5-2023

Meaning Matters: Cognitive Crafting as a Sensemaking Mechanism and Motivational Process to Enhance Gig Driver Well-being

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MEANING MATTERS: COGNITIVE CRAFTING AS A SENSEMAKING MECHANISM AND MOTIVATIONAL PROCESS TO ENHANCE GIG DRIVER WELL-BEING

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Industrial and Organizational Psychology

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by
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May 2023

Accepted by:
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ABSTRACT

As the gig work sector of the workforce continues to grow, organizational psychologists must actively contribute to raising the bar for gig drivers (e.g., ride-hailing, food delivery) so that they are not merely surviving but also thriving through their work. In my dissertation, I tested cognitive crafting as a positive meaning-making process that helps gig drivers make sense of their interactions with customers, generates positive, motivating states such as work engagement, and promotes positive outcomes such as work-related well-being and job satisfaction. My dissertation employed a mixed-methods design. The daily diary built on qualitative data results that identified interesting - and perhaps even counterintuitive - themes about gig drivers' experiences and perceptions of their work. The daily diary results demonstrated that daily positive customer interactions were positively related to daily cognitive crafting and work engagement, and daily negative customer interactions had a negative relationship with daily cognitive crafting. These relationships were moderated by psychological capital. The serial mediation effects and the moderated serial mediation effects were not supported. This study provided insight into the customer interactions – cognitive crafting relationship at the daily level. Additionally, the results supported that individual differences in psychological capital explained which gig drivers cognitively crafted in light of customer interactions. As a whole, this dissertation provides important contributions to the literature by examining cognitive crafting and well-being in the unique context of gig driving with a positive organizational scholarship lens.

Keywords: gig work, well-being, cognitive crafting, work engagement

ACKNOWLEDGMENTS

This achievement would not have been possible without the support from my wonderful community of family, friends, and mentors. I would like to express my gratitude for my advisor Dr. Bob Sinclair for his consistent support and guidance throughout graduate school. I would also like to thank my committee –Dr. Tom Britt, Dr. Mary Anne Taylor, and Dr. Patrick Rosopa – for their feedback and insight.

Thank you to my undergraduate research team for their diligent efforts to assist with participant recruitment, data collection, and anything else I requested of them: Neda Afzalichali, Claire Bardell, Ethan Hammond, Danielle Haley, Graylie Icard, Emily Mattison, Elizabeth Newman, Jack Patterson, Meredith Pool, Kendalle Quast, Mia Ricottilli, Anneliese Rypkema, Caroline Strinsky, and Shreya Tellur. This team's enthusiasm and dedication to learning inspired me. I would also like to gratefully acknowledge Clemson Creative Inquiry for providing funds for my dissertation.

Lastly, I would like to extend my deepest gratitude to my family and friends for their unwavering love and encouragement. Thank you to my parents (Pam and Shawn) for being my pillars of strength and to my grandparents (Sandra, Larry, Elaine, and Gary). I will forever be grateful for the sacrifices they made that contributed to me becoming a first-generation college graduate, earning my doctoral degree, and pursuing my dreams. Thank you to my sisters (Hope and Hannah Faith), best friend (Peyton), graduate school friends, and many other friends for always being there for me and cheering me on. And finally, thank you to my partner Kent for his selflessness and enduring support that uplifted and motivated me every step of the way.

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CHAPTER ONE

INTRODUCTION

“The meaning of any job is not fixed.” - Wrzesniewski et al. (2003, p. 100)

The shift to nonstandard work arrangements and advancements in technology has disrupted traditional conceptualizations of work (Spreitzer, 2017). Society has moved away from uniform expectations about how work should be structured (e.g., Monday – Friday, 40-hour weeks in the company office) to platforms that facilitate work anywhere and at any time. The changing world of work has created opportunities by offering unprecedented flexibility and accessibility for people of various skill levels who seek extra income or do not fit the mold of standard employment. Thus, rather than settling in careers with a standard 9-5 weekday position, a growing portion of the workforce is involved in nonstandard jobs – particularly gig work (McCue, 2018).

Gig work constitutes nonstandard work arrangements that meet three primary criteria; the work must be temporary, flexible, and based on project-based compensation (Watson et al., 2021). That is, these workers have loose boundaries around when and/or where they must work, are paid by the “gig” (e.g., ride, delivery, task) rather than a wage or salary, and are not bound by explicit or implicit contracts with their employer for a continuing work relationship. Although “gig work” and related terms like “gig economy” have been buzz words in recent years (Caza et al., 2022; Cropanzano et al., 2022; Watson et al., 2021), this type of work is not necessarily new. Traditional gig workers such as musicians, nannies, and substitute teachers have long existed (Watson et al., 2021); however, the changing nature of work has birthed a variety of emerging occupations that fall under the realm of gig work. This uptick in platform-based gig work has been colloquially referred to as the “Uberization” of work as many of these jobs rely on platforms to facilitate work, crowd work, and/or remote work such as rideshare drivers and delivery drivers (Fleming, 2017; Towers-Clark, 2019).

The growth in gig work has been attributed to several factors as outlined in (Scully-Ross & Torraco, 2020). First, advancements in technology have promoted development of applications (i.e., apps) that can efficiently connect the services and products offered by workers with consumers who seek them. Apps such as Uber and Lyft, for example, quickly match nearby drivers with people who are searching for a ride - a much quicker option than traditional ride-hailing approaches like taxis. Other apps such as InstaCart match customers seeking to order groceries with a gig driver who shops for and delivers the order to the customer’s requested destination.

Second, workers have become increasingly interested in flexible work arrangements that are not subjected to the restraints and formalities of standard employment roles within organizations (Chen & Fulmer, 2018; Eversole et al., 2012; Kauffeld et al., 2004; Kelliher & Anderson, 2008). Third, consumers are increasingly willing to acquire services and goods through the internet and/or purchase short-term/shared access to services and goods rather than owning them. Following the example of gig drivers, ridesharing has made this service more accessible as consumers are increasingly willing to be passengers through a ride-hailing platform rather than purchasing their own vehicle or hiring a personal driver for transportation purposes. Lastly, socioeconomic, political, and organizational shifts have promoted these changes as employers of gig workers are not required or expected to provide gig workers with the same protective policies as standard employees (e.g., health insurance, sick pay, retirement plan). Together, these factors reflect how the changing nature of work has contributed to gig work becoming an appealing option for workers, employers, and consumers.

Estimates of the number of gig workers in the United States vary depending on the definition of gig work used for the survey. Using broader definitions of gig work (app-based and non-platform gig work), the McKinsey Institute found that 36% of workers in the United States are involved in gig work (McCue, 2018). Similarly, studies conducted by the Freelancers Union and Upwork (2017, 2019) estimated 57 million American workers (35%) engaged in the gig economy in 2019 and predicted that over 50% of workers in the United States will be involved in the gig economy by 2017. Pew Research Center (2021) restricted their definition to include only platform-based work and suggested that 16% of United States workers have been employed by app-based gig work (e.g., Uber, TaskRabbit) in the past. Nonetheless, estimates reflect there is a substantial proportion of the population involved in this type of work as platforms have helped it become an accessible and user-friendly option for all parties (Scully-Ross & Torraco, 2020).

Despite potentially attractive features of gig work for workers such as flexibility and independence, gig workers experience unique challenges that threaten their health and well-being (Ashford et al., 2018; Caza et al., 2022; Sayre, 2022). Gig workers tend to face viability challenges (e.g., financial instability, job insecurity), identity challenges (e.g., coherent and personalized work identity), emotional challenges (e.g., intense and oscillating emotions), relational challenges (e.g., loneliness), and organizational challenges (e.g., structuring and managing one's schedule and logistics). Many of these challenges were exacerbated by the COVID-19 pandemic (Granger et al., 2022). Hence, gig work is often perceived as undesirable positions worked in out of necessity and really just to serve as a means to an end (Cameron, 2022; Josserand & Kaine, 2019; Liu et al., 2022). As such, existing research on gig workers tends to emphasize the negative aspects of gig work (Cropanzano et al., 2022). Limited research has unpacked how, and which, gig workers benefit from this work arrangement - particularly for low-skilled, low-prestige jobs such as gig drivers (e.g., ride-hailing, food delivery).

As the gig work sector of the workforce continues to grow, organizational psychologists must actively contribute to raising the bar for gig drivers so that they are not merely surviving but also thriving through their work (Ashford et al., 2018). Accordingly, I adopt a positive organizational scholarship approach to understanding factors that facilitate gig worker well-being (Cameron & Caza, 2004; Donaldson & Ko, 2010; Luthans, 2002a). Positive organizational scholarship emerged from the positive psychology movement which called researchers to shift away from solely studying how to "fix" mental illness and dysfunctional behavior and to devote more attention to exploring how to promote healthy individuals' well-being, optimal functioning, and productivity. Within the work domain, positive organizational scholarship is an umbrella term that "integrates a variety of positive scientific perspectives, including positive traits, states, processes, dynamics, and outcomes, all of which are of relevance to organizations"

(Luthans & Youssef-Morgan, 2017, p. 3). Applying this approach, I consider several positive organizational behavior constructs (e.g., work engagement, psychological capital, cognitive crafting, well-being) in the context of gig work to gain insight into gig workers' experiences, including *how* their well-being is fueled by their work.

My dissertation builds upon results from preliminary data collection (see Chapter 2). Most notably, after conducting interviews with gig drivers about their work experiences, I was surprised to find that gig drivers attached meaning to their work despite the challenges they faced and the stigma they acknowledged was associated with their job. The interviews indicated that gig drivers engage in cognitive crafting as a positive meaning-making strategy to shape how they perceive their work to benefit themselves and others. For example, gig drivers passionately discussed that they would think about how their job contributed to their sense of purpose and made meaningful impacts in the lives of their customers and community more broadly. To clarify, the drivers were not immune to or unaware of the difficulties of their job as they shared about the economic stressors, physical demands, and relational demands they faced. Yet, in light of these demands, they would actively seek to connect their work with a broader purpose. Furthermore, interactions with customers seem to be a central aspect of the gig drivers' workday. Participants frequently discussed positive interactions with customers as a relational resource that was motivating and energizing, while negative interactions with customers were emotionally challenging and deflating. But overall, the gig drivers expressed that the "people aspect" was one of the best parts of their job.

In this dissertation, I quantitatively test the relationships among the prominent themes identified in the interviews. Figure 1 summarizes my hypothesized model. Following a positive organizational scholarship approach, I test cognitive crafting (e.g., strategy to increase perceived significance and meaning in one's work) as a positive meaning-making process that helps gig drivers make sense of their interactions with customers, generates positive, motivating states such as work engagement, and promotes positive outcomes such as work-related well-being and job satisfaction. This study provides insight into *how* gig drivers obtain positive outcomes in a job that is not generally viewed in a positive light. Additionally, I examine how individual differences in psychological capital explain *for whom* of gig drivers are better able to cognitive craft to produce positive results. Specifically, I expect that gig drivers with higher levels of psychological capital will be more likely to engage in cognitive crafting and initiate the expected processes.

In summary, the changing nature of work calls into question traditional assumptions about workers and demands the need for extending theory to better understand emerging work groups such as gig drivers. Compared to the standard employees who were in mind when foundational organizational psychology theories were developed, perhaps different mechanisms are at play or certain mechanisms are more heavily emphasized/feasible in explaining occupational health and well-being outcomes for gig drivers (Brawley, 2017). In this dissertation, I am specifically interested in how gig drivers derive meaning through their interactions with customers to enhance work-related well-being outcomes.

Contributions

First, I describe cognitive job crafting (*cognitive crafting* going forward) as an important underlying process in understanding gig driver well-being and job attitudes. Cognitive crafting is a strategy employed by workers to change how they think about their job to see the benefits for their personal life, organization, or community/society more broadly (Bindl et al., 2019; Slemp & Vella-Brodrick, 2013; Wrzesniewski et al., 2013). Recent work in the job crafting literature has specifically called for more research on cognitive crafting as it has been relatively ignored in contemporary conceptualizations of job crafting (Melo et al., 2021; Rudolph et al., 2017; Tims et al., 2021; Zhang & Parker, 2019). I propose that cognitive crafting performs two important roles in gig drivers' work experiences: a) as a sensemaking mechanism for cultivating and protecting resources and b) as a motivation process that enhances work engagement. Examining cognitive crafting as a positive meaning-making process for gig drivers contributes to both the job crafting and gig work literatures by revealing *how* gig drivers experience positive outcomes through their work.

Second, I highlight how interactions with customers influence gig driver well-being. Much of the prior organizational psychology literature on relational aspects of work psychology focuses on relationships in the traditional organizational contexts such as coworkers and supervisors (Chiaburu et al., 2013; Mathieu et al., 2019; Ng & Sorensen, 2008); however, gig drivers do not have these consistent relationships with typical organization members. Rather, their work relationships generally revolve around customers (i.e., passengers for rideshare drivers, receivers of food or goods delivery). I specifically examine the influence of both positive and negative interactions with customers in promoting the cognitive crafting process.

