (i.e., only psychological detachment and relaxation) or all, recovery experiences decrease during the evening an increase again (do not increase again), resulting in U-shaped trajectories.

Another plausible profile may consist of trajectories that exhibit a positive "shift" in recovery experiences, where their trajectories begin low and do not begin to increase and have an upward trajectory until midway into the evening. For many individuals, the demands and stressors of work may not immediately cease to have negative effects just because they have stopped working. Rather, it is likely that demands of the workday continue to linger in the periods closer to the end of the work day (a few hours after work), preventing individuals from having recovery experiences right away. Previous evidence indicates that experiencing incivility from a coworker that day leads to individuals to continue to ruminate about the situation after hours, impairing their ability to psychologically detach (Nicholson & Griffin, 2015). From a more physiological standpoint, high job stress has been linked to higher physiological activation after work in the form of elevated heart rate and systolic blood pressure (Vrijkotte et al., 2000). This evidence indicates experiencing demands at work continues to affect individuals after work when the stressor has ceased, preventing the attainment of a state of relaxation.

Although the effects of these stressors continue to linger after work has ended, they may not linger the entire night. These trajectories may abruptly "shift" when individuals engage in certain recovery activities or experiences that cause the trajectories of all of their recovery experiences to curve upwards. For example, an individual may start their evening by not relaxing or not being psychologically detached as they continue to think about a dispute they had with their supervisor that day. Halfway through that night however, they engage in a mastery experience by playing in their local soccer league that distracts them from their experiences at work that day and helps improve their mood. Engaging in mastery activities like these may cause the negative effects of work stress to dissipate as they cease the psychological rumination and physiological activation due to work stress, and also help improve an individual's mood (Headrick et al., 2022; Sonnentag & Fritz, 2007). A similar argument could be made for relaxation, where an individual could go on a relaxing walk that lowers work-related rumination, beginning the recovery process for them that night. Engaging in these recovery activities would result in a positive "shift" in trajectories and allow individuals to start having recovery experiences that night. Based on this reasoning, I speculate that a profile of trajectories may emerge where recovery experiences begin low and have flat trajectories until around halfway into the evening, where they increase until bedtime. In summary, there are several potential distinct profiles that previous research suggests may emerge. Ultimately however, the number of profiles and the trajectories of recovery experiences each profile consists of is an empirical question to be answered by a person-centered analytic approach. Thus, I propose:

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

Antecedents of Recovery Experience Patterns: Job Demands and Resources

Without knowing the precise profiles until after running LGMM analyses, it is also difficult to create specific hypotheses regarding how other variables will relate to these profiles. That being said, I draw from relevant theories in the recovery literature that implicate the potential importance of job demands and resources. As mentioned above, rather than recovering more on days with high demands and an increased need for recovery, empirical evidence suggests individuals are actually less likely to have recovery experiences (Sonnentag et al., 2017). This pattern of results is more aligned with the Job-Demands Resources Model (JD-R; Bakker & Demerouti, 2007), which suggests that high daily job demands actually make individuals less likely to recover.

The first assumption of the JD-R model is that work conditions can be characterized as either job demands or job resources. Job demands are aspects of the job that require psychological or physiological effort, and are associated with physiological and/or psychological costs (Bakker & Demerouti, 2007). Some examples include high work pressure, demanding interactions with coworkers, and role ambiguity. Job resources are aspects of the job that are functional in achieving work goals, reduce job demands associated with physiological and psychological costs, and stimulate personal growth, learning, and development (Bakker & Demerouti, 2007). Some examples of job demands are receiving timely feedback, job control, and coworker social support.

The second core assumption of the JD-R model is that job demands and job resources impact health and well-being through two different processes: the health impairment process and the motivational process (Bakker & Demerouti, 2007). The health impairment process occurs when exposure to chronic job demands depletes employees' physical and psychological resources, leading to a state of exhaustion and health problems (Bakker & Demerouti, 2007). On the other hand, the motivational process occurs when individuals have sufficient amounts of job resources, which have motivational potential and lead to high work engagement, low cynicism, and high performance (Bakker & Demerouti, 2007).

Recently, the JD-R model has become incorporated into theorizing on recovery processes by researchers. For example, previous work suggests that at the daily level demands such time pressure, role ambiguity, and emotionally demanding situations are negatively related to recovery experiences, while resources like social support and job control are positively related to recovery experiences (Chawla et al., 2020; Kinnunen et al., 2011). The JD-R model helps explain these findings, suggesting that demands function as a health impairment process that depletes psychological and energetic resources, leaving employees with little energy to engage in effortful mastery experiences, and makes them perceive less control during non-work time as they continue to think about work (Bakker & Demerouti, 2007; Kinnunen et al., 2011). Experiencing high job demands may also result in individuals being more likely to ruminate about work and experience work-related negative affect after hours, decreasing psychological detachment and relaxation (Kinnunen et al., 2011).

On the other hand, when individuals have high job resources, they are more likely to have larger reserves of internal resources (e.g., positive mood and energy) that allow them to engage in mastery experiences and have control experiences (Bakker & Demerouti, 2007; Kinnunen et al., 2011). In turn, these recovery experiences can help build and restore internal resources that can be called upon the next day at work. Job resources are also theorized to minimize the negative effects of work, resulting in a more relaxed affective state that promotes recovery experiences as a whole (Demerouti et al., 2009; Mojza et al., 2010). For example, job control allows one to determine where, how, and when they complete their work tasks (Karasek et al., 1998). This control allows an individual to effectively manage their work demands (Taris et al., 2005), leading to higher levels of energy and allowing more time for recovery after work. However, because recovery experience trajectories have not been previously measured, it is unclear precisely how job demands and resources impact recovery patterns over a non-work period. High job demands that day could, for example, lead to initial low rates of psychological detachment that increase over the course of the evening. Or speculatively, demands could lead to uniformly low rates of psychological detachment across an evening. The same could be said for the three other recovery experiences. In sum, we know theoretically that demands and resources predict recovery experiences when measured at a single point, but whether or not they predict unique trajectories remains to be tested. Based on this, I will test how daily workload, which drains psychological and energetic resources (Ilies et al., 2015), and unfinished tasks, which make individuals more likely to engage in work tasks after hours (Eichberger et al., 2021), impact recovery experience trajectories. I also test daily job resources, job control and felt appreciation, as internal resources resulting from job control may spillover into the non-work domain, promoting engagement in recovery experiences (Sonnentag & Frtiz, 2007). Felt appreciation may also promote recovery after hours, as daily felt appreciation has been positively related to reports of higher energy by employees (Sheridan & Ambrose, 2022). Subsequently, this increased energy can be used for engaging in recovery after hours. Thus, I propose:

Research Question 2: Do daily job demands (workload and unfinished tasks) and job resources (job control and appreciation) predict profile membership for recovery experience trajectories?

Well-being and Work Outcomes Related to Profiles of Trajectories

In line with both the ERM and JD-R model, recovery experiences are theorized to protect and maintain well-being and work outcomes by supporting the cessation of work-related psychological and physiological activation through psychological detachment and relaxation, while mastery and control experiences help individuals restore and gain new resources (Sonnentag & Fritz, 2007). Indeed, a plethora of research supports this notion, linking recovery experiences to less fatigue, better sleep, high work engagement, and improved job performance, among others (Bennett et al., 2018; Headrick et al., 2022; Steed et al., 2019). In the present study, I chose to test how these profiles relate to well-being and work outcomes in order to represent both the health impairment process and motivational process from the JD-R model. As explained above, in the health impairment process exposure to job demands depletes psychological and energetic resources, which leads to exhaustion decreased well-being (Bakker & Demerouti, 2007). On the other hand, the motivational process leads to increased work engagement and improved job performance. For evenings with profiles of trajectories that allow individuals to adequately recover, this should lead to both improved next-day well-being and higher levels of both task performance in an employee's role and citizenship behavior outside their role. That is, recovery experiences will reduce the harmful effects on their well-being due to the health impairment process, and enhances the positive effects of the motivational process by increasing employee work engagement and their pool of internal resources that can be put toward job performance. This notion is supported by Kinnunen et al. (2011), who showed that recovery experiences mediate the relationship between job demands and job exhaustion and need for recovery, and also the relationship between job resources and work engagement. Therefore, I chose to examine sleep quality, emotional exhaustion, and fatigue to represent well-being, and work engagement, task performance, and organizational citizenship behavior to represent work outcomes.

However, how different trajectories of recovery experiences relate to these outcomes is unknown. These profiles of recovery experiences are important to understand as differing patterns may lead to differing outcomes. For example, one pattern of recovery experiences that starts low and increases quickly after work is likely to relate differently to outcomes than another pattern that starts low and does not increase until halfway into the non-work period. This reasoning can be applied to all four experiences. With this in mind, I will examine how different profiles of recovery experience trajectories relate to next-day well-being and work outcomes.

Research Question 3: Do profiles of trajectories of recovery experiences differentially relate to next-day well-being (sleep, fatigue, emotional exhaustion) and work-outcomes (work engagement, task performance, organizational citizenship behavior)?

CHAPTER 3

METHOD

Sample and Procedure

I utilized an interval-contingent ESM design for data collection. To a capture a wide array of employees and positions, I recruited full-time working adults using personal and professional networks. Specifically, I posted an advertisement detailing the nature of the study on social media platforms. Interested participants were also encouraged to send details and/or advertise the study to other full-time employees who may be interested in participating. To be eligible, participants had to work at least 35 hours per week in the United States on a daytime shift (e.g., arriving no later than 10 a.m. and not leaving earlier than 3:30 p.m.), have a bedtime that is typically more than 3 hours after the time they typically stop working or leave work, not work a second job, not be taking any vacation days or paid leave during the duration of the daily portion of the study, and not be self-employed. Participants were told that they would complete a baseline survey, followed by being surveyed seven times per day for five consecutive working days (i.e., one work week) and could earn up to $90. Participants first completed an eligibility survey and, if eligible, were sent their baseline surveys. After participants completed their baseline surveys, they were sent confirmation of their enrollment in the study and the start date for the daily portion of the study. Participants were compensated $10 for completing the baseline survey.

The daily surveys began on a Monday and were sent seven times per day for 5 consecutive workdays to participants' emails. To increase response rates, participants received a text message reminder at each time point to inform them that their survey had been delivered to their email inbox. The morning surveys measuring well-being outcomes (i.e., sleep quality, emotional exhaustion, energy) were sent at 7:00 AM local time and had to be completed by 10:00 AM. For the afternoon surveys measuring job demands, job resources, and work outcomes (i.e., workload, unfinished tasks, job control, appreciation, engagement, work goal accomplishment, OCB), participants were asked to indicate what time they typically ended their workday and told that this choice would determine the time when their afternoon surveys would be delivered. The afternoon surveys were sent 15 minutes before the time they indicated as the end of their workday, and they had one hour and 15 minutes to complete it. For example, if a participant indicated 5:00 PM as their end of work, they received their afternoon survey at 4:45 PM and had until 6 PM to complete it. The five evening surveys measuring recovery experiences (i.e., psychological detachment, relaxation, mastery, control) began one hour after the end of their workday. Participants received evening surveys each hour for five hours from one hour after work up until bedtime (e.g., 5 p.m., 6 p.m., 7 p.m., 8 p.m., 9 p.m., and 10 p.m.). To best capture the one-hour time period for each evening survey, participants had 45 minutes to complete each evening survey. Participants who successfully completed both the morning and afternoon survey and at least three of the five evening surveys for that day were compensated $13 for that day. Those who completed all seven surveys a day for at least 4 out of 5 days of the study received a $15 bonus. Those who completed who met all the compensation criteria throughout the study earned $90.

In total, 137 employees opted in 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 completed the baseline survey but then did not complete any of the daily surveys, and another also opted in but only completed two of the possible 35 daily surveys, reducing the final usable sample size to 133 participants.

Employees were 77.4% female and 87.2% white, 65.4% were married or living with a partner, with an average age of 34.59 (SD = 11.51). They worked on average 41.71 hours weekly (SD = 4.05) and were highly educated, with 91.7% holding a bachelor's degree or higher. Employees came from 16 unique industries, of which finance or insurance (33.8%), real estate (12.3%), information services (11.3%), and forestry, fishing, hunting or agriculture support (5.3%) were most common. At Level 1, participants generated 625 morning responses (4.7 surveys per person) and 598 afternoon responses (4.5 surveys per person) of a possible 665 (94.0% and 89.9% response rate, respectively). For the evening surveys, participants generated 2,780 evening responses (22.2 surveys per person) of a possible 3,325 (83.6% response rate).

Measures

A complete list of items can also be found in Appendix A.

Recovery experiences. Sonnentag and Fritz's (2007) Recovery Experiences Questionnaire was adapted to assess recovery experiences during the past hour using 12 items (three for each dimension) from their 16-item scale. Participants rated their recovery experiences during the past hour using a 5-point scale (1 = *not at all*, 5 = *very much*). Example items include "During the past hour, I was not thinking about work at all" (*psychological detachment*; α = .93); "During the past hour, I was kicking back and relaxing" (*relaxation*; α = .99); "During the past hour, I was doing something that challenges me" (*mastery*; α = .83); "During the past hour, I felt that I could decide for myself what to do" (*control*; α = .98).

Workload. Daily workload was measured using Spector and Jex's (1998) 5-item (α = .89) Quantitative Workload Inventory. Items were adapted to capture daily levels of workload. Participants rated their workload that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, I had a lot of work to do."

Unfinished tasks. Daily unfished tasks were measured using 3 items (α = .86) from Syrek et al.'s (2017) 6-item scale. Items were adapted to capture unfinished tasks at the daily level. Participants rated their unfinished tasks that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, I have not finished important tasks I had planned to do today."

Job control. Daily job control was measured using 5 items (α = .94) adapted from Morgeson and Humphrey's (2006) 9-item scale. Items were adapted to capture job control at the daily level. Participants rated their job control that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, my job allowed me to plan how I plan my work."

Appreciation. Daily felt appreciation was measured using Sheridan and Ambrose's (2022) 3-item scale (α = .92). Items were adapted to capture felt appreciation at the daily level. Participants rated their felt appreciation that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, people at work made sure I felt appreciated".

Work engagement. Daily work engagement was measured using the 9-item (α = .90) short version of the Utrecht Work Engagement Scale (Schaufeli et al., 2006). Following recommendations of prior research (Schaufeli et al., 2006), items were averaged to form a composite score across the three dimensions of work engagement (absorption, dedication, vigor).

The items were adapted to capture daily levels of work engagement. Participants rated their work engagement that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, I was immersed in my work."

Sleep quality. Based on prior research in recovery (Chawla et al., 2020; Hülsheger, 2016; Sonnentag et al., 2008) daily sleep quality was measured using a single item ("How would you evaluate your last night's sleep?") from the Pittsburgh Sleep Quality Index (Buysse et al., 1989). Participants rated their sleep quality on a 5-point scale (1 = *very poor*, 5 = *very good*).

Energy. Daily energy was measured using Sheridan and Ambrose's (2022) 3-item scale (α = .89) adapted to capture energy level at the daily level. Participants rated their energy level that day on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Right now, I feel energetic".

Emotional exhaustion. Daily emotional exhaustion was measured using 4 items from Pugh et al.'s (2011) 5-item scale (α = .94). The item "Right now, I feel rejected" was dropped from all further analyses due to a very low factor loading and given that reliability analyses indicated Cronbach's alpha would improve a great deal if this item was dropped. Items were adapted to assess emotional exhaustion in the current moment. Participants will rate how they currently feel on a 5-point scale (1 = *not at all*, 5 = *extremely*). An example item is "Right now, I feel tired."

Work goal accomplishment. Daily work goal accomplishment was measured using 6 items (α = .92) adapted from Wanberg et al. (2010). The items are adapted to capture daily levels of work goal accomplishment and are measured on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, I made good progress on my work goals."

Organizational citizenship behavior. Daily organizational citizenship behavior was measured using 6 items (α = .79) from Dalal et al.'s (2009) 25-item scale. The items were adapted to capture daily levels of organizational citizenship behavior and measured on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). An example item is "Today, I tried to help someone I work with."

Recovery Experience Trajectories

Given the above theorization and thought experiments suggesting that recovery experiences follow a dynamic change process across the evening, I operationalized recovery experiences occurring across an evening using quadratic change trajectories. Before estimating these quadratic change trajectories, I first conducted a three-level multilevel confirmatory factor analysis (MCFA) given the nested structure of the data (i.e., hours within days within people) of all four recovery experiences to confirm that the measurement model fit the data well. As can be seen in Table 1, MCFA results indicated the three-level model had good fit, $\chi^2_{(144)} = 352.85$, $p < .01$, CFI = 0.99, TLI = 0.99, RMSEA = 0.02, SRMR = .04. After finding support for my measurement model, I then used three-level latent growth modeling to confirm that a quadratic change model fit the data well. Separate three-level growth models were computed for all four recovery experiences, and a Satorra-Bentler scaled chi-square difference test was used to compare linear models to intercept-only models, and then quadratic models to linear models (Satorra & Bentler, 2010). As can be seen in Table 2, the quadratic growth models fit the data best for psychological detachment: $\chi^2_{(10)} = 29.36$, $p < .05$, CFI = 0.97, TLI = 0.94, RMSEA = 0.06, SRMR = .02; relaxation: $\chi^2_{(10)} = 12.13$, CFI = 0.99, TLI = 0.99, RMSEA = 0.02, SRMR = .03; mastery: $\chi^2_{(10)} = 27.60$, $p < .01$, CFI = 0.92, TLI = 0.85, RMSEA = 0.05, SRMR = .05; and control: $\chi^2_{(10)}$ = 27.16.36, $p < .02$, CFI = 0.97, TLI = 0.95, RMSEA = 0.05, SRMR = .04. The results of the Satorra-Bentler scaled chi-square difference tests further indicated that the quadratic growth models fit the data better than linear growth models for all four recovery experiences: psychological detachment: TRd = 65.97, $p < .01$, $\Delta df = 7$; relaxation: TRd = 84.19, $p < .01$, $\Delta df = 7$; mastery: TRd = 26.24, $p < .01$, $\Delta df = 7$; control: TRd = 65.97, $p < .01$, $\Delta df = 7$. These results provide evidence that quadratic trends were present in all four recovery experiences across the evening within my data. Thus, it is appropriate to model recovery experiences as quadratic change trajectories across the evening.

I used the five evening ratings of the four recovery experiences to estimate daily trajectories. Based on prior work examining change trajectories (e.g., Chen, 2005; Chen et al., 2011; Frank et al., 2021; Hausknecht et al., 2011; Liu et al., 2012), I used the Bayes slope estimate produced in hierarchical linear models to capture quadratic recovery experience change trajectories across the evening. More specifically, for each recovery experience I specified a mixed-level random slopes model where I regressed each daily recovery experience on a linear time term and a quadratic time term (hour2) for each one-hour measurement across the evening. This produces an intercept, linear slope coefficient, and quadratic slope coefficient for each recovery experiences spanning from Time 1 to Time 5 for each individual for each day of the study. I saved these change trajectory estimates for each day within individuals to serve as recovery experience trajectories to be used in multilevel latent profile analysis (MLPA). These trajectory variables represent how individuals have recovery experiences across the evening daily.

Given that they are linear and quadratic slopes, these uncentered trajectory variables can be both positive and negative numbers. The combinations of positive and negative linear and quadratic slope coefficients can result in multiple different types of quadratic trajectories. A value of zero for both the linear and quadratic slope coefficients indicates steady or flat trajectories of recovery experiences across the five evening measurements. For trajectories with a positive linear and positive quadratic slope coefficient, this results in a positive accelerating incline of recovery experiences across the evening. On the other hand, a combination of a negative linear slope coefficient and a negative quadratic slope coefficient result in a negative decelerating decline of recovery experiences across the evening. When the linear slope coefficient is positive and the quadratic coefficient is negative, this results in an inverted U-shaped curve where recovery experiences increase initially, level off, and then decrease the rest of the evening. A combination of a negative linear slope coefficient and a positive quadratic coefficient result in a U-shaped curve where recovery experiences initially decrease, level off at the bottom of the U, and then increase the rest of the evening. The exact shape of these quadratic trajectories depends on the size of both the linear and quadratic slope coefficients. The intercept values represent an individual's initial level of each recovery experience at the beginning of the evening after work. Using the intercept, linear slope, and quadratic slope values as input data for MLPA allowed me to examine how different profiles with different quadratic trends in recovery experiences emerge across the evening, shedding light on dynamic recovery processes occurring within individuals.

Analytic Approach

Given that the data were non-independent (i.e., days nested within people), I conducted MLPA (Chawla et al., 2020; Shockley et al., 2021). As a first step, I ran null models decomposing the between- and within-person variance for each variable. As can be seen in Table 3, 37.5% to 95.2% of the variance in the variables was within-person, supporting the use of

MLPA. After decomposing the variance, I next ran a MCFA to confirm the measurement model of my antecedent and outcome variables. I modeled the antecedents (job control, appreciation, workload, and unfinished tasks) and outcomes (sleep quality, emotional exhaustion, energy, engagement, work goal accomplishment and OCB) at Level 1. Results indicated marginally good fit, $\chi^2_{(1806)} = 2701.91$, $p < .01$, CFI = 0.91, TLI = 0.89, RMSEA = 0.04, SRMR = .07, supporting my factor structure and the validity of my measure. Based on prior recommendations, I used raw scores in my analyses rather than group-mean centering scores as group-mean centering in MLPA and LPA significantly alters model interpretation in a way that can make results difficult to interpret (Bliese et al., 2017). Following Chawla et al. (2020) and Shockley et al. (2022), when modeling my profile indicators (intercept, linear slope, and quadratic slope coefficients for each of the four recovery experiences) I allowed the means of the profile indicators to be freely estimated in my model, but the variances were fixed. Fixing the variances is the recommended decision when the model does not converge when the 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), which was the case for the within-person data. Based on LPA and MLPA best practice recommendations (Vermunt & Magidson, 2002) I screened the data for extreme outliers[1],

[1]Due to MLPA being an inductive approach, the number of profiles cannot be determined a priori. Based on this, I initially specified a two-profile solution and increased the number of [1]I also ran the MLPA analyses with the outlier cases still present in the data. Across all profile solutions, there was an extreme outlier profile present regardless of how many profiles were in the solution. This outlier profile had extreme values that resulted in uninterpretable quadratic curves for all four recovery experiences when plotted. Additionally, this profile account for < 1% of profile membership for each profile solution, thus providing further support to remove the outlier cases from the data.

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). In these situations, it is recommended to run an outlier analysis and remove the extreme outlier cases so they do not bias the outcomes of LPA and MLPA (Hirschi & Valero, 2017). Thus, I checked for multivariate outliers using the Mahalanobis distance of the recovery experience intercept and slope, and quadratic slope profile indicators, with a *p*-value of 0.001 used as a cutoff. This analysis resulted in 29 cases being removed for a final sample size of 578 daily observations to be used in the MLPA analyses.

Due to MLPA being an inductive approach, the number of profiles cannot be determined a priori. Based on this, I 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). I report several fit statistics that were considered in tandem with theoretical considerations of the nature of the profiles to choose the final profile solution (Howard et al., 2016; Marsh et al., 2009). Specifically, I report the Akaike Information Criterion (AIC), the Bayesian information criterion (BIC), the Consistent AIC (CAIC), the sample-adjusted BIC (SSA-BIC), the adjusted version of the Lo, Mendell, and Rubin likelihood ratio test (LMR; Lo et al., 2001), and Entropy[2]. Recent 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., 2016, 2017; Peugh & Fan, 2013, 2015). Values on the BIC, CAIC, and SSA-BIC should be lower when compared with other profile solutions. Based on these recommendations, I focused on the BIC, CAIC, and SSA-BIC for choosing a final profile solution.

[2] I 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).