A common misconception about positive organizational scholarship is that it encourages researchers to neglect negative aspects of work that are still present (Mills et al., 2013). This is not the case as positive organizational scholars seek to integrate the positive psychology perspective and negative circumstances/constructs to more holistically understand how positive processes (e.g. cognitive crafting) transpire at work. Thus, I intentionally consider cognitive crafting in light of negative customer interactions as these are regular events for many gig drivers. This is important because the broader customer mistreatment/incivility literature generally considers poor customer interactions to be uniformly negative with little attention devoted to how and when negative interactions may initiate positive processes (Han et al., 2022; Wilson & Holmvall, 2013; Yao et al., 2022).

My dissertation also contributes to the literature by considering customers as important relational resources for gig drivers. While a decent amount of empirical work has focused on customers as relational demands (Koopmann et al., 2015), only a few studies have investigated positive customer behavior as a resource (Kiffin-Petersen et al., 2012; Zimmermann et al., 2011). The positive interactions gig drivers experience with customers are expected to play a crucial role in initiating the positive meaning-making process and will demonstrate the relevance of customers as relational resources.

Third, I consider individual differences that may influence how the relationships unfold among customer interactions, cognitive crafting, and positive outcomes.

Specifically, I test psychological capital (e.g., resilience, optimism, hope, self-efficacy; Luthans et al., 2007; Newman et al., 2014) as a personal resource that moderates the proposed relationships. I expect gig drivers with greater psychological capital will have more resources available to engage in cognitive crafting. I propose that psychological capital better positions gig drivers to respond productively to customer interactions and initiate positive processes (e.g., cognitive crafting) that promote well-being.

While there is burgeoning literature on psychological capital over the past two decades (Avey et al., 2010, 2011; Loghman et al., 2023; Newman et al., 2014), there is little to no research on psychological capital in the context of gig work. However, psychological capital may be particularly important and effective in understanding gig drivers' outcomes as the work ebbs and flows and relies heavily on the self-directed initiatives and structuring of gig drivers for them to be successful. Recent research calls for more attention to be devoted to exploring the importance of psychological capital for gig workers and testing how psychological capital may moderate relationships to enhance gig worker well-being (Kauffeld & Spurk, 2022; Keith et al., 2020). To my knowledge, my dissertation is the first study to empirically examine psychological capital as a personal resource for gig drivers and a moderator of the customer interaction - cognitive crafting that indicates *who* is more likely to cognitive craft (and benefit from its subsequent positive outcomes).

Fourth, this study employs a strong methodological design (i.e., daily diary study, mixed-methods data collection). Most of the literature on cognitive crafting has been conceptual papers or qualitative studies, and the limited quantitative studies generally have been cross-sectional (Tims et al., 2021). My dissertation's research questions are particularly well-suited for a daily diary design. The daily diary design provides important quantitative insight into gig drivers' experiences by examining how these relationships occur over time and reduces susceptibility to retrospective bias (Ohly et al., 2010). For example, this design will allow me to examine gig drivers' fluctuating experiences (e.g., interactions with customers that vary day-to-day and gig-to-gig) and how they initiate cognitive crafting processes that motivate and enhance well-being for gig drivers. The use of the daily diary design will enable me to test how generally stable characteristics such as psychological capital influence how gig drivers' respond to these varying experiences with customers, the extent to which they engage in cognitive crating, and how they benefit from this process. Additionally, my dissertation draws from mixed-methods data collection (discussed in Chapter 2) that first identified interesting - and perhaps even counterintuitive - information via interviews about gig drivers' experiences and perceptions of their work. These findings can now be tested quantitatively across samples and timeframes (e.g., cross-sectional survey from preliminary data, daily diary data to be collected) to provide further support for the hypothesized processes.

As a whole, my dissertation provides important contributions to the literature by examining the unique context of gig driving with a positive organizational scholarship lens. Despite gig driving generally being viewed negatively, cognitive crafting shines a light on how and when gig drivers feel motivated and experience well-being through their work. By adopting this positive scientific approach to study ever-evolving precarious work groups, organizational psychologists can direct attention to ways these workers can thrive rather than restraining them to survival alone.

CHAPTER TWO

PRIOR DATA COLLECTION

This dissertation stems from a larger program of research I am conducting to better understand gig workers' experiences. In this larger program of research, I am working to answer research questions such as 1) How is the changing nature of work influencing worker experiences, specifically for gig workers?, 2) What factors promote and hinder gig worker well-being?, and 3) How can workers' experiences be improved through both top-down (e.g., organization-level initiatives such as policy transparency) and bottom-up (e.g., worker-level initiatives such as job crafting) approach? In this chapter, I provide brief summaries of the goals of the prior data collections, the methodology, and the results as well as how the results led to the birth of this dissertation.

Pre-Survey

One of the major challenges of studying gig workers is recruiting gig workers. These workers are dispersed with few centralized locations for recruitment outside of social media platforms. In response to this anticipated challenge, my first step of this series of studies was to ensure that I would be able to recruit gig workers to participate. Thus, the "pre-survey" was administered in pursuit of three goals: a) building a diverse pool of gig workers for future data collection, b) testing participant recruitment strategies, and c) gaining insight into *who* engages in gig work and *why*.

The pre-survey was a brief survey that took less than five minutes for participants to complete. Participants were not compensated for this survey given its short length and in order to deter fraudulent responses such as bots that do not respond to uncompensated surveys. However, the survey informed participants that the purpose of this survey was to build a participant pool for future, compensated studies as an incentive to complete the pre-survey. The pre-survey targeted a wide range of types of gig workers in alignment with the five gig work profiles outlined in Watson et al. (2021). The five profiles are Gig Service Providers (i.e., gig workers who provide services through technologically-enabled networks and crowdsourcing), Gig Goods Providers (i.e., gig workers who create and sells goods via a platform), Gig Data Providers (i.e., gig workers who are crowdsourced workers that complete surveys remotely via a platform), Agency Gig Workers (i.e., gig workers who are assigned to projects through a third-party intermediary or agency, not solely facilitated through an app), and Traditional Gig Workers (i.e., gig workers who provide services and/or goods without platforms or agency intermediaries). As the goals of the larger program of research on gig worker experiences and well-being, the pre-survey intended to recruit gig workers across these profiles.

I cast a wide net of efforts to recruit gig workers in light of the difficulties associated with sampling this population. With assistance from my undergraduate research team, we attempted to post the link to the pre-survey on over 150 social media pages (e.g., Facebook groups, LinkedIn groups, Instagram pages) and online sources (e.g., subreddit threads). While we were successful in posting on several dozens of these sites, our posts were unfortunately denied access, rejected, and/or blocked from many sites as they did not allow advertisements for surveys. Despite these hurdles, the final sample of the pre-survey consisted of 272 gig workers.

The sample consisted of 58% Gig Service Providers (e.g., ride-hailing drivers such as Uber, food delivery drivers such as DoorDash, pet care such as Rover), 27% Traditional Gig Workers (e.g., musicians, substitute teachers), 7% Gig Goods Providers (e.g., Etsy sellers), 6% Gig Data Providers (e.g., Amazon Mechanical Turkers), and 2% Agency Gig Workers (e.g., childcare nannies). Across profiles, 41% were female, 69% were white, 52% had an Associate's degree or higher. Participants on average were 37.44 years old and worked 29.87 hours per week with a tenure of 17.98 months. The Gig Service Providers profile is of particular importance to this dissertation as it includes gig drivers (e.g., ride-hailing, food delivery). The demographics for the Gig Service Providers (N = 158) and gig drivers specifically (N = 57) are as follows (gig driver statistics provided in parentheses): 43% female (25%), 68% white (64%), 61% with at least an Associate's degree (52%), 36.41years of age (40.65), job tenure of 16.17 months (16.35), and worked an average of 31.58 hours per week (34.31).

Qualitative Data Collection

To address the lack of empirical attention devoted to gig workers in the organizational psychology literature, I then conducted qualitative interviews with gig workers to gain more insight and context about gig workers' work experiences. Given that the changing nature of work and nonstandard work arrangements may challenge assumptions about work and workers, I wanted to hear from gig workers directly about their experiences to ensure that I did not unintentionally exclude relevant aspects of their work that contribute to their well-being. These interviews proved to be insightful and shifted the direction of the project towards the focus on customers interactions and cognitive crafting for my dissertation.

Participants for the qualitative data collection were recruited through the participant pool created via the pre-survey. Specifically, the opportunity to participate in the semi-structured interviews was only advertised to participants who completed the pre-survey, reported a tenure of at least three months as a gig driver, and worked at least 20 hours per week on average to ensure that interviewees had substantial experience to discuss. Interviews lasted 30-40 minutes, and participants received a $15 Starbucks gift card for their participation.

As part of the larger gig worker study, I interviewed 11 participants across gig worker profiles. The participants included six Gig Service Providers (all ride-hailing drivers and/or food delivery drivers), two Gig Goods Providers (both Etsy sellers), three Traditional Gig Workers (two musicians and one substitute teacher). For this dissertation, I will focus on the six Gig Service Providers as this sample aligns with the gig work sample used in my dissertation study. Of the gig drivers interviewed, four identified as male and two identified as female. The average age of the gig drivers was 42.17 years old. On average, the gig drivers had a tenure of 19.16 months and drove 37 hours per week.

Interview Questions

Following best practices (Adams, 2015; Adeoye-Olatunde & Olenik, 2021; Busetto et al., 2020; Harrell & Bradley, 2019.; McGrath et al., 2019), I developed an interview guide for the semi-structured interviews prior to data collection. The interview guide was developed over the course of four weeks. My undergraduate research team and I conducted a series of practice interviews with friends and family to assess the understandability of the interview questions, to generate a list of potential probing questions based on participants' responses, and to determine approximately how long the interviews lasted. After conducting the practice interviews each week, my research team discussed which questions flowed well, which questions/terminology practice participants struggled with, and any other suggestions that may improve the quality and flow of the interview guide.

For example, during the interview guide development process, we realized that practice participants tended to be confused and narrowly interpret questions related to their "resources" at work. They often responded about the quality and/or presence of the human resources department in their organization or expressed that they did not understand what we were asking. Thus, I updated the questions about "resources" in the interview guide (e.g., originally "What resources do you have at your job?") to use the phrase "positive aspects" (e.g., updated to "What are the positive aspects of your work that help you achieve your goals and reduce stress?") to reflect the general conceptualization of resources in the organizational psychology literature (Halbesleben et al., 2014; Hobfoll, 1989; Hobfoll et al., 2018).

The final interview guide used for interviewing gig drivers included questions that inquired about their job demands, job resources, job crafting behaviors, and perceived meaningfulness of work such as the following: "What are the stressful and demanding aspects of your work?", "What are the positive aspects of your work that help you achieve your goals and reduce stress?", "What personal qualities do you have that help you be successful in your job?", "How do you manage the positive and negative aspects of your job?", and "Do you find your job meaningful? Why or why not?".

Interview Coding

The qualitative data generated by the interviews were coded using both inductive and deductive approaches (Adeoye-Olatunde & Olenik, 2021; Bingham & Witkowsksy, 2021; Fereday & Muir-Cochrane, 2006). Deductive coding is a top-down approach in which qualitative data is analyzed using a pre-set list of codes, whereas inductive coding uses a bottom-up approach in which codes are developed based on information derived from the data (Bingham & Witkowsky, 2021). I deductively generated a list of potential codes based on prior gig work literature, particularly related to the resources and demands experienced by gig workers (Ashford et al., 2018; Caza et al., 2022; Watson et al., 2021). However, inductive coding was also necessary given that certain topics in the interview guide (e.g., job crafting, meaningfulness) had not been explored in the context of gig work. Furthermore, existing literature has primarily focused on demands and resources available to workers in traditional work arrangements (e.g., Crawford et al., 2010). Inductive coding helped ensure that all relevant demands and resources in the gig work context were noted in the data coding to prevent the neglect of gig work-specific demands/resources that may not have received attention in prior research.

Research assistants were trained to code the interviews following recommended practices (Adams, 2015; Adeoye-Olatunde & Olenik, 2021; Busetto et al., 2020). First, we practiced coding qualitative data using the practice interview data from the development of the interview guide. Then, we coded the first two interviews as a group, checked for consistency, discussed any points of confusion, and re-coded the first two interviews. The same training process was used for the second set of two interviews. If a participant's response could fit in more than sub-theme of a coding category, the coders would categorize the quote in the overall best fitting sub-theme. Once the research assistants received sufficient training and the group was coding with at least 80% consistency, each interview was coded by two trained research assistants. Consistency between coders was checked by a third trained research assistant, and discrepancies were resolved via discussion to reach 100% agreement.

Results

While the interviews produced many interesting results, I highlight in this section the results from themes that are of particular relevance to this dissertation: customers as relational resources, customers as relational demands, and cognitive crafting.

Customers as Relational Resources. Gig drivers in my sample emphasized that customers can be positive aspects of their work. This major theme is interesting as it highlights a unique aspect about the nature of gig driving - customers represent the primary social interactions that gig drivers engage in while working. The majority of the organizational psychology literature on work-related social resources focuses on supervisors and coworkers (Chiaburu et al., 2013; Chiaburu & Harrison, 2008; Ng & Sorensen, 2008), yet these typical organizational agents are not relevant in the context of gig driving. Consistent with the few studies that considered customers as relational resources in the context of the service industry (Kiffin-Petersen et al., 2012;

Zimmermann et al., 2011), I identified customers as a relational resource for gig drivers. I further identified two sub-themes of this relational resource - general positive interactions with customers and feeling appreciated.