That being said, a common occurrence is that as one increases the number of profiles in each subsequent solution, the BIC, CAIC, and SSA-BIC will continue to improve model fit without reaching a minimum value. When this occurs, it is recommended that the BIC, CAIC, and SSA-BIC be represented visually using elbow plots and the best fitting solution is identified at the point where the slope of the plot flattens or "elbows" (Howard et al., 2016; Morin & Marsh, 2015). Along with statistical considerations, I also took into account the theoretical parsimony of the profiles extracted, selecting a solution where the same profile was not theoretically represented twice (e.g., Howard et al., 2016) Following Chawla et al., (2020) and Shockley et al., (2022; see also Asparouhov & Muthén, 2014a), I used the automatic three-step approach for MLPA. In the first step, I conducted the profile enumeration process with the fit indices detailed above, selecting the best-fitting profile solution both statistically and theoretically. In the second step, I obtained the most likely class membership based on the posterior probability distribution generated from the first step. For the third step, I examined both antecedents and outcomes in relation to the final profile solution. It should be noted that an additional benefit of this three-step approach is that it takes into account the most likely class membership and classification error rate when running these antecedent and outcome analyses (Wang & Hanges, 2011). During this profile enumeration process, each model used 7,000 random sets of start values, 50 iterations for each random start, and the 3,000 best solutions were retained for final stage optimization. All models converged on well replicated solutions.

I modeled separately how antecedents predict membership in these profiles and how the profiles differentially relate to next-day work and well-being outcomes. For antecedents, I 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 to another profile (Chawla et al., 2020; Gabriel et al., 2015). I also calculated odds ratios (*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. The interpretation of this value now becomes "the change in likelihood of membership in a target profile versus a comparison profile associated for each unit increase in the predictor" (Morin et al., 2016, p. 246). Morin et al. (2016) provide an example of how this type of analysis is interpreted, where "an *OR* of 3 suggests that each unit increase in the predictor is associated with the participant being 3 times more likely to be a member of the target profile (vs. the comparison profile)" (p. 246). On the other hand, when a coefficient in the R3STEP analysis is negative, this coincides with an *OR* that is less than 1 and is interpreted as the likelihood of membership in the target profile being reduced (Morin et al., 2016). For example, "an *OR* of .5 shows that a one unit increase in the predictor reduces by 50% the likelihood of membership in the target vs. the comparison profile" (Morin et al. 2016, p. 246). For testing how profiles relate to outcomes, I used the BCH method in Mplus (Asparouhov & Muthén, 2014b; Bakk & Vermunt, 2015). 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, I modeled these outcomes (i.e., sleep quality, emotional exhaustion, energy, engagement, work goal accomplishment, and OCB) 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 2). Conducting lagged analyses allowed me to perform more rigorous tests of the empirical relationships between recovery experience trajectories and outcomes (Podsakoff et al., 2003).

CHAPTER 4

RESULTS

Descriptive statistics and within-person correlations are in Table 4. The results of my profile enumeration process can be seen in Table 5. Given that all the Entropy values for profiles were high (≥ .80), I based the decision on how many profiles to retain based on the BIC and CAIC (Diallo et al., 2016; Howard et al., 2016). These fit statistics also failed to reach a minimum value, so I relied on the elbow plot seen in Figure 3. The elbow plot shows that these information criteria values continued to decrease without a clear point where the slope flattens, but the slope elbows around five profiles. Thus, I examined the five-profile solution as well as the adjacent four- and six-profile solutions. As can be seen in Table 5, the five-profile solution exhibited better fit in the form of lower BIC, SSA-BIC, and CAIC, and a higher entropy value than the two-, three, and four-profile solutions. Compared to the four-profile solution, the five-profile solution resulted in the addition of a qualitatively and quantitively distinct and theoretically meaning profile to the solution. Although the six-profile solution exhibited slightly better fit for the information criteria, this solution also exhibited a theoretically redundant profile that only differed slightly in a quantitative way from a profile already present in the five-profile solution[3]. The addition of this additional profile did not add anything meaningful in theoretical terms, and thus based on theoretical parsimony and the fit of the information criteria the five-

[3] Due to the slope of the information criteria not reaching a clear point where the slope flattens, I also examined the qualitative nature of the profile in the 7, 8, and 9 profile solutions. The profiles present for the 7 through 9 profile solutions split profiles present in previous solutions into profiles with smaller membership that were not qualitatively distinct from each other and were thus not retained.

profile solution was retained. Further evidence for the five-profile solution comes from the classification probabilities presented in Table 6. These results show a high level of classification accuracy in the five-profile solutions, with average posterior probabilities of profile membership in the dominant profile ranging from 0.93 to 0.95. Additionally, the cross-probabilities for each profile are low, ranging from 0.00 to 0.07.

Research Question 1: Daily Profiles of Trajectories of Recovery Experiences

Table 7 displays the descriptive information associated with each profile of recovery trajectories. To ease interpretation, each profile is also plotted in Figure 4 using each profile's mean indicator of intercept, linear slope, and quadratic slope for each recovery experience across the evening. The profile with the largest membership (57.4%) reflected evenings for employees in which their control and relaxation began at moderate levels and steadily increased across the evening, along with their psychological detachment remaining at a moderately high level across the evening with a slightly inverted-U shaped curve, and low levels of mastery that remained relatively unchanged across the evening; I labeled this profile *non-mastery steady increase*. The profile with the second largest membership (19.7%) consisted of low mastery across the evening paired with psychological detachment, relaxation, and control beginning at moderate to moderately high levels, increasing for a short period of time, and then halfway through the evening these three recovery experiences saw a sharp decrease across the rest of the evening to lower levels by the end of the evening. Based on this trend of these three recovery experiences increasing for a short time into the evening and then sharply decreasing the rest of the evening, I labeled this profile *non-mastery inverted-U*. The profile with the third largest membership (10.8%) consisted of evenings where psychological detachment, relaxation, and control, began at, and stayed at, moderate to moderately high levels across the evening with slight inverted-U shaped curves, while mastery exhibited an inverted-U shaped curve that started low and then saw a sharp increased midway through the evening to moderate levels by the end of the evening. Based on this trend of mastery increasing at from halfway into the evening until bedtime, I labeled this profile *late mastery recovering*. The fourth profile (6.1%), which I labeled *non-mastery delayed increase*, consisted of evenings with low mastery across the evening while psychological detachment, relaxation, and control all began at moderate levels, saw a slight dip in the early portion of the evening, followed by a sharp increase to high levels of all three experiences across the rest of the evening. Finally, the profile with the smallest membership (6.0%) saw steady, moderately high levels of psychological detachment and control across the evening. Additionally, this profile reflected mastery levels that began at a moderate level earlier in the evening and saw a slight upward increase followed by a sharp decrease in mastery midway through the evening. This sharp decrease in mastery midway through the evening coincided with a steady increase in relaxation across the rest of the evening. Thus, I labeled this profile *early mastery recovering*. To answer Research Question 1, daily profiles of trajectories of recovery experiences across the evening do exist that are quantitatively and qualitatively distinct.

Research Question 2: Antecedents of Daily Profiles of Trajectories of Recovery Experiences

In terms of antecedents predicting profile membership of daily profiles of recovery trajectories, my results revealed that both job demands (workload) and job resources (job control) distinguish which profile individuals belong to (see Table 8). In terms of workload, I found that on workdays consisting of a higher workload for employees, this made individuals nearly one and a half times more likely to belong to the non-mastery inverted-U profile as compared to the non-mastery steady increase profile (OR = 1.46, p < .05). These results suggest that experiencing a large workload that day seems to inhibit employee recovery during non-work time. That is, people with a high workload initially have recovery experiences early in the evening, but then their recovery sharply declines the rest of the evening. Interestingly, unfinished tasks did not predict profile membership in any way. Thus, it appears that an individual's job demands (i.e., workload) across the workday have a larger impact on recovery outside of work than do job demands like unfinished tasks that are expected to linger with employees after hours.

Along with job demands, job resources also distinguished profile membership. Daily felt appreciation did not distinguish profile membership across any of the profiles. Interestingly, all of the job control relationships involved distinguishing profile membership in comparison to the late mastery recovering profile. Workdays characterized by higher amounts of job control made individuals 64% less likely to belong to the non-mastery inverted-U profile ($OR = 0.64$, $p < .01$), 68% less likely to belong to the non-mastery steady increase profile ($OR = 0.68$, $p < .05$), or 62% less likely to belong to the non-mastery delayed increase profile ($OR = 0.62$, $p < .05$) as compared to the late mastery recovering profile.

Research Question 3: Outcomes of Daily Profiles of Trajectories of Recovery Experiences

Finally, I examined whether daily profiles of trajectories of recovery experiences showed differential relationships with next-day work and well-being outcomes. As can be seen in Table 9, the only outcome that had a significant chi-square omnibus test was work goal accomplishment; none of the profiles differentially related to next-day well-being outcomes (i.e., sleep quality, emotional exhaustion, and energy), nor to work engagement and OCB. In terms of next-day work goal accomplishment, employees experienced more benefits when they belonged to either the early mastery recovering or late mastery recovering profiles. Specifically, for work goal accomplishment employees in the early mastery recovering ($M = 3.37$) and the late mastery recovering (M = 3.18; differences between these means were nonsignificant [$p > .05$]) profiles had significantly higher ($p < .05$) next-day work goal accomplishment compared with the non-mastery inverted-U ($M = 3.01$) and non-mastery delayed increase ($M = 2.83$) profiles. Along with these differences, the non-mastery steady increase profile ($M = 3.09$) had significantly higher ($p < .05$) next-day work goal accomplishment compared to the non-mastery delayed increase ($M = 2.83$) profile. The non-mastery inverted-U and non-mastery steady increase profiles were not significantly different from each other ($p > .05$). The non-mastery steady increase and non-mastery delayed increase were also not significantly different from each other ($p > .05$). Finally, the non-mastery inverted-U and non-mastery delayed increase profiles were not significantly different from each other ($p > .05$). In sum, these results indicate that experiencing psychological detachment, relaxation, and control at moderate to high levels across the entire evening paired with mastery either in the beginning or towards the end of the evening lead to the best outcomes in terms of next-day work goal accomplishment. Interestingly, it also appears that having a steadier increase in relaxation and control paired with steady levels of psychological detachment across the evening (i.e., the *non-mastery steady increase* profile) leads to better outcomes than does having a dip in experiences of psychological detachment, relaxation, and control followed by a sharp increase (i.e., the *non-mastery delayed increase* profile). This points to the importance of having recovery experiences across the majority of the evening, rather than only a portion of it.

Figure 1

Possible Profiles of Recovery Experience Trajectories

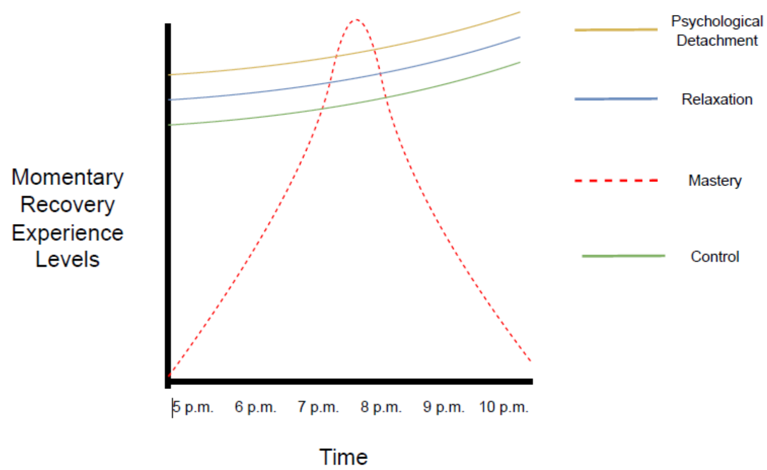
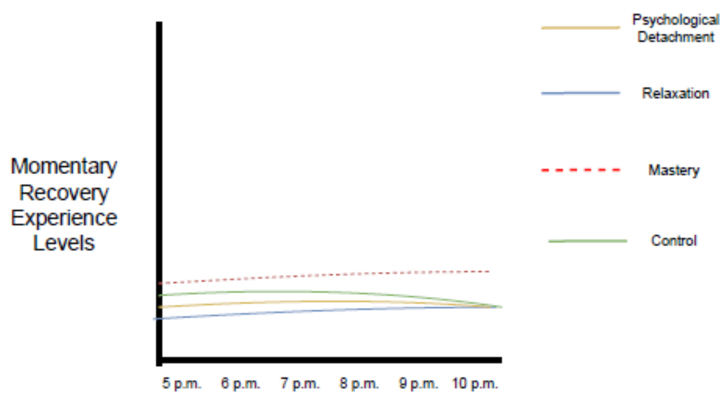
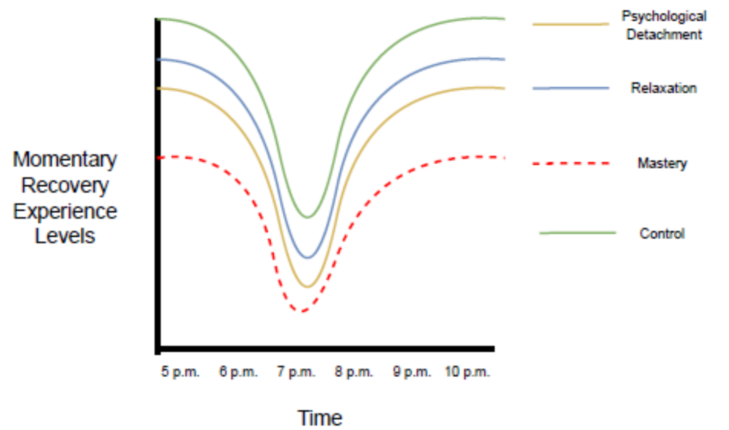
Hypothetical profile name	Hypothetical profile figure
High Recovery	
Low Recovery	

Figure 1 continued

Recovery Dip



Recovery Decline

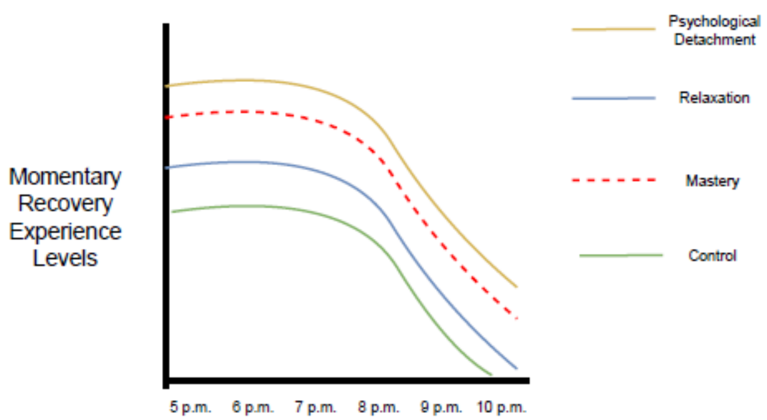
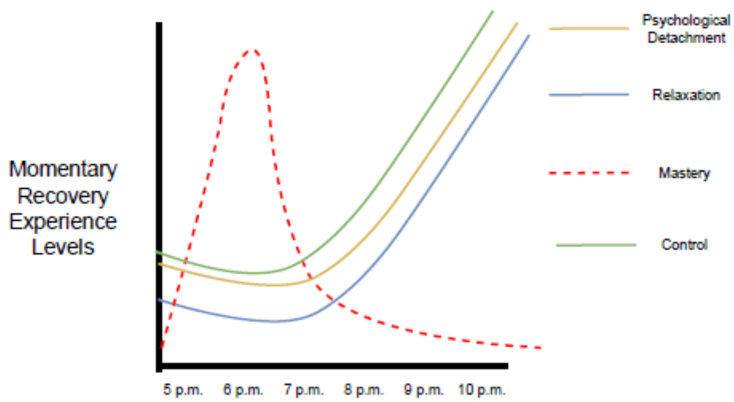


Figure 1 (continued)

Positive Recovery Shift



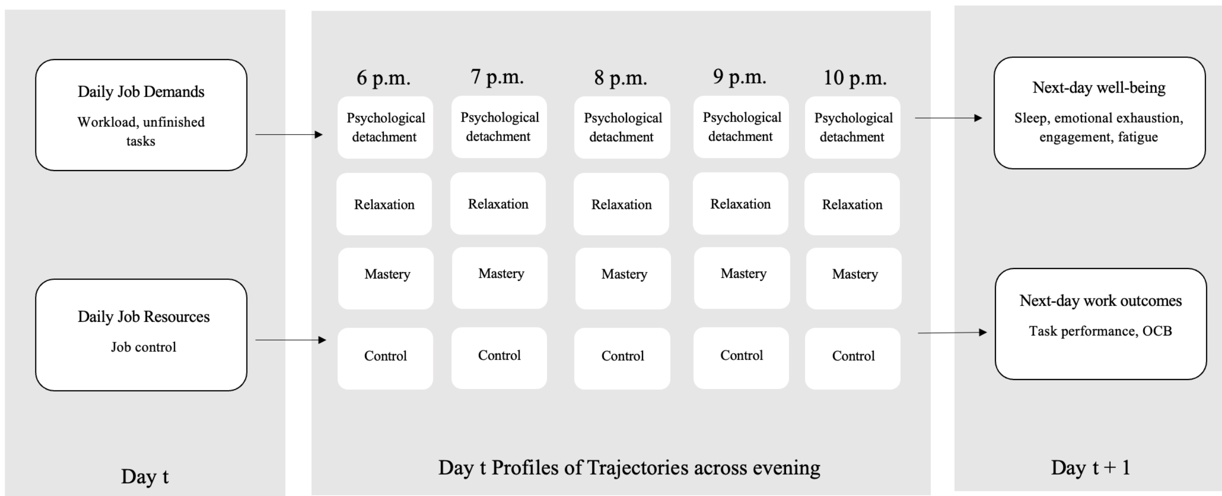


Figure 2. Theoretical Model.

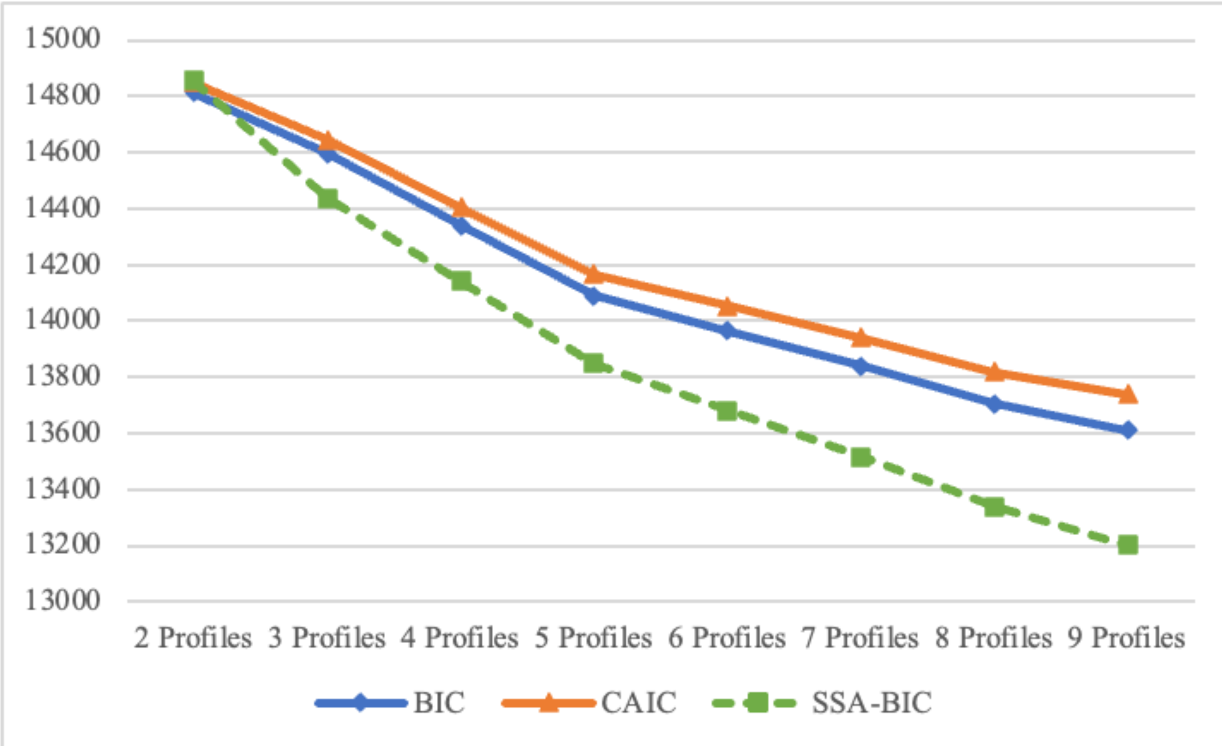


Figure 3. Elbow plot for BIC, CAIC, and SSA-BIC in determining profile solution. BIC = Bayesian information criterion; CAIC = consistent Akaike information criterion (calculated as the BIC value plus the number of free parameters); SSA-BIC = sample size adjusted Bayesian information criterion.

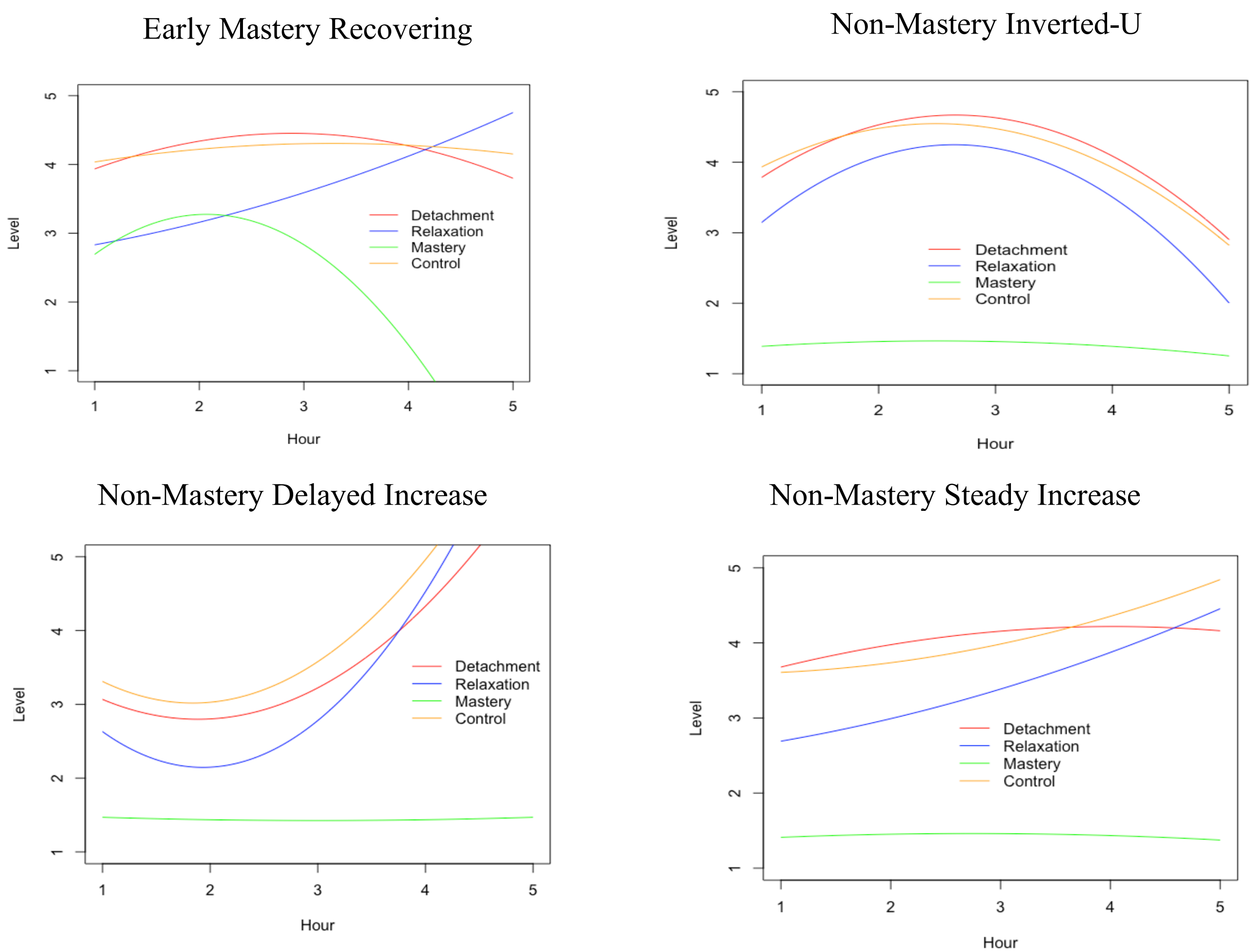


Figure 4. Latent profiles of trajectories of daily recovery experiences across the evening. The *y* axis refers to participants' level of each recovery experience on a 5-point Likert scale (1 = *not at all*; 5 = *very much*).