Positive Interactions with Customers. The first sub-theme of customers as a relational resource represents gig drivers' *general positive interactions with customers*. Gig drivers noted the value they found in meeting new people and engaging in conversations with customers. These positive interactions with customers seemed to mitigate the demands of the job such as dealing with traffic and having sad or emotional conversations with customers. Below are example quotes from this subtheme:

*"I **really like the people**. I've had quite a few repeat customers and those tend to be grocery delivery… I generally like the interaction. I guess it's like a double-edged sword with traffic, but **I love getting to the people that have orders and meeting people**" (P98)*

*"And you know, **meeting people [while driving] is an amazing part of my life**. With driving and having people in your car, it's amazing what people will tell you. **Their stories of who they are, where they come from, things that they they've struggled with or challenges**. I've had everything from people who had just been out of jail and taking them to a safe place so they could reintegrate themselves back into society to executive producers filming movies and going on to you know back lots and things like that… **The biggest thing is just this people aspect of it**. **A lot of people do love to talk, and I love to listen and be a part of that conversation**. The conversation does not cease to amaze me*

because it's not one specific how's the weather, it can go way more detailed than you ever thought it would go." (P232)

*"**There's definitely a personal touch when people tell you bits of their life**. And sometimes it's not a good time; sometimes it is sad, like they share they are dealing with cancer. **One time I had to pick up a lady and her daughter. Her brother had just died**, and I had to drive them to the airport from [removed city]. So that was an hour drive to have an emotional family in the car. **We talked about the good things about her brother, and we had a great talk** driving down. So **you get to spend a little bit of that time dealing with parts of people's lives**" (P224)*

Feeling Appreciated. The second sub-theme of the customers as a relational resource is a specific type of positive interaction with customers – *feeling appreciated*. Gig drivers provided specific examples of when customers would express their gratitude for the work conducted by the participants. In some cases, gratitude was expressed by customers through financial means (e.g., extra tips):

*"After I left, **she raised my tip** in the app. I wasn't expecting her to do that, but **it really made me feel thanked.** Like **she was really grateful** that I did bring the groceries inside… So, like that kind of thing just **makes me feel so special**." (P227)*

In other cases, gig drivers noted that they felt appreciated by customers through non-monetary methods such as positive reviews on the app:

*"I look forward to the end of the day. I'll pull up my account, and I'll look for the feedback. And **if I get someone saying nice feedback, that's awesome to me**. That's better than any tip I can get, you know." (P211)*

Customers as Relational Challenges. While the participants highlighted some customer interactions as positive, the gig drivers also acknowledged that customer interactions could be negative, stressful, and challenging. Thus, customer interactions had the potential to be relational resources or relational demands. This major theme focuses on *customers as relational challenges* for gig drivers. The sub-themes identified within this category are consistent with customer mistreatment frameworks that outline four types of customer mistreatment (Dudenhöffer & Dormann, 2015; Wang et al., 2011): *verbal aggression*, *disproportionate customer expectations*, *ambiguous customer expectations*, and *unpleasant customers.*

Verbal Aggression. The first sub-theme is verbal aggression. Gig drivers shared that customers could be verbally aggressive (e.g., shouting, cursing) towards the gig drivers. These negative interactions were frustrating and degrading for the drivers:

*"There are times when I've had a couple of riders that will say you know "I've been waiting forever on a ride". **Like this last weekend, [a passenger] goes, "I've been waiting for 20 minutes" and she's yelling at me**… and I go, "Time out here. I know you're having a bad day, but if you give me a second to explain." And then, you know when they get out of the car, we can rate the passenger. **I was like, man, I don't want to have this person again, you know**" (P211)*

Disproportionate Customer Expectations. Gig drivers also revealed that negative customer interactions occurred in the form of *disproportionate customer expectations*. Customers would demand special treatment and for gig drivers to provide work beyond their job description. For example, per Instacart's community guidelines for customers, Instacart shoppers are only required to shop for the customer's grocery order and deliver the order to the specified address; customers should never expect or require that Instacart shoppers enter the customer's home (Instacart, n.d.). Yet, the gig drivers explained that some customers still express disproportionate expectations such as having them carry the groceries into their residence:

"The other day I had a customer order eight 24-pack cases of water and they didn't help me bring it into their house and left it all on me *to take it from my car to their front door and* ***they just watched me do it.*** *So that was definitely frustrating, and I do have a shoulder injury, so I'm not supposed to be lifting that much." (P227)*

Ambiguous Customer Expectations. The next sub-theme, *ambiguous customer expectations*, captures complicated and/or confusing requests from customers. Gig drivers expressed frustration with customers for conveying conflicting information, not providing adequate information, and failing to respond to communication attempts to resolve issues with their pickup or delivery. This sub-theme of customer mistreatment is different than the previous sub-theme (*disproportionate customer expectations*) because it centers around confusion and complications, rather than expectations of special treatment. Below are examples of ambiguous customer expectations explained by the gig drivers:

*"**Now it gets pretty stressful when a customer doesn't want to answer**. Like an item is out of stock and **I'm messaging the customer and they're not getting back to me** about what they would like in place of it, or if they want a refund… **I had one customer who was like "no substitutions" and then when I would refund it they would be like "Oh, I wanted this instead if it wasn't there"** and I'm like "you said no substitution so I didn't give you any substitution". **Just like you know the typical quote unquote Karen**." (P227)*

*"I've had a few negative customers. **Be that through their expectations being unrealistic**. Like, "Oh, [the food] should be here right now, and you should know exactly where I live, even though that I don't have the right address, or you know, my porch light isn't on, and I didn't give you the gate code for my community." **They act like I should just know these things. And they won't answer**. We have the ability to call and text. I try to do everything in text so that everything is in writing, and they won't answer. It's pretty frustrating." (P98)*

Unpleasant Customers. Lastly, the gig drivers shared that some of the challenges they experienced were the customers being generally unlikeable, unpleasant, or hostile. For example, gig drivers discussed how customers would scam them through "tip baiting" (see example below) or filing false reports about unsuccessful deliveries. In addition, gig drivers expressed that some of the negative interactions with unpleasant customers stemmed from discrimination and prejudice against the driver due to their race. These negative interactions were stressful and disheartening for gig drivers:

"There's also just like straight up like ***people that try to scam us drivers by saying that it wasn't delivered*** *or something like that." (P98)*

*"**Some shoppers of different races will kind of like look down you**. They sort of band together… I had one thing that happened to me once where I picked up a batch because it a quick and easy one. I mean like 10 items with like 30 bucks tip - 30 bucks! I got all the items, you know, correct. The customer never reached out to me.* ***I left all items at the door, and she came to the door. I recognized her as another shopper. So the next day she gave me one star, and she took away the whole tip.*** *Because with Instacart, you have a full 24 hours to change your tip whether you want to make it less or bigger. Essentially,* ***it's called tipping baiting****. I reached out to support, and they didn't do anything about it." (P224)*

Cognitive Crafting. The last major theme that I will highlight for my dissertation reflects the ways that gig drivers engaged in *cognitive crafting*. Although the participants were not familiar with proper organizational psychology term "cognitive job crafting", I recognized that – consistent with the definition of cognitive crafting (Bindl et al., 2019; Wrzesniewski & Dutton, 2001) – the gig drivers described ways in which they reframed their work to recognize how it benefited themselves, their organization, or their community more broadly. Specifically, I identified sub-themes related to gig drivers' cognitive crafting to emphasize the importance of their work for themselves (*connecting* *with area*), others (*playing a prosocial role in customers' lives*), and their community (*helping the community*). Participants did not discuss cognitive crafting to recognize the benefits of their work for their organization; however, the lack of this type of cognitive crafting is not surprising given the nature of gig work and the disconnect gig drivers may feel from their parent company (Cameron, 2022; Van Fossen et al., Manuscript submitted for publication). Below are examples of the sub-themes:

Connecting with Area. One sub-theme of cognitive crafting captures how gig drivers reminded themselves how their job allowed them to *connect with their area.* This sub-theme was interesting because this aspect of gig driving has yet to be investigated in the extant literature. Gig drivers discussed how they enjoyed being able to explore their cities and having the opportunity to experience beautiful scenery through their work. Thinking about how they felt connected with their area through their work was positive and even motivating:

*"**I remind myself I'm really getting to know my city**... Being back in my hometown and getting to see all the nooks and crannies of these neighborhoods **makes me really appreciate my community**…As far as like, oh they're paving this road! Or this warehouse has been built, and there was a fire over there. I think that's a really positive aspect of it, that **it allows me to feel more connected to my area**, and I really like that." (P98)*

"**I went to a gentleman's house on Sunday night and delivered some pizzas. His place was right on Lake [removed lake name]. **I saw some of the most amazing views I have ever

seen. The sun was going down at the most perfect time; the colors and the lake were beautiful. *I got to meet him and speak with him for a little bit.* ***Just that part of my job for me works****." (P232)*

Helping the Community. In addition to cognitive crafting the personal benefits of gig driving, gig drivers noted that they cognitive craft to think about how their job serves the community. This sub-theme reflects dialogue with gig drivers in which they emphasized how their work *helps the community* more broadly and helps people who were not able to grocery shop for themselves (e.g., the elderly, sick, or injured):

"Me ***being able to help people around me and my community is nice,*** *and you know, being able to be paid for it.* ***I try to think about how I find joy and a purpose by engaging and helping my community****" (P224)*

"Like just that aspect of ***being able to help people who aren't able to do it themselves*** *is just an amazing experience." (P227)*

Playing a Prosocial Role in Customer's Lives. The last sub-theme captures how gig drivers engaged in cognitive crafting to increase the perceived significance of their work for customers. Interestingly, the participants' cognitive crafting extended beyond perceiving the benefits of their work for the community to viewing themselves as *playing a prosocial role in their customers' lives*. Gig drivers shared how they remind themselves of how their job allows them to positively impact others which motivates them to engage in their work, and in some cases, go above and beyond for their customers:

*"**I think about my bigger impact personally being when I am helping others go to and from the doctor.** I often pick up patients from dialysis, and **my whole goal is to make them as comfortable as possible** when getting them back to their home. I know a lot of times they want the car to be as hot as it can be, so **I will put the heat as hot as they want it, stop at the store to pick up anything to drink for them** as we are driving, or whatever they need." (P232)*

*"[This job] has put me out there, and it's put me in my community. All these opportunities to not only deliver groceries, but it's allowed me **that opportunity to interact in some small way to be a part of not only my community, but these people's lives**. For example, **I think about how I have a fairly regular [removed name] grocery order,** and i**t's always too far and not quite enough money to make it justifiable**. **But I always take it.** Because I know she's a single mother with like four kids, and I know how hard that must be for her to get out and do the grocery shopping and stuff like that." (P98)*

Discussion

The themes that emerged from the interviews highlighted a few important aspects of gig drivers' work. First, gig drivers emphasized customer interactions as part of their day-to-day experiences. Customers were the primary social agents discussed in the interviews as gig drivers do not have traditional workplace social networks such as supervisors and coworkers. Customer interactions ranged in valence with some interactions being positive (e.g., good conversations with customers, customers showing gratitude towards the driver) to negative (e.g., difficult customer who yelled at driver about issues beyond his control).

Second, gig drivers discussed ways that they actively ascribed meaning to their work by emphasizing how their work benefits themselves and others. I was particularly surprised by how these meaning-making efforts extended beyond seeing their contributions to the community broadly (e.g., generally helpful to deliver groceries to others). The gig drivers viewed themselves as prosocial agents in their customers' lives and reminded themselves of more personal and intentional ways that they benefit their customers (e.g., accepting less profitable deliveries to intentionally deliver to a single mom, driving near a dialysis clinic and engaging in intentional efforts to ensure passengers are comfortable to and from their appointments). These findings were surprising as they were counter to the assumptions often made about the precarity of gig drivers' jobs equating to a lack of meaning and primary focus on monotonously completing rides/deliveries to make ends meet (Allan et al., 2021; Patulny et al., 2020). Based on the themes identified from the interviews, I recognized that the gig drivers were often describing ways - without knowing the proper organizational psychology terminology - that they engaged in cognitive job crafting to accentuate how their work is meaningful.

Third, gig drivers generally seemed to enjoy and be fulfilled by their job despite the challenges associated with the work (e.g., relational challenges as highlighted in my dissertation but also other challenges such as economic stress and physical demands). While causality cannot be determined based on qualitative interviews, the nature and flow of the dialogue gave insight into factors contributing to gig drivers' well-being. For example, one participant (#224) discussed how people (e.g., customers) often look down on her job as a delivery driver as if it is shameful. But rather than letting these negative interactions discourage her from working as a gig driver, she tries to remind herself that there is nothing shameful about her work, she has flexibility in her schedule, is adding to her savings, and helping people in her community. She spoke about how this reminder is motivating for her to continue in her work and even helps her find joy from her job. Another participant (#227) shared stories about ways that her customers demonstrated appreciation for her work (e.g., through tips or verbal expressions of gratitude) which reminded her of the impact she could have through her work. Feeling appreciated motivated her to be intentional in going above and beyond in her deliveries (e.g., adding a kind message on a cake order to a regular customer struggling with depression) so that she can continue to positively impact others and feel better about her job for doing so.

These findings suggest that gig drivers were able to make sense of their interactions with customers (both positive and negative) by cognitive crafting which led to productive outcomes and feelings about their work. Based on these interviews, my dissertation further explores this process quantitatively to better understand the role of cognitive crafting in being a contributor to gig drivers' motivation and well-being. Given the emphasis on customer interactions being both a demand and a resource, customers being the primary social interactions gig drivers have on the job, and the frequency and variety of customer interactions, my dissertation also intentionally captures a wide range of positive and negative interactions and how the fluctuations in these interactions day-to-day influence cognitive crafting and its subsequent outcomes.

CHAPTER THREE

COGNITIVE CRAFTING

Cognitive Crafting Overview

The desire for meaning is a universal instinct across life domains, including work (Frankl, 2014; Lysova et al., 2019). Accordingly, organizational psychology scholars have increasingly emphasized the importance of workers perceiving their work to be meaningful as a contributor to their motivation and well-being (Bailey et al., 2019; Blustein et al., 2023; Lysova et al., 2019). Recognizing the value of one's work is related to both work- and well-being related outcomes such as work engagement, job performance, job satisfaction, life satisfaction, and general health (Allan et al., 2019; Bailey et al., 2019).

As noted in a review by Bailey et al. (2019), most of the prior literature investigating how meaningfulness is derived from one's work has focused on job design theories (e.g., Job Characteristics Model; Hackman & Oldham, 1975, 1976), leadership theories (e.g., transformational leadership; Arnold et al., 2007; Ghadi et al., 2013), or theories related to callings and spirituality (Duffy & Dik, 2012; Molloy & Foust, 2016). These approaches primarily focus on the influences of job-, organizational-, and deity-level factors to experiencing meaningful work and do not consider how individuals may reframe how they view their work to better perceive its meaningfulness. Meaningfulness reflects the amount of significance an individual holds towards something (Pratt & Ashforth, 2003; Rosso et al., 2010). Cognitive job crafting offers an avenue for workers to influence their perceptions of work meaningfulness using a bottom-up approach without relying solely on top-down influences.

Cognitive job crafting (*cognitive crafting* going forward) is a strategy workers employ to increase the perceived significance and meaningfulness of their job (Bindl et al., 2019; Wrzesniewski & Dutton, 2001). Compared to other forms of job crafting (e.g., task crafting, relational crafting), cognitive crafting does not require any physical or structural changes to one's job. Rather, cognitive crafting is primarily a mental activity in which workers psychologically modify their job perceptions. By reframing how one views their job, cognitive crafting highlights the potential good that stems from one's work that benefits themselves, their organization, and/or community more broadly. Workers may cognitively craft to better align their work with their passions (Batova, 2018), emphasize the positive features of their job (Vuori et al., 2012), or enhance one's self-image (Niessen et al., 2016; Wrzesniewski & Dutton, 2001).

Consistent with approach-avoidance motivation theory (Elliot, 2006), cognitive crafting has been recently categorized as approach-oriented versus avoidance-oriented (Bruning & Campion, 2018; Lazazzara et al., 2020; Zhang & Parker, 2019). Approach cognitive crafting reflects efforts towards positive psychological aspects such as through reframing to gain positive resources or reframing demands to mitigate their negative impact (Zhang & Parker, 2019). For example, workers may focus on their job as a meaningful whole with prosocial impacts rather than the separate, more mundane tasks required on their job (e.g., associate at a non-profit emphasizing that her job promotes the economic advancement of women rather than thinking about her job as the individual administrative tasks; Berg et al., 2010). Bruning and Campion (2018) specify metacognition (i.e., "cognitive activity involving organization, sensemaking, and the manipulation of one's own psychological states", p. 508) as a type of approach cognitive crafting in which workers psychologically construct meaning, sense, and identity from their work. Ultimately, approach cognitive crafting focuses on hones in on the positives of one's job to seek greater personal or job resources through their view of work.

In contrast, avoidance cognitive crafting involves psychological shifts away from negative aspects of work. Zhang and Parker (2019) suggested avoidance cognitive crafting may occur via shifting one's perspective to diminish aspects of the job that lack resources (e.g., parts of the job that are not meaningful) or to avoid the experience of demands. Mental withdrawal is another example of avoidance cognitive crafting. Workers may voluntarily distance themselves mentally from a person, situation, or event that they consider stressful (Bruning & Campion, 2018). Again, the purpose of avoidance cognitive crafting efforts is to cognitively mitigate negative aspects of the job.

In this dissertation, I focus on approach cognitive crafting. As will be further discussed later in this chapter, I am interested in how approach cognitive crafting contributes to sensemaking and motivation in the context of gig work. I am focusing on approach cognitive crafting rather than avoidance cognitive crafting because avoidance cognitive crafting is less pertinent to the sensemaking process and not consistent with the definitions of meaning-making techniques proposed in existing models (Vuori et al., 2012; Wrzesniewski et al., 2021). Despite stigma often attached to low-skilled, low-prestige types of gig work such as gig drivers (Cameron, 2022; Josserand & Kaine, 2019;

Liu et al., 2022), gig drivers in the prior data collection (Chapter 2) often reported that they found their job meaningful. Approach cognitive crafting may provide important insight into how gig drivers derive this positive reframing of their job to appreciate the positive impacts of their work and to acknowledge the value their job holds in their life.

Approach cognitive crafting (just referred to as *cognitive crafting* going forward unless noted otherwise) differs from related concepts like appraisal-based coping. Appraisal-based coping involves the use of thoughts and behaviors to manage distress when situations are evaluated to be stressful (Dewe et al., 2010; Folkman & Moskowitz, 2004; Lazarus & Folkman, 1984). More recent directions in coping research have identified strategies that focus on creating meaning in response to negative events that seem particularly relevant to cognitive crafting (e.g., benefit-reminding coping, Affleck & Tennen, 1996; meaning-making coping, Park & Folkman, 1997; stress-related growth; Park et al., 1996). However, coping is similar to cognitive crafting in that both can elicit positive emotions and promote worker well-being when practiced successfully, but cognitive crafting offers new insight into how workers can reframe their work experiences than currently captured in the coping literature.

First, by definition, appraisal-based coping only occurs in response to events that have been appraised as stressful which limits coping to the context of negative events. As will be discussed throughout this paper, my dissertation examines cognitive crafting in the context of both positive and negative customer interactions. Cognitive crafting thus contributes to understanding how workers can *foster* resources through positive events rather than only *replenishing* resources following negative events. Second, even in the context of negative events, the scope of cognitive crafting differs from coping. Coping strategies have a narrower scope such that they focus on managing and benefiting from specific negative events (e.g., perceptions of growth and learning are the ideal outcomes; Folkman & Moskowitz, 2004), whereas cognitive crafting focuses on the influence of these events to generate positive conclusions about the broader meaningfulness of work (e.g., significance of work for one's personal life and others; Slemp & Vella-Brodrick, 2013; Wrzesniewski & Dutton, 2001).

Cognitive Crafting in the Broader Job Crafting Literature

The idea of job crafting stemmed from trying to understand surprising findings from qualitative studies in which employees' reported perceptions and experiences in their jobs did not necessarily align with researchers' expectations based on objective features of and pervasive narratives/stigma associated with the work (e.g., hospital janitors that positively viewed their work as part of providing quality healthcare to patients). Wrzesniewski and Dutton (2001) introduced job crafting to capture the ways employees proactively modify the cognitive, relational, and task boundaries of their jobs to promote meaning in their work and enhance their work identity.

Cognitive crafting is an interesting component of job crafting as it has been questioned and, in some cases, dropped from the job crafting literature over time (Costantini, 2022; Melo et al., 2021; Tims & Bakker, 2010). Although cognitive crafting was included as a prominent form of job crafting in the conception of job crafting (Wrzesniewski & Dutton, 2001), recent conceptualizations have disregarded cognitive crafting (Petrou et al., 2012; Tims et al., 2012; Tims & Bakker, 2010). Perhaps most notably, Bakker & Demerouti (2017) adopted job crafting into the Job Demands-Resources (JD-R; Demerouti et al., 2001) framework but abandoned the cognitive crafting dimension (Tims & Bakker, 2010). The rationale behind dropping cognitive crafting seemed to center on not being able to easily tie actionable behaviors to operationalize cognitive crafting (perhaps unsurprising given the implication of it involving *cognitive* changes). Thus, job crafting in the JD-R model focuses on crafting external resources/demands (e.g., organizational and social) that tend to align better with task and relational crafting than personal resources (e.g., meaningfulness) derived more directly from cognitive crafting (Melo et al., 2021). This perspective shifted away from job crafting being a process-based theory focused on "open" concepts (e.g., meaningfulness and identity) and redirected to more commonly studied management variables like social support and workload.

Given the prominence of the JD-R model in organizational behavior and occupational health psychology research (Bakker & Demerouti, 2017; Lesener et al., 2019), many scholars latched onto this more limited scope of job crafting behaviors that focuses on the modification of external demands (e.g., reducing hindrance demands such as limiting time with problematic coworkers; increasing challenge demands like learning skills to tackle new, interesting projects) and resources such as seeking social support from supervisors or coworkers (Petrou et al., 2012; Tims et al., 2012). While the JD-R conceptualization of job crafting has benefitted the field in that it involves specific, behavioral job crafting practices that can be measured relatively easily, it has disrupted and arguably hindered the job crafting literature by eliminating cognitive crafting.

Ignoring cognitive crafting limits understanding of how job crafting unfolds and how workers can reframe perceptions of their job to reap positive outcomes without having to change structural or social aspects of their job.

More recently, there have been efforts to reintegrate cognitive crafting into job crafting models and bridge the two prominent streams of job crafting research (Bruning & Campion, 2018; Zhang & Parker, 2019)[1]. Bruning and Campion (2018) suggested that job crafting behaviors exist on a two-by-two continuum (approach-avoidance crafting versus role-resource crafting) with cognitive crafting reflected as metacognition (approach-resource crafting) and withdrawal (avoidance-resource crafting). Zhang and Parker (2019) proposed a hierarchical structure in which job crafting consists of three levels (listed highest to lowest): approach versus avoidance, behavioral versus cognitive, and resources versus demands. Both of these influential integrations of the job crafting literature advocate for the inclusion of cognitive crafting in broader models of job crafting. For example, Zhang and Parker (2019) stated, "implicit in this distinction [between cognitive and behavioral crafting] is that we assert *cognitive crafting is indeed crafting,* which some scholars have disputed", p. 130). Thus, the importance of cognitive crafting has received attention in recent years. Yet, given that cognitive crafting has been hindered by its exclusion in prevailing frameworks (e.g., JD-R model), much of the cognitive crafting territory remains unexplored.

Cognitive Crafting and Gig Work

[1] An in-depth review of the integration of the broader job crafting literature is beyond the scope of this dissertation as I focus specifically on the cognitive crafting component. Please see Bruning and Campion (2018) and Zhang and Parker (2019) for more information on the broader integration of job crafting.

Considering the context is important to understand when and how job crafting occurs (Lazazzara et al., 2020). While cognitive crafting occurs by workers in many occupations, this dissertation focuses on cognitive crafting in the context of gig work. Cognitive crafting is expected to be more pervasive in less structured working environments such as gig driving. As gig drivers do not have a consistent work space with routine relationships, they may engage in cognitive crafting to better align with the impact of their work rather than with the organization they work for (Asik-Dizdar & Esen, 2016; Melo et al., 2021).

Growing interest in the overlap between decent work and meaningful work (Blustein et al., 2023) suggests that workers in precarious and low-status work (e.g., gig drivers) may have to engage in more directed efforts to shape their perceptions of their work. For example, perceiving one's work to be meaningful may be limited in jobs characterized by job insecurity and underemployment (Allan et al., 2020; Arnoux-Nicolas et al., 2016; Bailey & Madden, 2020; Kim & Allan, 2020; Kost et al., 2020). Cognitive crafting may counteract the powerlessness felt in this type of work (Bailey & Madden, 2019; Glavin et al., 2021) and help workers find meaning in their job. By crafting this perception of the broader impacts of their work, workers can view their efforts at work in alignment with a prosocial purpose that mitigates the challenges that stem from the precarity of their work or negative perceptions they have of the organization they work for (e.g., Uber, Doordash; Van Fossen et al., Manuscript submitted for publication).

Gig drivers may also be inclined to cognitive craft as this type of job crafting is more "readily available" and does not necessarily require behavioral changes (Melo et al., 2021; Zhang & Parker, 2019). More commonly studied types of job crafting imply changes to one's behaviors and physical environments (Slemp & Vella-Brodrick, 2013; Tims et al., 2012). For example, job crafting is often conceptualized as modifying tasks (e.g., volunteering to join new and interesting projects), skills (e.g., attending professional development workshops), or relationships (e.g., organizing work-related social functions). Yet these types of job crafting generally are not relevant or feasible in the context of gig driving[2]. Cognitive crafting offers a strategy that allows gig drivers to positively alter their perceptions of their work rather than physically or socially changing their job characteristics that may be difficult or impossible to change.