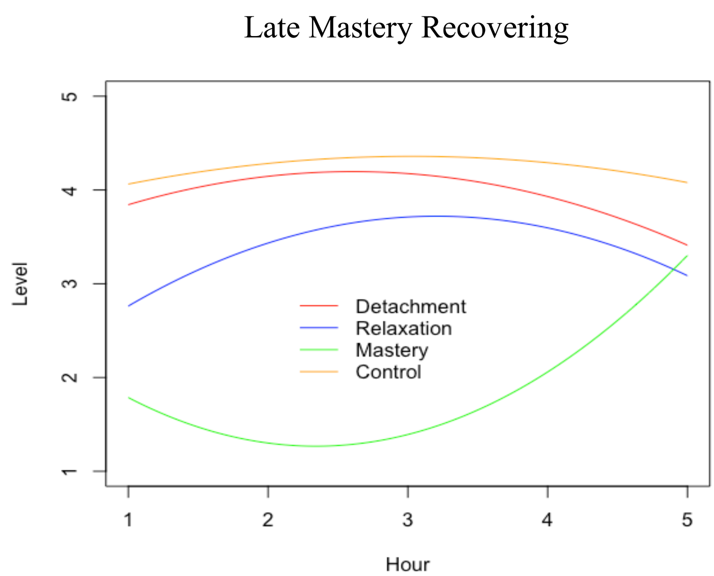


Figure 4 (continued). Latent profiles of trajectories of daily recovery experiences across the evening. The *y* axis refers to participants' level of each recovery experience on a 5-point Likert scale (1 = *not at all*; 5 = *very much*).

Table 1
Fit Indices for Multilevel CFA Measurement Models

Model	CFI	TLI	RMSEA	SRMR	*χ2*	*df*
Three-level Recovery Experiences	0.99	0.99	0.02	0.04	352.85**	144
Two-level Antecedents and Outcomes Only	0.91	0.89	0.04	0.07	2701.91**	1,601

Note. ** $p < .01$. CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation; SRMR = root-mean-square residual; *χ2* = chi-square omnibus test; *df* = degrees of freedom.

Table 2
Fit Indices for 3-level Growth Curve Models

Model	CFI	TLI	RMSEA	SRMR	$\chi2$	*df*	Satorra-Bentler Difference Test	Δdf
Psychological Detachment Intercept Only	.54	.58	.15	.14	320.67**	22		
Psychological Detachment Linear	.73	.68	.15	.11	192.05**	17	100.01**	5
Psychological Detachment Quadratic	.97	.94	.06	.02	29.36*	10	142.88**	7
Relaxation Intercept Only	.22	.29	.17	.12	435.75**	22		
Relaxation Linear	.83	.80	.09	.09	106.53**	17	264.20**	5
Relaxation Quadratic	.99	.99	.02	.03	12.13	10	84.19**	7
Mastery Intercept Only	.62	.66	.08	.12	109.42**	22		
Mastery Linear	.83	.80	.06	.07	55.81**	17	43.11**	5
Mastery Quadratic	.92	.85	.05	.05	27.60**	10	26.24**	7
Control Intercept Only	.49	.53	.15	.15	347.63**	22		
Control Linear	.87	.84	.09	.11	101.42**	17	250.81**	5
Control Quadratic	.97	.95	.05	.04	27.16**	10	65.97**	7

Note. * $p < .05$. ** $p < .01$. CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation; SRMR = root-mean-square residual; $\chi2$ = chi-square omnibus test; *df* = degrees of freedom.

Table 3
Variance Decomposition for Variables

Variable	Within-person variance (σ^2)	Between-person variance (τ_{00})	Percentage of within-person variance
Morning Survey			
Sleep quality	.50	.42	54.7%
Emotional exhaustion	.41	.57	41.9%
Energy	.48	.52	48.0%
Afternoon Survey			
Workload	.55	.51	51.8%
Unfinished tasks	.62	.81	55.1%
Appreciation	.70	.66	51.7%
Job control	.43	.71	37.5%
Engagement	.30	.43	41.0%
Work goal accomplishment	.12	.05	70.7%
OCB	.35	.35	50.6%
Evening Surveys			
Detachment Intercept	1.43	.57	71.5%
Detachment Slope	1.42	.10	93.6%
Detachment Quadratic Slope	.08	.01	90.9%
Relaxation Intercept	1.89	.39	82.7%
Relaxation Slope	2.06	.13	94.0%
Relaxation Quadratic Slope	.11	.01	95.2%
Mastery Intercept	.54	.08	86.7%
Mastery Slope	.68	.05	92.6%
Mastery Quadratic Slope	.04	.00	91.1%
Control Intercept	1.30	.77	62.9%
Control Slope	1.31	.20	86.9%
Control Quadratic Slope	.08	.01	88.6%

Note. N = 475-627. Percentage of within-person variance was computed as $\sigma^2/(\sigma^2 + \tau_{00})$.

Table 4

Means, Standard Deviations, and Correlations of Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Sleep Quality	3.39	0.96	–									
2. Emotional Exhaustion	2.06	0.98	–0.56	(.94)								
3. Energy	2.98	1.00	0.54	–0.61	(.89)							
4. Engagement	3.06	0.85	**0.14****	–0.23	0.21	(.90)						
5. Work Goal Accomplishment	3.09	0.41	0.02	–0.06	–0.05	–0.01	(.92)					
6. OCB	3.36	0.84	0.06	0.02	0.04	**0.21****	–0.05	(.79)				
7. Workload	3.21	1.04	–0.03	0.06	–0.04	–0.10	–0.05	–0.01	(.89)			
8. Unfinished Tasks	2.57	1.21	–0.08	0.09	–0.11	**0.15***	–0.03	–0.01	**0.24****	(.86)		
9. Appreciation	3.24	1.17	0.00	0.08	–0.02	–0.10	–0.09	–0.05	**0.18****	0.06	(.92)	
10. Job Control	3.96	1.07	–0.06	0.03	–0.05	–0.09	0.10	–0.02	**–0.13***	**–0.14***	–0.02	(.94)
11. Psychological Detachment Intercept	3.14	1.42	**0.13***	–0.10	0.06	0.03	0.07	0.16	**–0.14***	**–0.28****	–0.01	0.00
12. Psychological Detachment Slope	0.66	1.23	–0.08	0.11	0.02	0.06	0.04	**–0.09****	0.06	0.07	0.03	–0.03
13. Psychological Detachment Quadratic	–0.10	0.29	0.03	–0.07	–0.04	–0.09	–0.07	0.06	–0.02	0.01	–0.03	0.03
14. Relaxation Intercept	2.30	1.51	**0.13***	**–0.13***	0.10	–0.01	0.01	–0.04	**–0.17****	**–0.24****	0.00	0.05
15. Relaxation Slope	0.53	1.48	–0.01	0.04	–0.04	0.08	0.05	0.11	0.07	0.05	0.00	–0.06
16. Relaxation Quadratic	–0.04	0.35	–0.01	–0.01	0.02	–0.10	–0.07	–0.12	–0.05	–0.01	–0.01	0.08
17. Mastery Intercept	1.48	0.79	–0.09	0.07	–0.07	0.04	0.03	**0.14***	0.07	0.06	–0.05	0.10
18. Mastery Slope	0.06	0.86	0.07	–0.05	–0.02	–0.08	0.02	–0.06	0.01	–0.02	**0.12****	–0.08
19. Mastery Quadratic	–0.02	0.21	–0.05	0.01	0.04	0.01	–0.03	0.02	–0.04	0.01	**–0.13***	0.03
20. Control Intercept	3.52	1.44	0.03	–0.06	0.00	0.03	0.09	–0.05	**–0.15****	**–0.19****	0.03	0.11
21. Control Slope	0.22	1.23	0.00	0.02	–0.01	0.06	–0.05	0.09	0.05	0.05	–0.01	**–0.15***
22. Control Quadratic	–0.01	0.30	–0.01	0.00	0.01	–0.08	0.03	–0.07	–0.02	–0.01	–0.01	**0.15***

Note. Level 1 $n = 476–578$ (after accounting for lagged data); Level 2 $n = 133$. M = mean; SD = standard deviation. Average reliability across days is reported along the diagonal. Well-being and work outcomes (i.e., sleep quality, emotional exhaustion, energy, engagement, work goal accomplishment, and OCB) were modeled on the subsequent workday ($t + 1$). Job demands (i.e., workload and unfinished tasks) and resources (i.e., job control and appreciation) were modeled during the afternoon of day t, with profiles of daily recovery experiences during the evening of day t (please see Analytic Approach for more details).

* $p < .05$. ** $p < .01$.

Table 4 Continued

Means, Standard Deviations, and Correlations of Study Variables

Variable	*M*	*SD*	11	12	13	14	15	16	17	18	19	20	21	22
1. Sleep Quality	3.39	0.96												
2. Emotional Exhaustion	2.06	0.98												
3. Energy	2.98	1.00												
4. Engagement	3.06	0.85												
5. Work Goal Accomplishment	3.09	0.41												
6. OCB	3.36	0.84												
7. Workload	3.21	1.04												
8. Unfinished Tasks	2.57	1.21												
9. Appreciation	3.24	1.17												
10. Job Control	3.96	1.07												
11. Psychological Detachment Intercept	3.14	1.42	–											
12. Psychological Detachment Slope	0.66	1.23	**–0.66****	–										
13. Psychological Detachment Quadratic	–0.10	0.29	**0.47****	**–0.94****	–									
14. Relaxation Intercept	2.30	1.51	**0.40****	**–0.31****	**0.22****	–								
15. Relaxation Slope	0.53	1.48	**–0.16****	**0.32****	**–0.27****	**–0.68****	–							
16. Relaxation Quadratic	–0.04	0.35	0.09	**–0.28****	**0.28****	**0.48****	**–0.94****	–						
17. Mastery Intercept	1.48	0.79	0.01	0.00	–0.02	**–0.18****	0.03	0.02	–					
18. Mastery Slope	0.06	0.86	0.03	–0.02	0.03	**0.18****	–0.10	0.06	**–0.68****	–				
19. Mastery Quadratic	–0.02	0.21	–0.01	0.02	–0.04	**–0.12***	0.10	–0.09	**0.46****	**–0.94***	–			
20. Control Intercept	3.52	1.44	**0.32****	**–0.22****	**0.15***	**0.35****	**–0.17****	0.10	–0.03	0.08	–0.05	–		
21. Control Slope	0.22	1.23	**–0.15***	**0.27****	**–0.25****	**–0.25****	**0.42****	**–0.40****	–0.03	–0.01	0.02	**–0.65****	–	
22. Control Quadratic	–0.01	0.30	0.09	**–0.26****	**0.26****	**0.17****	**–0.43****	**0.44****	0.06	–0.04	0.00	**0.46****	**–0.95****	–

Note. Level 1 $n = 476–578\%$ (after accounting for lagged data); Level 2 $n = 133$. M = mean; SD = standard deviation. Average reliability across days is reported along the diagonal. Well-being and work outcomes (i.e., sleep quality, emotional exhaustion, energy, engagement, work goal accomplishment, and OCB) were modeled on the subsequent workday ($t + 1$). Job demands (i.e., workload and unfinished tasks) and resources (i.e., job control and appreciation) were modeled during the afternoon of day t, with profiles of daily recovery experiences during the evening of day t (please see Analytic Approach for more details).

* $p < .05$. ** $p < .01$.

Table 5
Fit Statistics for Profile Structures

No. of profiles	LL	FP	AIC	BIC	SSA-BIC	CAIC	LMR (*p*)	Entropy
2	-7369.044	37	14812.088	14812.088	14855.932	14849.088	.0041	.79
3	-7138.963	50	14377.927	14595.905	14437.175	14645.905	.4638	.88
4	-6969.865	63	14065.730	14340.383	14140.383	14403.383	.3831	.88
5	-6802.644	76	13757.288	14088.616	13847.346	14164.616	.2053	.91
6	-6698.773	89	13575.545	13963.547	13681.008	14052.547	.6936	.89
7	-6595.038	102	13394.075	13838.752	13514.942	13940.752	.2995	.91
8	-6486.529	115	13203.059	13704.410	13339.331	13819.410	.4431	.91
9	-6397.719	128	13051.437	13609.462	13203.114	13737.462	.4839	.89

Note. 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, Mendell, and Rubin (2001) test. CAIC is calculated by adding the number of free parameters to the BIC value.

Table 6

Posterior Classification Probabilities for the Most Likely Latent Profile Membership (Row) by Latent Profile (Column).

	Early Mastery Recovering	Non-Mastery Inverted-U	Non-Mastery Steady Increase	Non-Mastery Delayed Increase	Late Mastery Recovering
Early Mastery Recovering	0.95	0.02	0.03	0.00	0.00
Non-Mastery Inverted-U	0.01	0.93	0.07	0.00	0.00
Non-Mastery Steady Increase	0.00	0.04	0.95	0.01	0.01
Non-Mastery Delayed Increase	0.00	0.00	0.05	0.95	0.00
Late Mastery Recovering	0.00	0.01	0.05	0.00	0.94

Table 7

Descriptive Information for Within-Person Latent Recovery Trajectory Profiles

Profile	Percentage of evenings	Detachment Intercept		Detachment Slope		Detachment Quadratic		Relaxation Intercept		Relaxation Slope		Relaxation Quadratic	
		M	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI
Early Mastery Recovering	6.0%	3.24	[2.65, 3.83]	0.84	[0.37, 1.31]	–0.15	[–0.26, –0.03]	2.61	[1.85, 3.37]	0.18	[–0.71, 1.07]	0.05	[–0.14, 0.24]
Non-Mastery Inverted-U	19.7%	2.40	[1.97, 2.83]	1.71	[1.32, 2.10]	–0.32	[–0.41, –0.23]	1.41	[1.10, 1.72]	2.15	[1.78, 2.52]	–0.41	[–0.50, –0.32]
Non-Mastery Steady Increase	57.4%	3.26	[3.02, 3.50]	0.48	[0.32, 0.70]	–0.06	[–0.10, –0.03]	2.40	[2.27, 2.71]	0.16	[–0.07, 0.39]	0.05	[0.00, 0.10]
Non-Mastery Delayed Increase	6.1%	4.02	[3.41, 4.63]	–1.29	[–2.03, –0.55]	0.34	[0.17, 0.51]	4.23	[3.49, 4.96]	–2.15	[–2.60, –1.71]	0.56	[0.46, 0.66]
Late Mastery Recovering	10.8%	3.27	[2.90, 3.64]	0.71	[0.39, 1.04]	–0.14	[–0.21, –0.06]	1.70	[1.16, 2.23]	1.26	[0.68, 1.85]	–0.20	[–0.32, –0.08]

Note. M = Mean. CI = Confidence interval.

Table 7 Continued

Descriptive Information for Within-Person Latent Recovery Trajectory Profiles

Profile	Percentage of evenings	Mastery Intercept		Mastery Slope		Mastery Quadratic		Control Intercept		Control Slope		Control Quadratic	
		M	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI
Early Mastery Recovering	6.0%	1.10	[0.63, 1.39]	2.11	[1.55, 2.67]	–0.51	[–0.68, –0.34]	3.75	[3.18, 4.31]	0.34	[0.01, 0.67]	–0.05	[–0.12, 0.02]
Non-Mastery Inverted-U	19.7%	1.25	[1.16, 1.34]	0.17	[0.01, 0.33]	–0.03	[–0.07, 0.01]	2.84	[2.24, 3.44]	1.37	[0.82, 1.92]	–0.28	[–0.40, –0.16]
Non-Mastery Steady Increase	57.4%	1.33	[1.25, 1.41]	0.09	[0.01, 0.17]	–0.02	[–0.04, 0.00]	3.60	[3.35, 3.85]	–0.05	[–0.18, 0.08]	0.06	[0.03, 0.09]
Non-Mastery Delayed Increase	6.1%	1.52	[1.11, 1.94]	–0.07	[–0.39, 0.26]	0.01	[–0.06, 0.08]	4.42	[4.01, 4.84]	–1.53	[–2.10, –0.96]	0.42	[0.25, 0.58]
Late Mastery Recovering	10.8%	2.85	[2.44, 3.26]	–1.35	[–1.61, –1.09]	0.29	[0.24, 0.34]	3.70	[3.25, 4.15]	0.44	[–0.03, 0.90]	–0.07	[–0.17, 0.03]

Note. M = Mean. CI = Confidence interval.

Table 8

Three-Step Results for Antecedents (R3STEP; Research Question 2)

Variable	Early Mastery Recovering vs. Non-Mastery Inverted-U			Early Mastery Recovering vs. Non-Mastery Steady Increase			Early Mastery Recovering vs. Non-Mastery Delayed Increase			Early Mastery Recovering vs. Late Mastery Recovering			Non-Mastery Inverted-U vs. Non-Mastery Steady Increase		
	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*
Workload	0.03	.32	1.03	0.40	.32	1.50	0.17	.35	1.18	0.23	.34	1.26	0.38*	.19	1.46
Unfinished Tasks	–0.20	.29	0.82	–0.23	.29	0.80	–0.01	.34	0.99	0.01	.31	1.00	–0.03	.14	0.97
Appreciation	–0.09	.17	0.91	–0.08	.18	0.93	–0.05	.23	0.96	–0.28	.21	.76	0.02	.13	1.02
Job Control	0.29	.23	1.34	0.24	.23	1.27	0.32	.27	1.38	–0.15	.24	.86	–0.06	.13	0.95

Variable	Non-Mastery Inverted-U vs. Non-Mastery Delayed Increase			Non-Mastery Inverted-U vs. Late Mastery Recovering			Non-Mastery Steady Increase vs. Non-Mastery Delayed Increase			Non-Mastery Steady Increase vs. Late Mastery Recovering			Non-Mastery Delayed Increase vs. Late Mastery Recovering		
	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*
Workload	0.14	.25	1.15	0.20	.24	1.22	–0.24	.18	0.79	–0.18	.20	0.84	0.06	.23	1.06
Unfinished Tasks	0.19	.22	1.21	0.20	.19	1.22	0.19	.18	1.24	0.23	.16	1.25	0.01	.21	1.01
Appreciation	0.05	.18	1.05	–0.19	.18	0.83	0.05	.15	1.03	–0.20	.13	0.82	–0.23	.20	0.79
Job Control	0.03	.19	1.03	–0.44**	.17	0.64	0.03	.16	1.09	–0.39*	.16	0.68	–0.48*	.19	0.62

Note. N = 541. Coef. = the estimate (β) from the R3STEP multinomial logistic regression analysis, which uses listwise deletion; *SE* = standard error of the coefficient; *OR* = odds ratio. 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 unfinished tasks) and job resources (i.e., appreciation and job control) were modeled during the same workday with daily profiles of trajectories of recovery experiences.

* $p < .05$. ** $p < .01$.

Table 9

Three-Step Results for Distal Outcomes (BCH: Research Question 3)

	Early Mastery Recovering (A)	Non-Mastery Inverted-U (B)	Non-Mastery Steady increase (C)	Non-Mastery Delayed increase (D)	Late Mastery Recovering (E)	Chi-square (χ^2)
Next-day morning						
Emotional Exhaustion	2.07	2.04	2.06	2.06	2.05	0.02
Sleep quality	3.56	3.44	3.38	3.25	3.32	2.53
Energy	2.81	2.94	3.01	3.08	2.99	1.38
Next-day afternoon						
Engagement	2.90	3.11	3.01	3.09	3.31	5.47
Work Goal Accomplishment	$3.37^{B, D}$	3.01^{E}	3.09^{D}	2.83^{E}	3.18	14.28^{**}
OCB	3.40	3.32^{e}	3.33^{e}	3.26	3.69	6.20

Note. $N = 578$. 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. Lowercase superscripts represent significant differences when the overall chi-square is non-significant. These mean differences between profiles should be interpreted with caution when the chi-square statistic is non-significant.
$^{*}p < .05$. $^{**}p < .01$.

CHAPTER 5

DISCUSSION

In contrast to previous studies in the recovery literature that only measure recovery experiences once daily, the present study uncovered the dynamic nature of the daily recovery process by examining profiles of trajectories of recovery experiences across an entire evening after work. MLPA revealed five theoretically distinct profiles of recovery experience trajectories (*early mastery recovering*, *non-mastery inverted-U*, *non-mastery delayed increase*, *non-mastery steady increase*, *late mastery recovering*) that all exhibit a curvilinear change pattern across the course of the evening. Two clear patterns stand out when inspecting these profiles. First, one of the largest differentiators of the profiles was the shape of their mastery trajectories. The results suggest that some days individuals engage in little to no mastery across the evening, resulting in a flat mastery trajectory, as seen in the *non-mastery inverted-U*, *non-mastery delayed increase*, and *non-mastery steady increase* profiles. However, when individuals do have mastery experiences, they tend to only do so for a portion of the evening, either at the beginning with a declining trajectory, as show in the *early mastery recovering* profile, or towards the latter half of the evening with a trajectory that shows an incline midway into the evening, as seen in the late mastery recovering profile. This finding partially coincides with the thought experiments above which predicted that mastery would only be engaged in for a portion of the evening, although the shapes of mastery trajectories that emerged here were different than my predictions. Given that mastery experiences require individuals to exhibit effort and self-control (Sonnentag & Fritz, 2007), it appears that individuals try not to overtax their resources by only engaging in them for a portion of the evening, like in the early mastery recovering and late mastery recovering profiles. On the other hand, it appears that on a large number of days individuals are having little to no mastery. This may be due to due strain reactions to job demands like fatigue depleting energetic and self-control resources, which in turn may be related to engaging less in effortful mastery experiences (Sonnentag, 2018). Future research should uncover what underlying mechanisms help explain how mastery trajectories unfold.

While mastery experience trajectories appear to act rather independently of the other recovery experiences, the trajectories of psychological detachment, relaxation, and control that appear to ebb and flow together across the evening. All five profiles exhibited different patterns of trajectories where these three experiences had similar trajectories that changed together. This can be seen within the *non-mastery inverted-U*, *non-mastery delayed increase*, and *non-mastery steady increase* profiles, where the trajectories for psychological detachment, relaxation, and control all ebbed and flowed together. Similarly, the *early mastery recovering* and *late mastery recovering* profiles had these three recovery experiences exhibit similar patterns of trajectories that began together at moderate to moderately high levels and these trajectories remained unchanged across the evening. The results here suggest that not only do people have differing levels of recovery experiences simultaneously as seen in previous person-centered recovery work (Bennett et al., 2016; Chawla et al., 2020), but that recovery experiences (i.e., psychological detachment, relaxation, and control) appear to change together simultaneously across the evening. Uncovering these patterns improves our understanding of the daily recovery process as these profiles exhibit that the recovery process can not only look much different from day to day (Chawla et al., 2020), but within the day as well. This study provides an important first step towards uncovering how the daily recovery process actually unfolds over time (Sonnentag et al., 2017). Future work could use a similar longitudinal approach to examine what other factors impact how the recovery process unfolds both in the short-term (i.e., daily level) and the long-term (i.e., weekly, monthly).

In terms of antecedents, both daily workload and daily job control differentially related to daily profile membership. On days consisting of a high daily workload, individuals were more likely to belong to the *non-mastery inverted-U* profile (i.e., little to no mastery across the evening in combination with the other three recovery experiences at moderate levels only until midway into the evening after which the three recovery experiences sharply declined until bedtime) as compared to the *non-mastery steady increase* profile. This pattern of results suggests that having a high daily workload may impair the evening recovery process by leading to a decline in recovery in the latter half of the evening in combination with not engaging in mastery at all. In terms of the mastery trajectory, it may be that having a high workload that day has a depleting effect that results in individuals feeling fatigued and lacking the internal resources to engage in effortful mastery activities after work (Sonnentag & Fritz, 2007; Sonnentag, 2018). For the other three recovery experiences with inverted U-shaped trajectories, one possibility explaining this decline is that those with a high workload may begin ruminating about work tasks that need to be completed the next day, reducing recovery experiences in the second half of the evening (Sonnentag & Bayer, 2005; Sonnentag et al., 2010; Syrek et al., 2017). Another possibility is that having a large workload may result in individuals deciding to begin working on work tasks in the second half of the evening as they feel compelled to reduce their workload, also prohibiting recovery from occurring. Future research could examine if the factors that cause this decline in the second half of the evening are related more to rumination or are more behavioral in nature.