Dual Roles of Cognitive Crafting

I propose that cognitive crafting plays two important roles for gig drivers: 1) cognitive crafting is a sensemaking mechanism for gig drivers to interpret their interactions with customers and 2) cognitive crafting is a motivational process that enhances gig drivers' work engagement. Through these processes, cognitive crafting protects and promotes gig drivers' resources to facilitate positive outcomes in a job that is not often associated with positive outcomes. The Conservation of Resources (COR) theory (Hobfoll, 1989) provides an overarching theoretical framework for the proposed dual roles of cognitive crafting.

[2] With this being said, it is possible for these types of job crafting behaviors to occur in the context of gig driving (Cameron, 2022). However, existing measures and examples generally assume behaviors that occur in a traditional work environment with consistent work spaces, relationships, and career trajectories. I will discuss in more detail in the Future Research Directions section about how more research is needed on how other kinds of job crafting (e.g., task crafting, skill crafting, relational crafting) manifest in gig drivers.

COR theory suggests that individuals strive to obtain, retain, and foster resources to mitigate stress and promote well-being (Hobfoll, 1989; Hobfoll et al., 2018). Resources are broadly defined as things that people centrally value that may be personal, social, material, or job-related (Halbesleben et al., 2014; Hobfoll, 1989; Hobfoll et al., 2018). Examples of resources include health, sense of purpose, meaning, positive relationships, and self-esteem (Hobfoll et al., 2018). When people lose resources, this loss tends to be more salient than the gain of other resources, and people may become defensive to preserve themselves if their resources become stretched too thin. However, COR theory posits that individuals who possess greater resources are less vulnerable to resource loss and more capable of resource gain. When people have sufficient resources, they may invest these resources to buffer future losses and better position themselves for future resource gain.

Cognitive Crafting as a Sensemaking Mechanism

Despite perceptions that gig work is lonely and remote (Ashford et al., 2018; Caza et al., 2022), gig driving involves regular interactions with passengers and customers who order food/groceries. Customer interactions are the primary social interactions that gig drivers have at work given that they do not work with traditional organizational agents like supervisors and coworkers. These interactions are important for gig drivers as their interactions with customers often drive the rating provided by customers which is one of the primary evaluations of performance for gig drivers (Chan, 2019a; Ma et al., 2022; Roshdy & Erhua, 2020). The valence of these interactions ranges from positive (e.g., grateful customers, fun conversations with customers) to negative (e.g., verbal abuse from customers, complicated customers). Although there has not been much work done on customer interactions in the context of gig work, extant literature on workers in general shows that customer treatment of workers is impactful on worker experiences and well-being (Han et al., 2022; Kiffin-Petersen et al., 2012; Koopmann et al., 2015; Zimmermann et al., 2011). Thus, it is expected that customer interactions will also influence gig drivers' work experience and well-being. In this dissertation, I seek to understand how gig drivers may engage in cognitive crafting to derive meaning from their interactions with customers.

I propose that cognitive crafting serves as a sensemaking mechanism for these interactions. Recent efforts to reinstate cognitive crafting into the mainstream job crafting literature have integrated cognitive crafting and sensemaking theory to specify cognitive crafting as a meaning-making process (Melo et al., 2021). Sensemaking reflects individuals' efforts to interpret cues from their environment to construct realities based on these cues that ascribe meaning to their experiences (Maitlis & Christianson, 2014; Weick, 1995). Cognitive crafting has been framed as a sensemaking tool that helps workers find meaning in their work experiences and create positive outcomes such as motivation, well-being, and satisfaction (Asik-Dizdar & Esen, 2016; Melo et al., 2021; Vuori et al., 2012). Multiple forms of sensemaking may occur in the occupational setting; however, I will focus on interpersonal sensemaking as particularly important in understanding the relationship between customer interactions and cognitive crafting (Maitlis & Christianson, 2014; Wrzesniewski et al., 2003, 2013).

According to Wrzesniewski et al. (2003), the motivation for interpersonal sensemaking is “the desire to reclaim, for oneself and for others, the value in one’s work, and by extension in one’s personhood” (p. 99). Additionally, interpersonal sensemaking involves using “interpersonal cues from others in helping employees make meaning of their jobs, roles, and selves at work” (p. 102). Wrzesniewski et al.’s definition and purpose of interpersonal sensemaking aligns well with the goals of cognitive crafting (i.e., reframe how workers view their job to highlight the potential good that stems from their work that benefits themselves, their organization, and/or society more broadly). More recent models of interpersonal sensemaking also support the connection between work interactions and cognitive crafting (Vuori et al., 2012). Although these models do not explicitly refer to cognitive crafting, cognitive crafting is an example of a meaning-making technique (from Vuori et al., 2012) and response to altered meaning (from Wrzesniewski et al., 2003) stemming from interpersonal cues.

Interpersonal sensemaking models (Vuori et al., 2012; Wrzesniewski et al., 2003) suggest that workers engage in interactions with others, extract cues from these interactions, then determine if the interaction was affirming (i.e., positive) or disaffirming (i.e., negative). When the interaction is considered positive, workers are expected to ascribe greater value to their job, role, and/or self (e.g., “I am contributing”, “I am benefiting and feeling pleasure”; Vouri et al., 2012, p. 238). When an interaction is considered negative, workers are likely to feel that the value of their job, role, and/or self are disaffirmed (e.g., “I am not contributing”, “I am not benefitting nor feeling pleasure”; Vouri et al., 2012, p. 238). Per these models, meaning-making techniques such as cognitive crafting primarily occur in response to disaffirmation to regenerate meaning after negative interactions. Yet, little attention is given to why workers cognitive craft following positive interactions. In this dissertation, I am integrating existing interpersonal sensemaking models with COR theory to explain why gig drivers are expected to cognitive craft in response to both positive and negative interactions with customers.

Negative Interactions. Gig drivers may experience varying kinds of negative interactions with customers (e.g., passengers, recipients of food/grocery orders). Customer mistreatment of workers may occur through various behaviors such as verbal aggression, disproportionate customer expectations (e.g., customers demanding special treatment), ambiguous customer expectations (e.g., complicated requests from customers), and unlikeable customers such as hostile and unpleasant customers (Dudenhöffer & Dormann, 2015; Wang et al., 2011). These categories of customer mistreatment in the broader organizational psychology literature are relevant and applicable to the context of gig drivers.

As examples (Chan, 2019b; Morris et al., 2020), gig drivers report negative interactions with customers such as being verbally attacked often for things beyond their control (e.g., for how long it took the passenger to connect with a driver via the app, for grocery stores being out of requested items, for mistakes made by restaurants to the customer's order). Customers may have unrealistic expectations about how quickly food or groceries should be delivered to them or provide confusing instructions about where to pick them up for their ride when they relocate from the initial pick-up point. Gig drivers also interact with generally unpleasant customers (e.g., unfriendly).

Negative interactions with customers may be perceived as a *threat to* or *loss of* gig drivers' resources (Hobfoll, 1989; Hobfoll et al., 2018; Koopmann et al., 2015; Leiter et al., 2015; Pindek & Spector, 2015). Of particular importance to this study, negative interactions with customers may jeopardize the extent to which gig drivers view their work as meaningful. Negative interactions serve as disaffirming cues that may be interpreted as gig drivers' jobs not being valued and the workers not being respected by others. This interpretation challenges and/or depletes how gig drivers perceive meaning in their job, role, and self (Koopmann et al., 2015; Wrzesniewski et al., 2013). Indeed, prior research on gig drivers supported that negative customer treatment was associated with lower perceptions of work meaningfulness (Xiongtao et al., 2021). In alignment with COR theory (Hobfoll, 1989; Hobfoll et al., 2018), gig drivers will be motivated to mitigate this resource threat in order to prevent stress and protect the perceived meaning of their work. Cognitive crafting is a strategy that gig drivers can use to protect the meaningfulness derived from their work (Berg et al., 2013; Melo et al., 2021; Wrzesniewski et al., 2003).

By engaging in cognitive crafting, gig drivers actively remind themselves about the significance of their work in positively impacting their community and think about how their job gives them purpose (Slemp & Vella-Brodrick, 2013). Despite the theoretical connection between negative interactions with customers and cognitive crafting as an interpersonal sensemaking mechanism and meaning-making technique (Melo et al., 2021; Vuori et al., 2012; Wrzesniewski et al., 2003), empirical studies have not examined this relationship[3]. Yet, this relationship is important to uncover ways that workers - particularly gig drivers who frequently experience negative interactions with customers due to the low-prestige associated with their job - can make sense of these negative interactions in a way that attaches positive meaning to their work (Berg et al., 2013; Vuori et al., 2012; Wrzesniewski et al., 2003). This is the first study to my knowledge that empirically tests the relationship between negative interactions with customers and cognitive crafting. *Hypothesis 1* predicts that negative interactions with customers will be positively related to cognitive crafting.

Hypothesis 1: Daily negative interactions with customers are positively related to daily cognitive crafting.

Positive Interactions. Gig drivers' interactions with customers may also be positive (Kameswaran et al., 2018). Positive interactions between gig drivers and customers may occur via engaging in fun conversations, providing instrumental or emotional support, receiving gratitude, or just meeting generally nice people. Although there has been a vast amount of literature on customer incivility and negative interactions with customers (Dudenhöffer & Dormann, 2015), there has been substantially less attention given to effects of positive interactions with customers. The one potential exception would be the growing literature on the importance of receiving gratitude (Davis et al., 2021; Lee et al., 2019; Ni et al., 2022; Starkey et al., 2019), but the wider range of

[3] Several empirical studies have been conducted on customer mistreatment and other types of job crafting, particularly using the Tims et al. (2012) job crafting dimensions (Lu, Liu, et al., 2022; Lu, Wu, et al., 2022; Shin & Hur, 2022)- perhaps due to cognitive crafting being largely ignored in the job crafting literature over the past decade. Given the starkly different nature of cognitive crafting compared to these types of job crafting, these studies will not be reviewed in this dissertation.

common positive interactions with customers such as the examples listed above have not been acknowledged in the literature. Yet, the limited empirical studies available support that positive behaviors from customers produce positive emotions and experiences for workers (Kiffin-Petersen et al., 2012; Zimmermann et al., 2011).

For example, Zimmermann et al. (2011) considered positive interactions with customers (e.g., helpful conversations with customers, feeling valued by a customer) to be a resource for car dealers and found that positive customer interactions were associated with the employees reporting greater positive affect post-interaction. In a qualitative diary study, Kiffin-Petersen et al. (2012) found that positive interactions with customers (e.g., being able to help a customer, interacting with a generally pleasant customer) had positive emotional outcomes for employees in sales. These studies provide empirical insight into the benefits of multiple types of positive customer interactions and the positive emotional states driven by these interactions.

My dissertation extends their work in a couple of ways. Zimmerman et al. (2011) and Kiffin-Peterson et al. (2012) focused on samples with employees in sales-oriented roles likely due to the frequent interactions sales employees tend to have with clients/customers. My dissertation uses a non-sales-oriented sample by focusing on gig drivers who also have frequent interactions with customers. Beyond the content of the work, sales roles tend to be more lucrative than gig driving, and the sales samples consisted of primarily full-time employees who likely receive benefits not available to gig drivers. Thus, my dissertation examines the influence of positive interactions in non-sales jobs, focusing instead on gig drivers who have more precarious roles. Additionally, my dissertation advances understanding of how workers benefit from positive interactions with customers. Zimmerman et al. (2011) and Kiffin-Peterson et al. (2012) established that positive customer interactions are related to positive emotional states for workers. My dissertation extends the positive influence of positive interactions to work- and well-being related outcomes through cognitive crafting.

To my knowledge, no prior studies have quantitatively examined the relationship between positive customer interactions customers and cognitive crafting. I propose that cognitive crafting serves as a sensemaking mechanism that explains how gig drivers react to positive customer interactions. Following the interpersonal sensemaking frameworks provided by Vuori et al. (2012) and Wrzesniewski et al. (2003), positive interactions serve as cues from customers that affirm the meaning of their job, role, and self ("I am contributing", "I am benefitting", Vuori et al., 2012, p. 238). Connecting this meaning derived from positive interactions to cognitive crafting, my expectations diverge from the theoretical model proposed by Vuori et al. The model proposed by Vuori et al. (2012) suggests that positive interpretations of cues lead to increased meaningfulness and *decreased* engagement in meaning-making techniques. Their proposed negative path was rooted in an example from their qualitative data in which a worker who consistently found high levels of meaning in their work was less likely to engage in strategies to change aspects of their job, including perceived levels of meaningfulness. Contrarily, based on COR theory (Hobfoll, 1989; Hobfoll et al., 2018), I argue that positive interactions with customers will still promote cognitive crafting in gig drivers.

COR theory posits that individuals are not only motivated to *protect* resources (e.g., in response to resource threats such as negative interactions with customers, *H1*); individuals also strive to *retain* and *foster* resources to grow their repository of resources so that they are less vulnerable to future resource less and more capable of resource gain (Hobfoll, 1989; Hobfoll et al., 2018). In the context of meaningfulness as a resource, when gig drivers extract positive cues about the meaningfulness of their work through customer interactions, gig drivers will cognitively craft to further cultivate this resource. Positive interactions with customers will facilitate cognitive crafting as gig drivers reflect on the value of gig drivers' job, role, and self (Wrzesniewski et al., 2003). Further aligning with COR theory, gig drivers will be motivated to cognitive craft in response to positive customer interactions to retain and foster meaningfulness as a resource that can be used to better weather future threats of resource loss (e.g., future negative interactions with customers). Thus, I hypothesize that positive interactions with customers will be positively related to cognitive crafting.