Further, future work could examine what strategies can be used by employees to promote having recovery experiences across the entire evening even when facing a high daily workload.

My results also add to current knowledge on job resources that promote recovery experiences. Across the profiles of trajectories that emerged, job control related to profile membership in a consistent pattern where days consisting of high job control resulted in individuals being more likely to belong to profiles that consisted of engaging in mastery experiences for a portion of the evening. Along with engaging in more mastery, individuals in these profiles more consistently had moderate to moderately high levels of psychological detachment, relaxation, and control across the entire evening. On the other hand, the profiles that job control distinguished late mastery recovering from were characterized by either recovery only happening a partial amount of the evening paired with low levels of mastery (i.e., *non-mastery delayed increase* and *non-mastery inverted-U*), or by recovery experiences not reaching high levels in a steadier fashion until later in the evening (i.e., *non-mastery steady increase*), paired with low mastery across the evening. Thus, it appears that individuals having daily control over their jobs appears to impact trajectories of recovery experiences in two ways. First, job control promotes detachment, relaxation, and control experiences to begin earlier in the evening and to remain at these higher levels across the entire evening, rather than occur just part of the evening. Second, higher levels of job control also promote having mastery experiences in the later parts of the evening. In sum, job control promotes individuals to not only engage in all four recovery experiences in combination, but also encourages individuals beginning to recover early in the evening and continue to recover across the entire evening rather than only part of it. These results concerning job control promoting mastery are important given that previous profile work has called for an improved understanding is needed regarding factors that promotes mastery (Chawla et al., 2020). Considering previous empirical profile results suggesting that the best work and well-being outcomes result when individuals engage in all four recovery experiences daily (Chawla et al., 2020), the results of the present study suggest that daily job control is an important factor in promoting individuals using all four recovery experiences after work.

Along with promoting mastery, it appears that job control serves as an important resource that can promote individuals consistently having recovery experiences at higher levels across the evening in the other three experiences, like in the *late mastery recovering* profile. It has been theorized that job control may have a negative impact on detachment and relaxation as it may result in individuals remaining connected to work after hours (Agolii & Holtz, 2023; Sonnentag & Fritz, 2007). Indeed, Bennett et al.'s (2016) cross-sectional profile work indicates that that job control is negatively related to psychological detachment, making individuals more likely to belong to profiles that include low detachment. However, the results of the present study suggest the opposite, in that job control actually promotes individuals to detach and relax early and often after work. From a JD-R perspective, job control may be reducing the strain and fatigue that individuals experience resulting from daily job demands (Bakker & Demerouti, 2007; Demerouti et al., 2001). By reducing strain and fatigue, individuals will subsequently have more energy and resources available to engage in both effortful mastery and have the other recovery experiences after work across the entire evening. Another possible explanation is that higher job control allows individuals to adapt how much effort they are putting towards work to their current energetic state (Taris et al., 2006). For example, an employee who is highly fatigued in the afternoon who has high job control may decide to work on less depleting tasks in the afternoon, which in turns leaves with them with more resources for recovery after work. Additionally, recent work on energy management strategies for at work recovery (see Chan et al., 2022 for a review) suggest that viewing job characteristics from a self-determination theory (Ryan & Deci, 2017) lens and examining their ability to fulfill an individual's needs for autonomy, competency, and relatedness may be important as having these needs met can be energizing for employees and make work demands experienced as less straining (Parker et al., 2021; Ryan & Deci, 2008, van Hooff & Guerts, 2015). Future research should further examine the underlying processes of how job control and other positive job resources and job characteristics can promote recovery experiences after work.

The present study also found a lack of support for daily appreciation and daily unfinished tasks distinguishing profile membership. For daily appreciation, one possible explanation is that these experiences are not having a large enough impact as compared to other job resources as theorized by the JD-R model (Bakker & Demerouti, 2007). More specifically, daily appreciation may only result in short-term positive emotional benefits that are short-lived and fleeting in nature, and therefore do not have as large of an impact on the factors that promote recovery like reducing strain and fatigue. Given the lack of support for a social support resource like appreciation from this study and previous profile studies (Chawla et al., 2020), it may be that more structural job resources and characteristics like task significance and task identity play a larger role in predicting evening recovery experiences than does social support. Furthermore, I expected that having daily unfinished tasks would negatively impact evening recovery by causing individuals to continue to ruminate about work issues and even working on tasks after hours, but I found no such association. Although I had theoretical and practical reasons for expecting this type of demand to relate to the shape of recovery experience trajectories, future research should continue to focus specifically on demands that continue to impact individuals after hours and inhibit their recovery across the evening. One particularly fruitful avenue for future research that is currently missing from the recovery literature is how non-work demands impact daily recovery, like family demands or non-preferred choice activities, such as running errands (Sonnentag et al., 2017). Essentially, just because the workday has ended does not mean that demands placed on individuals end, and these activities may limit opportunities for effective recovery. Examining non-work demands would greatly add to our knowledge of how individuals recover during nonwork time.

The results of this study also have important implications regarding how recovery experience trajectories relate to next-day work performance outcomes. Critically, this study answers calls for an improved understanding of how recovery relates to performance given a dearth of studies examining the relationship between recovery and performance in the literature (Chawla et al., 2020; Sonnentag et al., 2022; Steed et al., 2019). My results suggest that the best next-day work performance results when individuals belonged to either the late mastery recovering or early mastering recovery profiles. When looking at the patterns of trajectories of these profiles compared to the other profiles, two patterns emerge. First, both profiles include engaging in mastery at some point during the evening, while the profiles with worse performance all engaged in little to no mastery across the evening (i.e., *non-mastery inverted-U* and *non-mastery delayed increase*). This result aligns with previous profile work suggesting that individuals who experience all four recovery experiences have better outcomes than those who only engage in a select few (Chawla et al., 2020). This also aligns with existing recovery theory suggesting that mastery experiences help individuals build and/or restore personal resources that can be used at work the next day (Headrick et al., 2022; Sonnentag & Fritz, 2007). Overall, the present results suggest that mastery plays a vital role in the recovery process when used in combination with the other recovery experiences.

Second, the profiles that had the highest next-day work performance (i.e., *early mastery recovering* and *late mastery recovering*) each consist of patterns of trajectories where individuals were psychologically detaching, relaxing, and perceiving control at moderate to moderately high levels beginning early in the evening, and these levels remained consistent across the entire evening. On the other hand, the *non-mastery inverted-U* and *non-mastery delayed increase* profiles only engaged in these three experiences for part of the evening. Even though individuals in the *non-mastery delayed increase* profile may have increased to higher levels of psychological detachment, relaxation, and control experiences by the end of the evening as compared to those in the *late mastery recovering* or *early mastery recovering* profiles, it is worth noting that they still performed worse the next day. Further evidence for the importance of consistent recovery experiences across the evening comes from the *non-mastery steady increase* profile having better next-day performance than the non-mastery delayed increase profile. Thus, these results suggest that an optimal pattern of recovery experiences consists of having psychological detachment, mastery, and control experiences early and often across the entire evening in combination with mastery at some point in the evening.

Although profile membership differentially predicted work performance outcomes, no significant effects were found between profiles regarding the other work and well-being outcomes (well-being, OCB, and engagement). I see four potential explanations for these null findings. First, I lagged the outcome variables to provide a more rigorous test of the profiles in relation to the outcomes (Podsakoff et al., 2003), but this resulted in a relatively small sample size (Level 1 $n = 476$). Therefore, my analyses may have lacked the statistical power to detect significant effects. Second, it may also be that the medium levels of recovery, well-being, OCB, and engagement in my sample paired with only measuring these variables for one work week precluded me from observing differences in outcomes between profiles. Even people with days in the more "unfavorable" profiles with the lowest work performance (i.e., *non-mastery inverted-U* and *non-mastery-delayed increase*) were still engaging in some recovery during the evening, and these profiles only made up 25.8% of days in the study. Thus, most participants were engaging in some form of beneficial recovery experience trajectories for most of the days of the study, which could result in having generally higher levels of well-being and work outcomes. Indeed, it can be seen in Table 4 that on average the sample had medium levels of energy, sleep quality, engagement, OCB, and lower levels of emotional exhaustion. Table 9 exhibits similar results across the profiles.

Third, individuals were only surveyed across five workdays. Although my measurement design more accurately captured daily recovery across an evening and only one workweek was used to reduce participant burden, there was a general lack of significant effects in terms of outcomes of the profiles. This lack of significant outcomes may have been due to one work week not being a long enough time frame to detect changes in the outcome variables due to acute changes in recovery experiences. Both the JD-R model and ERM suggest that negative well-being outcomes like burnout and other psychosomatic health issues manifest when individuals repeatedly experience strain due to job demands without proper recovery (Bakker & Demerouti, 2007; Meijman & Mulder, 1998). Given that this study only occurred over one work week, this may have not been enough time to detect significant fluctuations in well-being, engagement, and OCB levels due to differences between profiles of recovery experience trajectories. For example, over the course of a month, people who belonged to the *non-mastery inverted-U* on more days may have seen worsened well-being outcomes than those who belonged to the *late mastery recovering profile*. Accordingly, I add to previous calls in the recovery literature (Sonnentag et al., 2017; Sonnentag et al., 2022) and suggest that future researchers should examine how short-term, within-person recovery processes accumulate to impact long-term well-being and work outcomes. For example, researchers could examine how week-level recovery trajectories predict monthly well-being outcomes.

Fourth, from a statistical standpoint, it may have been that accounting for the curvilinear trajectories in daily recovery experiences resulted in more null outcomes. Liu and West (2016) provide evidence with an empirical dataset and simulation study that not accounting for a longitudinal trend or cycle in a model can significantly bias a relationship between a predictor and outcome and result in more Type-I errors where the relationship appears to be significant. Once this trend is accounted for however, the previously significant relationship will disappear (Liu & West, 2016). A similar situation may have been occurring in the present dataset, where accounting for the curvilinear trajectory of recovery experiences resulted in more null outcomes. To test this notion, I engaged in the profile enumeration process using only linear profiles without quadratic terms as input for MLPA. I found in the best-fitting linear profile solution that profile membership resulted in significant differences on all outcomes except for emotional exhaustion, as compared to only work performance being significant for the quadratic profiles. Thus, accounting for the curvilinear trends in daily recovery experiences may have allowed me to better capture the "true" predictor-outcome relationship by reducing biased estimates, resulting in only work performance being significant.

Theoretical Implications

This study's longitudinal design allowed me to capture and describe the often theorized, but rarely measured, daily recovery process after work more accurately. In doing so, the present work extends theory on the recovery process in two ways. First, the operationalization of recovery experiences as dynamic trajectories more directly captures how the recovery process unfolds. The present results suggest that recovery experiences not only fluctuate between days (Chawla et al., 2020), but also that they fluctuate within days. Across the evening, recovery experiences ebb and flow in patterns that can often be quite different across individuals. Importantly, these differences would not be captured by using mean level recovery experience states, which is the measurement norm in the recovery literature. Further, the results suggest that it is not the mean level across the evening that is most relevant, but rather an individual's trajectory. For example, those in the late mastery recovering and non-mastery delayed increase profiles have similar mean levels of psychological detachment, relaxation, and control if averaged across the timepoints. However, the descriptive and outcome analyses revealed that these profiles had much different trajectories and that the non-mastery delayed increase profile resulted in worsened outcomes, despite the mean levels appearing to be similar to the late mastery recovering profile. Importantly, this study shows that by having our measurement of recovery experiences match our conceptualization recovery experiences, we can improve our understanding of how individuals are recovering and how this process unfolds. Future research should continue to incorporate research designs that more accurately match recovery as a process, rather than a state.

Second, the profiles and their relations to work performance help elucidate the optimal temporal patterns of the daily recovery process. These patterns imply that those only engaging in recovery for a portion of the evening, even if at a high-level like in the *non-mastery delayed* *increase* profile, may not be ceasing work activation and restoring resources in a way that is as beneficial as having more moderate recovery experiences across the entire evening. Along with sub-optimal resource restoration, not engaging in recovery early in the evening (i.e., the *non-mastery delayed increase* profile) may result in individuals continuing to have their psychological and physiological resources depleted and allow the psychophysiological systems required for work to remain activated as suggested by the JD-R model and ERM (Bakker & Demerouti, 2007; Meijmann & Mulder, 1998). A similar effect may be occurring for those in the *non-mastery inverted-U* profile, as the decrease in recovery in the latter half of the evening signals that recovery is declining, and that the recovery process is not occurring. These findings regarding the consistency of recovery trajectories are theoretically significant as it suggests that recovery experiences like psychological detachment, relaxation, and control are best when they are experienced across the entire evening rather than just part of it, even if at moderate levels. By having these experiences early and across the entire evening, individuals can halt the load reactions as soon as possible due to work-related activation through psychological detachment and relaxation and restore more resources to be put toward performance the next day at work using control (Sonnentag & Fritz, 2007). In sum, it appears that the optimal temporal pattern of daily is recovery experiences having psychological detachment, relaxation, and control experiences early and consistently across the evening for in combination with some mastery.

Practical Implications

My results concerning daily profiles of trajectories have important practical implications for employees, supervisors, and organizations alike. Like the work of Chawla et al. (2020), my results suggest that employees should be using all four recovery experiences in combination daily, and that mastery should be prioritized for at least some portion of the evening. My results also suggest that employees can reap the best benefits from the other three recovery experiences (i.e., psychological detachment, relaxation, and control) when they have these experiences consistently across the evening by starting early. It appears that if employees allow the negative effects of job demands to continue into the early part of the evening, they cannot make up for this with high amounts of recovery later in the evening. I should also note that individuals do not need to have mastery across the entire evening. In the profiles present here, mastery was only experienced for part of the evening. Engaging in highly engaging and taxing mastery activities for a prolonged amount of time may also not be beneficial, if not harmful, as it may impair sleep, although research in this area is still limited (Sonnentag et al., 2017). Therefore, employees should start the recovery process as quickly as possible upon ending work with psychological detachment, relaxation, and control early, and have these experiences consistently across the evening. These early and consistent experiences should also be paired with mastery at some point in the evening, ideally as early as possible to reap the best benefits.

My results also highlight that organizations and supervisors should promote job control whenever possible. On days when job control is high, individuals belonged to the profiles that had the most optimal recovery experience trajectory patterns for next-day work performance. Along with making work less straining in general (Bakker & Demerouti, 2007), promoting job control may allow individuals to schedule how and when they complete work tasks in a way that allows them to better match their current energy and fatigue levels. For example, previous empirical work on daily fatigue trajectories results suggest that the most demanding tasks should be done during midday before a lunch break (Hülsheger, 2016). By allowing employees control over when to complete more depleting tasks, employees can complete tasks that require the most attention and energy during times that match when their own energy and attentional resources are highest (Hülsheger, 2016). Conversely, allowing employees low control over their jobs and requiring employees to engage in difficult tasks during times of the day when energy reserves are low may exacerbate strain effects and deplete energy resources, making recovery less likely after hours (Sonnentag, 2018). In sum, organizations and supervisors should allow employees as much decision latitude as possible of how and when they complete work tasks to promote both recovery that day and next-day performance.

Along with promoting job control, organizations and supervisors should become highly aware of the daily workload of their employees and reduce it to manageable levels whenever possible. Although workload has been previously viewed as a challenge demand that generates positives outcomes like increased motivation to complete work tasks (Cavanaugh et al., 2000; Lepine et al., 2005), the results in this study suggest that daily workload results in suboptimal recovery trajectories in the evening. The negative impact of workload on recovery trajectories here aligns with recent meta-analytic results showing that workload is negatively related to motivation and recovery experiences, and positively related to strain (Bennett et al., 2018; Kubicek et al., 2022). Thus, I echo the recommendations of Kubicek et al. (2022) that high workloads provide no benefits to either the organization or to employees themselves, and thus should be reduced to manageable levels whenever possible. Accordingly, both supervisors and employees should pay increased attention to employee workloads and identify when an employee's workload is becoming too high and reduce it accordingly.

Methodological Implications

Along with theoretical and practical contributions, this study provides an important methodological contribution to the literature by showing how within-person Bayes slopes trajectories can be used in combination with MLPA to examine profiles of trajectories of recovery experiences. To my knowledge, these two analyses have never been used in combination before in a published paper. This methodological approach provides a more nuanced, person-centered method to examine the recovery process that can both contribute to theory and better capture how individuals actually experience recovery to provide more practical recommendations. Given multiple calls to examine the recovery process in the longer term (Sonnentag et al., 2022; Steed et al., 2019), future research may want to examine profiles of trajectories and their antecedents and outcomes using the methods present in this study over longer time frames. For example, researchers could examine what profiles emerge for trajectories of recovery experiences over weeks or months, which would provide much needed knowledge on how the recovery process occurs in the longer term past just the daily time frame (Sonnentag et al., 2022).

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 sample. The vast majority of the sample were White and over 90% held a bachelor's degree or higher. Accordingly, my sample is likely not an accurate representation of the workforce and may be overly made up of higher-income, white-collar occupations. This is a concern given that nearly all studies in the recovery literature focus on white-collar samples (Sonnentag et al., 2017; Sonnentag et al., 2022). By using less generalizable samples, we may be missing out on whether the findings of which recovery experiences and recovery processes found in white-collar workers generalize to other occupational groups as well (Sonnentag et al., 2022). For example, the constellation of job demands and job resources and their relationship with specific recovery experiences may be much different for a construction worker than for a software engineer. It may be that a software engineer benefits from mastery, but a construction worker may find relaxation is more important after a day of high physical demands. By ignoring these underrepresented populations, we are limiting our understanding of how the recovery process may be different across different occupations and groups within the workforce. Therefore, future recovery research should examine how daily profiles of job demands and job resources differ across white-collar, high-income and blue-collar, lower-income occupations, and further how these profiles of job demands and resources impact daily recovery.

In terms of future directions, an important next step would be to further examine the characteristics of an individual's work experiences that impact their daily recovery after work. Although the recovery literature has recently shifted towards using the JD-R model (Bakker & Demerouti, 2007) as a framework for predicting recovery, our understanding of how the characteristics of one's job situation impacts recovery is still limited. Given the results here and in previous profile recovery research (Bennett et al., 2016; Chawla et al., 2020) regarding how aspects of individual's jobs appear to play an important role in determining how individuals recover after work, future research could examine how aspects of the job like those described in the extended job characteristics model (Humphrey et al., 2007) impact recovery. This could be done by examining profiles of job characteristics at the daily level and how they impact recovery experiences and subsequent work and well-being outcomes. Alternatively, this could be done by examining these relationships in more mid-term time frames like weeks or months. Examining how more long-term job characteristics impact recovery and subsequent well-being and work outcomes could help bridge the gap between day-level and more long-term studies in recovery (Sonnentag et al., 2022). Not only would more comprehensively examining individual's work situations provide the literature with a more complete understanding of how characteristics of individual's jobs impact their recovery, but it could also provide organizations with more actionable insights for how they can design jobs to improve employee recovery.

An additional 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, it would be theoretically and practically relevant to examine how at-work recovery strategies, like microbreaks and other energy management strategies used at work impact daily 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 don't 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 non-work time to examine how the various recovery opportunities one has throughout the day influence each other.

CHAPTER 5

CONCLUSION

Daily studies of recovery have only measured psychological detachment, relaxation, mastery, and control only once daily, limiting our understanding of the daily recovery process after work. In the present study, I used a longitudinal, person-centered approach to study profiles of dynamic recovery experience trajectories across entire evenings after work. My findings elucidate how individuals actually engage in recovery experiences in combination across an entire evening, antecedents of daily profile membership, and how the differing patterns of these trajectories within profiles impact next-day well-being and work outcomes. My results highlight that all four recovery experiences should be used in combination, but also the vital importance that recovery experiences are engaged in early and consistently across the entire evening. In doing so, this study takes an important step toward examining the underlying dynamic nature of daily recovery experiences after work and their optimal temporal patterns.

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APPENDIX A

STUDY MEASURES

Daily Surveys

Pittsburgh Sleep Quality Index (Buysse et al., 1989). Adapted to assess the previous night's sleep.

Response scale: (1 = *very poor*, 5 = *very good*).

1. How would you evaluate your last night's sleep?

Energy (Sheridan & Ambrose, 2022). Adapted to assess daily energy.

Please indicate your agreement with the following statements. Response scale: (1 = *not at all*, 5 = *extremely*).

1. Right now, I feel refreshed.
2. Right now, I feel very resilient, mentally.
3. Right now, I feel energetic.

Emotional Exhaustion (Pugh et al., 2011). Adapted to assess momentary exhaustion.

Right now, I feel…

Response scale: (1 = *not at all*, 5 = *extremely*).

1. Tired
2. Wiped out.
3. Run-down
4. Rejected
5. Exhausted

Workload (Spector & Jex, 1998). Adapted to assess daily workload.

Please rate the extent to which you agree with the following statements.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. Today, I had a lot of work to do.
2. Today, my job required me to work very hard.
3. Today, my job left me with little time to get things done.
4. Today, there was a great deal to be done.
5. Today, I had more work than I could do well.

Unfinished Tasks (Syrek et al., 2017). Adapted to capture daily unfinished tasks.

Please rate the extent to which you agree with the following statements.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. I have not finished important tasks I had planned to do today.
2. I have not completed today's urgent asks.
3. I need to carry many of today's tasks into tomorrow.

Job Control (Morgeson & Humphrey, 2006). Adapted to capture daily job control.

Please indicate the extent to which you agree with the following statements.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. Today, my job allowed me to make my own decisions about how to schedule my work.
2. Today, my job allowed me to decide on the order in which things are done on the job.
3. Today, my job allowed me to plan how I do my work.
4. Today, my job allowed me to make decisions about what methods I use to complete my work.
5. Today, my job allowed me to decide on my own how to go about doing my work.

Work Engagement (Schaufeli et al., 2006). Adapted to capture daily work engagement.

The following 9 statements refer to how you felt at work today. Please read each statement carefully and decide if you felt this way about your job today.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. Today at work, I felt bursting with energy.
2. Today at my job, I felt strong and vigorous.
3. I was enthusiastic about my job today.
4. Today, my job inspired me.
5. When I got up this morning, I felt like going to work.
6. Today at work, I felt happy when I was working intensely.
7. Today, I was proud of the work that I do.
8. Today, I was immersed in my work.
9. Today, I got carried away while I was working.

Work Goal Accomplishment (Wanberg et al., 2010). Adapted to assess daily work goal accomplishment.

Please indicate the extent to which you agree with the following statements.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. Today, I adequately completed my assigned duties.
2. Today, I performed the tasks that were expected of me.
3. Today, I met the formal performance requirements of my job.
4. Today, did not go well with my work goals (R)
5. Today, I got a lot less done for my work goals than I had hoped Today, I hardly made any progress in my work goals (R)

6. Today, I hardly made any progress in my work goals

OCB (Dalal et al., 2009). Adapted to assess daily OCB.

The statements below refer to behaviors that you may have engaged in since arriving at work today. Please indicate the extent to which you agree with each statement.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

1. Today, I went out of my way to be nice to someone I work with.
2. Today, I tried to help someone I work with.
3. Today, I defended the opinion or suggestion of someone I work with.
4. Today, I volunteered for additional work tasks.
5. Today I went above and beyond what was required for the work task.

Today, I persisted enthusiastically in completing a task.

Recovery Experiences (Sonnentag & Fritz, 2007). Adapted to assess momentary recovery experiences.

During the past hour…

Response scale: (1 = *not at all*, 5 = *very much*).

Psychological Detachment

1. ... I was not thinking about work at all.

Response scale: (1 = *strongly disagree*, 5 = *strongly agree*).

2. ... I was distancing myself from my work.
3. ... I had forgotten about work.

Relaxation

1. ... I was kicking back and relaxing.
2. ... I was doing relaxing things.

3. ... I was using my time to relax.

Mastery

1. ... I was learning new things.
2. ... I was seeking out intellectual challenges.
3. ... I was doing something that challenges me.

Control

1. ... I felt that I could decide for myself what to do.
2. ... I was determining for myself how I will spend my time.
3. ... I felt that I decided my own schedule.