Hypothesis 2: Daily positive interactions with customers are positively related to daily cognitive crafting.

Cognitive Crafting as a Motivational Process

In addition to serving as a sensemaking mechanism, I propose that cognitive crafting also initiates a motivational process. Specifically, I expect that cognitive crafting will be positively related to work engagement. Work engagement is one of the most prominent positive organizational constructs and is an increasingly studied area in organizational psychology for both researchers and practitioners (Bakker & Albrecht, 2018; Bakker & Leiter, 2010; Christian et al., 2011; Knight et al., 2017; Mazzetti et al., 2021; Rich et al., 2010).

Work Engagement Overview. The definition of work engagement has evolved over time. Engagement was first applied to the workplace by Kahn (1990) and defined as the "the simultaneous employment and expression of a person's 'preferred self' in task behaviors that promote connections to work and to others, personal presence (physical, cognitive, and emotional) and active, full performances" (p. 700). That is, engaged workers apply themselves physically, cognitively, and/or emotionally to satisfy their needs for self-employment and self-expression in their work. This definition reflects that work engagement is a motivational concept in which workers invest physical, cognitive, or emotional resources to connect with and conduct their work (Kahn, 1990). Furthermore, Kahn (1990) suggested that three psychological domains influence the extent to which workers experience engagement: meaningfulness (e.g., feeling valued for their work, recognizing the significance of their efforts, seeing rewards for their investments in their work), safety (e.g., sensing their work to be trustworthy and secure), and availability (e.g., perceiving they have the resources needed for the job).

Less than a decade later, work engagement was adopted into the burnout literature and considered to be the antithesis of burnout (Maslach & Leiter, 1997). Burnout is characterized by emotional exhaustion, depersonalization, and lack of personal accomplishment (Maslach et al., 1996). Maslach and Leiter (1997) proposed that work engagement and burnout existed on a continuum with engagement reflecting the positive end and burnout reflecting the negative end. In other words, a lack of work engagement would indicate burnout and vice versa. However, other researchers (Schaufeli et al., 2002) disagreed with this single continuum, burnout-antithesis approach to engagement and argued that engagement is a unique construct.

Rather than positioning work engagement as the opposite of burnout, Schauefli et al. (2002) demonstrated that work engagement is a distinct construct that is negatively related to burnout and a potential antidote for burnout. Schaufeli et al. (2002) went on to define work engagement as "a positive, fulfilling, work-related state of mind characterized by vigor, dedication, and absorption" (p. 74). Vigor reflects when workers exhibit high levels of energy and mental resilience particularly when faced with challenging work situations. Workers demonstrate dedication when they are heavily involved in their work which invokes positive emotions such as significance, pride, enthusiasm, and challenge. Absorption occurs when workers concentrate on and enjoy their work such that they do not want to detach themselves from their work. Schaufeli et al.'s (2002) definition is arguably the predominant definition used for work engagement in contemporary organizational psychology research. This is likely the case as this definition was used to create the Utrecht Work Engagement Scale which is the most popular assessment of work engagement in the current literature (Schaufeli, 2012; Schaufeli et al., 2006).

Work engagement is an important component of resource-based theories such as COR theory (Bakker & Demerouti, 2017; Halbesleben et al., 2014; Hobfoll et al., 2018). Work engagement is theorized to occur when workers have adequate resources to be able to invest and engage in their job. By investing their resources, work engagement has been found to buffer negative outcomes (e.g., burnout) and promote various positive job attitudes (e.g., job satisfaction; organizational commitment), work-related outcomes (e.g., task performance, contextual performance, turnover intentions), and well-being (Christian et al., 2011; Halbesleben, 2010; Simbula & Guglielmi, 2013).

Cognitive Crafting and Work Engagement. The relationship between job crafting and work engagement has been well-established in the literature (Lichtenthaler & Fischbach, 2019; Rudolph et al., 2017). Empirical studies support that job crafting is positively related to work engagement over time and that this relationship exists across various time frames such as years (Harju et al., 2016), months (Vogt et al., 2016; Watson & Sinclair, 2022), or at the day-level (Petrou et al., 2012). However, the majority of this research examines broader job crafting behaviors (e.g., approach crafting; Lichtenthaler & Fischbach, 2019) that categorize cognitive crafting with other types of approach-oriented job crafting or uses the Tims et al. (2012) conceptualization of job crafting in the Job Demands-Resources model that ignores cognitive crafting entirely. Only a handful of empirical studies have included the relationship between work engagement and cognitive crafting (Costantini, 2022; Jutengren et al., 2020; Letona-Ibañez et al., 2019; Nguyen et al., 2019; Pimenta de Devotto et al., 2020; Sakuraya et al., 2020), and none of which have studied gig workers.

For example, Pimenta de Devotto et al. (2020) cross-sectionally examined the relationship between work engagement and different types of job crafting (cognitive crafting, task crafting, and relational crafting) in two groups of Brazilian professionals - professionals with and without management responsibility. The results indicated that cognitive crafting had the strongest relationship with work engagement in both samples. Similarly, in a cross-sectional sample of Vietnamese bankers, Nguyen et al. (2019) found that work engagement's relationship with cognitive crafting was stronger than with relational crafting. Using a three-wave design (one month between data collections), Costantini (2022) reported that cognitive crafting predicted work engagement over time even when controlling for behavioral job crafting. Jutengren et al. (2020) also supported the relationship between cognitive crafting and work engagement over six to eight months for healthcare workers in Sweden. Lastly, job crafting interventions that included a cognitive crafting component have been found to successfully improve work engagement at the three month and six month follow-ups for Japanese workers who initially reported lower levels of job crafting (Sakuraya et al., 2020).

While these studies provide a foundation for empirical support of the cognitive crafting and work engagement relationship, my dissertation extends this literature in a few ways. First, none of the existing studies on cognitive crafting and work engagement have tested the relationship in a sample from the United States or a sample of precarious workers. While I expect that the relationship will still exist in this dissertation's sample, prior work suggests that job crafting and its outcomes may differ across cultures (Boehnlein & Baum, 2022; Zhang & Parker, 2019). Additionally, workers such as gig drivers lack the traditional benefits held by employees in standard work arrangements (i.e., most of the participants in samples of prior cognitive crafting - work engagement studies). This may influence the extent to which gig drivers rely on cognitive crafting to highlight the meaningfulness of their work as a motivational process to compensate for the precarity of their job.

Second, there has been little exploration of how the cognitive crafting - work engagement relationship unfolds over time. Costantini (2022) and Jutengren et al. (2020) showed that cognitive crafting was positively associated with work engagement over the course of months; however, no studies have examined this relationship in shorter time frames such as the daily-level and how the relationship unfolds within-person. Other forms of job crafting (e.g., following the conceptualization from Tims et al., 2012) have been found to predict work engagement at the daily, within-person level (Bakker & Oerlemans, 2019; Petrou et al., 2012). The daily diary survey design of my dissertation will allow me to examine the cognitive crafting - work engagement at this level as well. I will offer insight into the motivational nature of cognitive crafting at the daily level to demonstrate the benefits of regular engagement in this meaning-making strategy.

Lastly, prior studies incorporated little to no theory to explain the relationship between this specific type of job crafting and work engagement. Some of these studies simply refer to “job crafting theory” (e.g., Costantini, 2022) which generally is not considered a standalone theory or does not include theory at all (e.g., Nguyen et al., 2019). I employ the COR theory (Hobfoll, 1989; Hobfoll et al., 2018) to better explain the underlying mechanisms connecting cognitive crafting and work engagement.

I propose that the relationship between cognitive crafting and work engagement may be understood through COR theory. Again, COR theory suggests that workers are motivated to accumulate resources. By cognitive crafting to foster prized resources such as meaningfulness and sense of purpose (Hobfoll et al., 2018), gig drivers will be better positioned to feel engaged in their work. Thus, I hypothesized that cognitive crafting will be positively related to work engagement (*H3*). Furthermore, I expect that cognitive crafting will mediate the relationships of positive interactions with customers (*H4a*) and negative interactions with customers (*H4b*) with work engagement as cognitive crafting will first be employed to make sense of these interactions then transform these interactions into motivation for gig drivers.

Hypothesis 3a: Daily cognitive crafting when reflecting on negative customer interactions is positively related to daily work engagement.

Hypothesis 3b: Daily cognitive crafting when reflecting on positive customer interactions is positively related to daily work engagement.

Hypothesis 4: Daily cognitive crafting mediates the relationship between daily positive interactions with customers and daily work engagement.

Hypothesis 5: Daily cognitive crafting mediates the relationship between daily negative interactions with customers and daily work engagement.

CHAPTER FOUR

OUTCOMES

Worker well-being continues to be a topic of broad interest to social scientists and of particular interest in organizational researchers (Bliese et al., 2017; Danna & Griffin, 1999; Sinclair et al., 2022; Wijngaards et al., 2022). Well-being refers to not only the absence of physical/mental illness but also the presence of positive experiences in a given domain (Danna & Griffin, 1999; Ryff, 1989, 2014). Within the context of the work, workers' well-being has been found to be an important outcome of work experiences (der Kinderen & Khapova, 2020; Häusser et al., 2010; Judge et al., 2017, 2020; Ryff, 2014; Wilkin, 2013).

Worker well-being has been conceptualized in various ways. According to a recent review (Sinclair et al., 2022), well-being in the occupational health psychology literature is captured in a two-by-two typology in which *hedonic* versus *eudaimonic* is one dimension and *general* versus *work-specific* is on the other. Along the first axis, hedonic reflects original definitions of well-being by focusing on the experience of mental/physical pleasure and the absence of mental/physical pain; contrarily, eudaimonic captures a deeper meaning of well-being in which workers align with their values and feel authentic in their activities (Ryan & Deci, 2001). The second axis accounts for whether well-being is being considered in a specific domain (e.g., work, family) or in general (e.g., life, overall). Organizing the concept of worker well-being with this typology provides a framework for organizational psychologists to be intentional in studying well-being constructs that align with their research questions.

Ultimately, my dissertation sought to understand how gig drivers' interactions with customers initiate processes that explain gig drivers' work-related well-being. In line with positive organizational scholarship, worker well-being reflects a positive outcome that is essential to workers' flourishing. Despite assumptions that gig workers' well-being is hindered by the challenges related to the work (Ashford et al., 2018; Cameron, 2022; Caza et al., 2022; Josserand & Kaine, 2019; Liu et al., 2022), prior work suggests that gig workers - and gig drivers specifically - experience indicators of well-being (Berger et al., 2019; Petriglieri et al., 2019).

For example, Petriglieri et al. (2019) conducted a qualitative study examining a broad range of gig workers and how they developed precarious and personalized work identities. They found that even though the gig workers reported anxiety associated with their jobs, they also highlighted how they were able to connect with a broader purpose and a sense of fulfillment through their work. Berger et al. (2019) specifically compared gig drivers (i.e., Uber) to the general workforce in London. Although gig drivers reported higher anxiety levels and were on the lower end of the London income distribution, the results suggested that gig drivers experienced higher levels of life satisfaction than other workers. Findings from Petriglieri et al. and Berger et al. demonstrated that work may benefit gig workers' well-being but leave ample space for additional research to better understand the underlying processes and conditional factors that may help explain gig driver well-being.

In my dissertation, I assess both eudaimonic (e.g., psychological well-being) and hedonic well-being (e.g., job satisfaction) for a more holistic understanding of how customer interactions, cognitive crafting, and work engagement influence gig worker well-being. I focus on domain-specific well-being indicators in the context of work (rather than more general indicators such as life satisfaction) as I want to direct particular attention to factors influencing gig drivers' perceptions of "wholeness" (e.g., eudaimonic work well-being) and pleasure (e.g., hedonic worker well-being) in their work. These work-specific perceptions of gig drivers have received little to no attention in the organizational psychology literature, leaving room for exploration of the extent to which gig drivers experience well-being and factors that may promote or hinder gig drivers' pursuit of work-related hedonia and eudaimonia.

Work-related Psychological Well-being

Psychological well-being as conceptualized by Ryff (1989) reflects eudaimonic well-being. Ryff's model includes six dimensions of eudaimonic well-being that are theorized to contribute to positive human functioning (Ryff, 2014, p. 11):

"(1) the extent to which respondents felt their lives had meaning, purpose and direction (*sense of purpose*); (2) whether they viewed themselves to be living in accord with their own personal convictions (*autonomy*); (3) the extent to which they were making use of their personal talents and potential (*personal growth*); (4) how well they were managing their situations (*environmental mastery*); (5) the depth of connection they had in ties with others (*positive relationships*), and (6) the knowledge and acceptance they had of themselves, including awareness of personal limitations (*self-acceptance*)".

This eudaimonic perspective of psychological well-being can be applied to the work context to gain insight into how one's work contributes to their well-being (e.g., "work-related psychological well-being", Culbertson et al., 2010). That is, the psychological well-being dimensions are specifically applied to the work setting. For example, in the work domain, this construct captures the sense of purpose a worker derives from their job and the extent to which their work challenges them and makes them grow as a person.

I chose Ryff's model to respond to a gap in the occupational health psychology and gig work literature about how non-standard, precarious work arrangements influence gig workers. Most of the well-being literature has been conducted with standard employees in mind. Yet, well-being is intertwined with workers' income, employment, and working conditions, and the nature of gig work threatens well-being as the work is often risky, uncertain, and unpredictable and without typical organizational structures, relationships, and benefits of standard employment. It is possible that well-being manifests differently for gig drivers given the challenging nature of gig work. Thus, I want to uncover factors that influence gig drivers' eudaimonic well-being (i.e., feeling nurtured by their work) rather than just the presence/absence of pleasure (i.e., hedonic well-being). In other words, this dissertation is intended to show that gig drivers can experience psychological well-being despite the challenges associated with their work. Specifically, I examined how interactions with customers influence gig drivers' eudaimonic psychological well-being through cognitive crafting and engagement.

Prior work on positive workplace interactions and psychological well-being has focused on support stemming from supervisor and coworkers (Monnot & Beehr, 2014; Yasmeen et al., 2022) and reported a positive relationship between workplace social support and eudaimonic indicators of well-being. For example, Monnot and Beehr (2014) found that positive, communicative supervisors had a larger, positive effect on workers' eudaimonic well-being (e.g., meaningfulness) than the negative effects of supervisors who were considered as causing stress. Similarly, concerning the direct relationships between gig drivers' psychological well-being and their interactions with customers, positive interactions should be associated with higher levels of psychological well-being. Positive interactions with customers serve as a social resource - which are particularly valued in COR theory (Hobfoll et al., 1990) - that are expected to positively influence the deeper meaning and connectedness gig drivers experience from their work.

Hypothesis 6: Daily positive interactions with customers have a positive direct effect on daily work-related psychological well-being.

Contrarily, negative interactions with customers are expected to have a negative relationship with psychological well-being. That is, when gig drivers experience poor interactions with customers, they will also experience lower levels of psychological well-being. Negative interactions with customers have consistently been negatively related to Ryff's psychological well-being (Gordon et al., 2021; Sood & Kour, 2022). In line with COR theory, social interactions are a valued resource (Hobfoll et al., 1990; Hobfoll, 2002), and the threat and/or loss of this resource would be stressful and reduce work-related psychological well-being.

Hypothesis 7: Daily negative interactions with customers have a negative direct effect on daily work-related psychological well-being.

Job Satisfaction

While Ryff's psychological well-being reflects eudaimonic well-being, job satisfaction is a commonly studied example of hedonic well-being (Judge et al., 2017; Sinclair et al., 2022). That is, job satisfaction focuses on the presence or absence of pleasure stemming from the domain of one's work. Locke (1976) formally defined job satisfaction as "a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences" (p. 1300). Job satisfaction is one of the most widely studied job attitudes in organizational psychology due to its association with numerous important outcomes such as task performance and turnover (Judge et al., 2017).

Despite the attention devoted to job satisfaction, additional work is needed on job satisfaction in the changing nature of work (Kuhn, 2016). Job satisfaction has been found to vary by employment type (Wilkin, 2013). In a meta-analysis by Wilkin (2013), job satisfaction was compared between permanent workers and contingent workers (agency workers, contractors, direct-hire temporary workers; (Connelly & Gallagher, 2004). The overall results suggested that contingent workers experienced lower job satisfaction than permanent workers. Additionally, the type of contingent work was tested as a moderator which supported that contingent workers are not a homogenous group, and certain contingent workers (e.g., agency workers) had greater differences from permanent workers than other contingent work groups (e.g., contractors).

Wilkin's (2013) highlights the importance of studying job satisfaction in gig drivers. Gig workers and contingent workers are both types of nonstandard work arrangements (Watson et al., 2021); the meta-analytic results underscored that job attitudes differ for workers in nonstandard employment arrangements and standard employees. Similarly, Watson et al. (2021) proposed that gig work consists of different profiles with varying work experiences. Thus, rather than sampling gig workers as a homogenous group, my dissertation focuses on the experiences of gig drivers specifically to build understanding of how these workers experience job satisfaction.

The hypothesized direct relationships between job satisfaction and customer interactions are also expected to be positive for positive interactions. The limited prior research available on positive customer interactions supports that these interactions are resources that boost hedonic well-being for workers. For example, Zimmerman et al. (2011) demonstrated a positive spiral in which positive interactions with customers (e.g., liked customers, emotional support) generated positive affect in employees. Kiffin-Peterson et al. (2012) also found that positive events with customers (e.g., pleasant customer, recognition of service from customer) induced positive emotions such as satisfaction, pride, happiness, and excitement through appraising these events as positive encounters that contributed to their sense of self-worth and self-agency. While these studies highlight how positive customer interactions contribute to general, hedonic well-being, my dissertation will demonstrate that gig drivers' positive customer interactions also promote domain-specific, hedonic well-being (i.e., job satisfaction). Furthermore, the extant literature supports that other social agents in the workplace significantly predict job satisfaction. For example, Baruch-Feldman et al. (2002) found that traffic enforcement agents' perceived support from coworkers, immediate supervisor, unit supervisor, and even family uniquely contributed to their job satisfaction. Especially with customers being the primary daily interactions gig drivers have at work, I expect that positive interactions with customers will have a positive relationship with job satisfaction.

Hypothesis 8: Daily positive interactions with customers have a positive direct effect on daily job satisfaction.

Likewise, negative customer interactions are expected to have negative direct effects with job satisfaction. Existing literature on customer mistreatment (e.g., customer incivility, customer aggression) provides empirical support for this hypothesis (Hershcovis & Barling, 2010; Kim et al., 2014; Walker et al., 2014; Wilson & Holmvall, 2013; Yao et al., 2022). As previously mentioned, negative interactions with customers are interpersonal job demands that threaten or deplete gig drivers' valued resources (Hobfoll et al., 1990; Hobfoll, 2002). This threat or loss of resources from negative customer interactions induces stress and diminishes the extent to which gig drivers perceive pleasurable evaluations of their job (Kim et al., 2014). Thus, I hypothesize that negative interactions with customers will have a negative direct effect on job satisfaction.

Hypothesis 9: Daily negative interactions with customers have a negative direct effect on daily job satisfaction.

Indirect Effects

Based on COR theory (Hobfoll et al., 1990; Hobfoll et al., 2018), I expect that gig drivers' interactions with customers will have positive indirect effects on work-related psychological well-being and job satisfaction through cognitive crafting and work engagement. That is, by cognitive crafting after interacting with customers (e.g., to foster resources for positive interactions, to protect resources for negative interactions), gig drivers should have more resources to invest in work engagement and subsequent positive outcomes. When gig drivers feel dedicated, absorbed, and vigorous in their work, they are likely to appraise their job positively and experience higher levels of job satisfaction (Alarcon & Edwards, 2011; Mazzetti et al., 2021). Additionally, gig drivers with more energy, enjoyment, and involvement in their work should report higher levels of work-related well-being. Specifically, positive customer interactions are indirectly related to job satisfaction and work-related psychological well-being as these interactions reflect the positive impact gig drivers have through their work, initiate cognitive crafting processes to foster resources of meaningfulness, and generate motivation (e.g., work engagement) that enhances worker hedonic and eudaimonic well-being.

Hypothesis 10: Daily positive interactions with customers have a positive, indirect effect on daily psychological well-being via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 11: Daily positive interactions with customers have a positive, indirect effect on daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement.

Negative interactions with customers are expected to be positively related to job satisfaction and work-related psychological well-being through similar mechanisms. While it may seem counterintuitive for negative customer interactions to also have positive indirect effects on worker well-being (e.g., *Hypotheses 7* and *9* suggest negative direct effects), negative customer interactions may not have uniformly negative outcomes. Rather, through cognitive crafting and engagement, gig drivers may be able to generate hedonic and eudaimonic well-being from negative interactions with customers. Cognitive crafting serves as an interpersonal sensemaking process for gig drivers to experience job satisfaction even when faced with negative customer events. Negative customer interactions represent cues that gig drivers' work is not benefiting or contributing to others, potentially threatening or depleting gig drivers' resources related to meaningfulness (Vuori et al., 2012). Gig drivers are expected to engage in cognitive crafting as a meaning-making technique that boosts work engagement and the pleasure gig drivers find in their work (e.g., job satisfaction) as well as the connectedness and deeper meaning derived from their work (e.g., work-related psychological well-being).

Hypothesis 12: Daily negative interactions with customers have a positive, indirect effect on daily work-related psychological well-being via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 13: Daily negative interactions with customers have a positive, indirect effect on daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement.

CHAPTER FIVE

PSYCHOLOGICAL CAPITAL AS A MODERATOR

Psychological Capital Overview

Psychological capital is an important concept that emerged from the positive psychology movement (Donaldson & Ko, 2010). Psychological capital is a higher-order factor consisting of four subdimensions - *hope*, *self-efficacy*, *resilience*, and *optimism* - that reflect positive appraisals of situations, a sense of control, intentionality, and agentic goal pursuit (Luthans et al., 2004; Luthans, Youssef, et al., 2007). These constructs met the criteria imposed to ensure the positive organizational behavior scholarship is positively-oriented, scientifically rigorous (e.g., theory- and evidence-based, valid and reliable measures), and practically relevant to workers and the workplace (Luthans, 2002a, 2002b; Pfeffer & Sutton, 2006). The comprehensive definition of psychological capital is:

> An individual's positive psychological state of development that is characterized by: (1) having confidence (self-efficacy) to take on and put in the necessary effort to succeed at challenging tasks; (2) making a positive attribution (optimism) about succeeding now and in the future; (3) persevering toward goals and, when necessary, redirecting paths to goals (hope) in order to succeed; and (4) when beset by problems and adversity, sustaining and bouncing back and even beyond (resilience) to attain success. (Luthans, Youssef, et al., 2007, p. 3)

Psychological capital has gained traction in the occupational health psychology literature as it has been deemed an important *personal resource* (i.e., valued aspects about oneself that improve effective functioning within a given domain) across resource-based theories (Bakker & Demerouti, 2017; Halbesleben et al., 2014; Hobfoll et al., 2018; ten Brummelhuis & Bakker, 2012; Xanthopoulou et al., 2007). Psychological capital has been further proposed as a *key resource* which is positioned at a higher level above other personal resources (Luthans, Youssef, et al., 2007; ten Brummelhuis & Bakker, 2012). That is, psychological capital is considered a key resource that helps workers manage and obtain other valuable resources (Hobfoll, 2002; Thoits, 1994). In further alignment with COR theory, the different elements of psychological capital likely function together as a resource caravan (Hobfoll et al., 2018). COR theory suggests that resources are not entirely independent of each other; rather, individual and organizational resources are expected to travel in packs (i.e., caravans). Thus, the facets of psychological capital are interactive and synergistic (e.g., workers who are optimistic and self-efficacious are often also hopeful and resilient).

Empirical work supports psychological capital as a positive force in the work setting (Newman et al., 2014). Meta-analyses support that this key resource is positively associated with desirable attitudes (e.g., job satisfaction, organizational commitment, well-being), desirable behaviors (e.g., organizational citizenship behaviors), and task performance (Avey et al., 2011; Wu & Nguyen, 2019). Psychological capital was also negatively associated with undesirable attitudes (e.g., cynicism, stress, anxiety, turnover intentions) and behavior (e.g., counterproductive work behaviors). Furthermore, psychological capital has been found to be an effective moderator to enhance positive outcomes and buffer negative outcomes (Newman et al., 2014).

Psychological Capital as a Moderator

The literature on the psychological capital of gig drivers specifically - or even gig workers more broadly - is scant. In a conceptual paper, Keith et al. (2020) posit that psychological capital may be a particularly helpful personal resource to mitigate the difficulties of gig work. For example, gig drivers are responsible managing the ebbs and flows of their work. Based on the preliminary data collected for my dissertation, interviews with gig drivers revealed that some days were very successful (e.g., profitable, pleasant) with a consistent flow of rides/orders while other days were slow, boring, and money was sometimes lost rather than gained (e.g., driving between rides/orders cost more than the day's income). To weather these challenges, gig drivers would benefit from being resilient (i.e., bouncing back from the bad days), optimistic about continued success, hopeful that they can modify their path to meet their goals (i.e., try driving in new areas), and self-efficacious about their capabilities to succeed as a gig driver. Studies on workers who face high job insecurity (Costa & Neves, 2017; Shoss et al., 2018) and entrepreneurs (Baron et al., 2016; Stephan, 2018) have demonstrated the importance of psychological capital and its facets in reducing stress and promoting well-being. Given that these samples resemble gig drivers in some respects psychological capital should play a similar role for this group.

There have been specific calls to test psychological capital as a moderator to better understand insecure work contexts such as gig work (Kauffeld & Spurk, 2022). I propose that psychological capital moderates the relationships between gig drivers' interactions with customers and cognitive crafting. The limited research available (Cenciotti et al., 2017; Sesen & Ertan, 2019; Tho, 2022; Vogt et al., 2016; Xue & Woo, 2022) that examines psychological capital and job crafting typically focuses on the Tims et al. (2012) version of job crafting which excludes cognitive crafting. However, a couple of studies demonstrated a relationship between psychological capital and cognitive crafting. For example, Arasli et al. (2019) found positive correlations among cognitive crafting, psychological capital, and work engagement in a sample of full-time immigrant workers in hotels. Morales-Solis et al. (2022) examined resilience specifically and hypothesized that more resilient workers would be more likely to cognitive craft to reframe the challenging aspects of their work to visualize how their work benefits others as a way to feel more efficacious. Their results support a positive relationship between cognitive crafting and resilience in United States law enforcement officers.

In a qualitative study on how personal and contextual resources influence job crafting, Buonocore et al. (2022) found that workers drew on personal resources such as psychological capital to cognitive craft in response to organizational change. Almost all of the managers interviewed reported engaging in cognitive crafting to some extent to cope with the demand of the change. Buonocore et al. concluded that managers with greater personal resources were better equipped to cognitively craft (e.g., being resilient in light of the change and optimistic about the results of the change allowed them to focus more on the meaning and purpose of their work).

Tying in COR theory (Hobfoll, 1989; Hobfoll et al., 2018), psychological capital should moderate gig drivers' customer interactions and cognitive crafting as well as the indirect effects from customer interactions to worker well-being. Gig drivers who possess higher levels of psychological capital will have more resources to invest in cognitive crafting. Thus, cognitive crafting's relationship with both positive and negative interactions with customers will be stronger for gig drivers who report higher levels of psychological capital. For example, gig drivers with greater psychological capital are generally more resilient (e.g., take negative interactions in stride), self-efficacious (e.g., confident that they perform their job well regardless of the negative interactions), optimistic (e.g., expect that future interactions with this customer and other customers have the potential to be positive), and hopeful (e.g., feel positive about persevering towards their work goals such as maintaining a certain customer review score despite the negative interaction); therefore, when they experience negative interactions with customers, they should be able to maintain psychological resources to engage in cognitive crafting to still consider the meaning of their work.

Similarly, higher levels of psychological capital should exacerbate the positive effects of positive customer interactions on cognitive crafting. That is, when gig drivers experience positive customer interactions and have more psychological capital, they will be more likely to engage in and reap the benefits of meaning-making techniques (e.g., cognitive crafting). Ultimately, gig drivers with greater psychological capital are better positioned to respond productively to customers and initiate positive processes (e.g., cognitive crafting) that promotes well-being. Therefore, I predict that psychological capital will moderate the relationships between customer interactions and cognitive crafting (*Hypotheses 14* and *15*) and the positive, indirect effects of customer interactions on worker well-being (e.g., work-related psychological well-being, job satisfaction) via the sequential mediators of cognitive crafting and work engagement.

Hypothesis 14: Psychological capital moderates the relationship between daily negative interactions with customers and daily cognitive crafting such that gig drivers with greater psychological capital are more likely to daily cognitive craft when reporting more negative customer interactions than gig drivers with lower psychological capital.

Hypothesis 15: Psychological capital moderates the relationship between daily positive interactions with customers and daily cognitive crafting such that gig drivers with greater psychological capital are more likely to daily cognitive craft when reporting more positive customer interactions than gig drivers with lower psychological capital.

Hypothesis 16: The positive, indirect effect of daily negative interactions with customers on (a) daily worker-related psychological well-being and (b) daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement is moderated by psychological capital, such that the indirect effect is stronger when psychological capital is high than when it is low.

Hypothesis 17: The positive, indirect effect of daily positive interactions with customers on (a) daily work-related psychological well-being and (b) daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement is moderated by psychological capital, such that the indirect effect is stronger when psychological capital is high than when it is low.

CHAPTER SIX

SUMMARY OF HYPOTHESES

This chapter provides a summary of the hypotheses proposed in my dissertation. Figure 1 reflects the full hypothesized model.

Hypothesis 1: Daily negative interactions with customers are positively related to daily cognitive crafting.

Hypothesis 2: Daily positive interactions with customers are positively related to daily cognitive crafting.

Hypothesis 3a: Daily cognitive crafting when reflecting on negative customer interactions is positively related to daily work engagement.

Hypothesis 3b: Daily cognitive crafting when reflecting on positive customer interactions is positively related to daily work engagement.

Hypothesis 4: Daily cognitive crafting mediates the relationship between daily positive interactions with customers and daily work engagement.

Hypothesis 5: Daily cognitive crafting mediates the relationship between daily negative interactions with customers and daily work engagement.

Hypothesis 6: Daily positive interactions with customers have a positive direct effect on daily work-related psychological well-being.

Hypothesis 7: Daily negative interactions with customers have a negative direct effect on daily work-related psychological well-being.

Hypothesis 8: Daily positive interactions with customers have a positive direct effect on daily job satisfaction.

Hypothesis 9: Daily negative interactions with customers have a negative direct effect on daily job satisfaction.

Hypothesis 10: Daily positive interactions with customers have a positive, indirect effect on daily psychological well-being via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 11: Daily positive interactions with customers have a positive, indirect effect on daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 12: Daily negative interactions with customers have a positive, indirect effect on daily work-related psychological well-being via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 13: Daily negative interactions with customers have a positive, indirect effect on daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement.

Hypothesis 14: Psychological capital moderates the relationship between daily negative interactions with customers and daily cognitive crafting such that gig drivers with greater psychological capital are more likely to daily cognitive craft when reporting more negative customer interactions than gig drivers with lower psychological capital.

Hypothesis 15: Psychological capital moderates the relationship between daily positive interactions with customers and daily cognitive crafting such that gig drivers *with greater psychological capital are more likely to daily cognitive craft when reporting more positive customer interactions than gig drivers with lower psychological capital.*

Hypothesis 16: The positive, indirect effect of daily negative interactions with customers on (a) daily worker-related psychological well-being and (b) daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement is moderated by psychological capital, such that the indirect effect is stronger when psychological capital is high than when it is low.

Hypothesis 17: The positive, indirect effect of daily positive interactions with customers on (a) daily work-related psychological well-being and (b) daily job satisfaction via the sequential mediators of daily cognitive crafting and daily work engagement is moderated by psychological capital, such that the indirect effect is stronger when psychological capital is high than when it is low.

CHAPTER SEVEN

METHOD

Participants and Procedure

In the main study of my dissertation, I employed a daily diary design in a sample of gig drivers (e.g., rideshare drivers, food delivery drivers). Examples of companies that participants may drive for are Uber, Lyft, GrubHub, DoorDash, and Instacart. Given that a decent portion of gig drivers work on a part-time and/or inconsistent basis (Campbell, 2021), I required that participants have worked as a gig driver for at least three months and currently work at least 20 hours per week as a gig driver.

Participants first completed a registration survey that outlines the commitment expected in the daily diary survey. As an overview of the study for participants who successfully completed the registration survey and deemed eligible, the study consisted of multiple waves of data collection over the course of a few weeks. Participants completed an initial survey and five daily surveys. This data collection approach allowed me to consider both within-person and between-person factors that influence the hypothesized relationships as well as reduce common method bias through temporal separation of the collection of different study variables (Doty & Glick, 1998; Podsakoff et al., 2003; Tehseen et al., 2017).

Recruitment. Participants were recruited by advertising the registration survey through multiple strategies. I first advertised the study to gig drivers who completed my prior studies related to gig work and agreed to be contacted about future studies. I also recruited through social media[4] (e.g., Facebook groups, LinkedIn groups, Instagram pages), other online sources (e.g., Reddit), and direct contact (e.g., LinkedIn). Lastly, I attempted to recruit a pool of potential participants through Amazon Mechanical Turk (MTurk). These approaches to recruitment have been successfully employed in top-tier organizational psychology and management journals (e.g., Sessions et al., 2021; Vogel et al., 2016).

Fraudulent Response Detection. Survey bots (i.e., automated programs designed to complete surveys acting as human respondents) and scammers (i.e., human respondents who complete surveys pretending to meet eligibility requirements and/or complete the survey multiple times by assuming multiple identities) are a growing issue for researchers conducting online surveys as bots contaminate data quality when their fraudulent responses go undetected (Kennedy et al., 2021; Pozzar et al., 2020; Zhang et al., 2022). Given my heavy reliance on online recruitment, I followed prior recommendations (e.g., Buchanan & Scofield, 2018; Griffin et al., 2022; Kennedy et al., 2021; Storozuk et al., 2020; Teitcher et al., 2015) to implement several strategies to detect and/or prevent survey bots and scammers. Participants first had to complete an *uncompensated* registration survey to determine their eligibility for the daily diary study. Having an uncompensated registration/eligibility survey that does not promise eligibility or compensation in future surveys deters bots/scammers as there is no guaranteed

[4] I would like to acknowledge Harry Campbell, Founder and CEO at The Rideshare Guy, for his assistance in recruiting gig driver participants through his social media platforms. Learn more about Harry's efforts to elevate and advocate for the gig driving community at www.therideshareguy.com.

incentive for completing the survey. The specific eligibility requirements regarding tenure (at least three months) and weekly hours (at least 20 per week) were not listed in the registration survey to further prevent fraudulent responses that report false information to be eligible for future studies and compensation.

Beyond the registration survey as an initial hurdle, I incorporated detection strategies into the registration survey in case some survey bots/scammers are not deterred. These strategies include Qualtrics fraud detection features (i.e., reCAPTCHA, RelevantID), honeypot questions (i.e., only visible to bots and hidden from humans), consistency checks (i.e., respondent's report age at the beginning and end of the survey), attention checks (i.e., respondents enter the answer of a simple math equation), truthfulness checks (i.e., respondents indicate where they heard about this survey which includes answer options that could not be true like Craigslist and a fake website), speed of survey completion, Qualtrics timing features (e.g., number of clicks per page, amount of time spent on each page), and manual checks (i.e., open text responses, email addresses). Additionally, respondents were informed that a phone call may be scheduled for the phone number provided in the registration survey if needed for participant verification purposes. I am confident the various combined techniques employed in the registration survey screened out bots for the daily diary study. However, to ensure the best data quality possible, I included several of these strategies (e.g., reCAPTCHA, RelevantID, honeypot questions, speed of survey completion, an attention check item, manual checks of the open-text response) in the daily surveys as well.

The fraudulent response detection strategies were successful in identifying fraudulent in the eligibility survey. The eligibility survey received 2711 responses; however, 96% of these responses ($N = 2598$) were deemed fraudulent. Examples of the number of responses identified by each detection filter were as follows: Relevant ID fraud score $N = 880$, Recaptcha score $N = 971$, Relevant ID duplicate score $N = 140$, age consistency check $N = 233$, source truthfulness check $N = 362$, bogus items $N = 1621$, and duplicated emails $N = 366$. Responses to the open-ended item supported the conclusions from the other detection techniques (e.g., duplicated responses, non-sensical responses, gibberish). I sent verification messages to 82 potentially fraudulent responses, but only three of these cases were verified and included in the valid group. After carefully reviewing the eligibility data and employing the fraudulent detection techniques, there were 113 valid responses to the registration survey for potential study participants.

Procedure. The registration survey detailed that the study involves an initial survey and five daily surveys over the course of ten days. The registration survey supported best practices for daily diary studies to increase respondents' awareness of the commitment required to participate in this type of study design (Gabriel et al., 2019). In this survey, participants provided their demographic information (e.g., age, gender, race/ethnicity, student status), contact information (e.g., email address, phone number), gig driving type (e.g., rideshare driver, food delivery driver), gig driving hours per week, gig driving tenure, percentage of gig driving contribution to household income, and other jobs they may have concurrently with their gig driving position. Participants were deemed eligible if they were at least 18 years old, currently work as a gig driver for at least 20 hours per week, and have been a gig driver for at least three months.

Participants who qualified for the daily diary study received a link to the Wave 1 study. The Wave 1 study asked a series of questions about the gig drivers' personal resources (i.e., psychological capital), interactions with customers (i.e., positive and negative interactions), cognitive crafting, work engagement, and outcomes (i.e., stress, psychological well-being, job satisfaction). The daily diary survey began the following week. The daily diary survey consisted of five surveys completed on days that the participants drove for their gig work job. Although participants only needed to complete the survey for five days, the survey period was open for ten days to account for days that participants may not have worked since gig drivers have inconsistent work schedules. Participants completed the survey at the end of their workday. Each daily survey asked participants about positive interactions with customers, negative interactions with customers, cognitive crafting behaviors, work engagement, and outcome variables (e.g., stress, psychological well-being, job satisfaction). The daily surveys used single items and short-form versions of the measures when possible to reduce respondent fatigue (Beal, 2015; Christensen et al., 2003; Gabriel et al., 2019; Uy et al., 2010). Participants who completed at least 3 daily surveys were included in analyses.

Gig drivers received up to $50.00 in Amazon gift cards for their participation. This payment consisted of $5.00 per survey. If participants completed all surveys (initial survey, five daily surveys), they received a bonus Amazon gift card. The Amazon gift cards were emailed to participants.

Sample. As previously stated, 113 participants who completed the registration survey were deemed valid and eligible and sent the Wave 1 survey. One email address bounced, and the participant was not able to receive the survey. The Wave 1 survey initially received 65 responses; however, four responses were removed due to failed attention checks. The remaining 61 participants were sent the daily diary surveys (57.52% response rate). Two participants did not complete any of the daily diary surveys, three participants completed only one daily diary survey, and five participants completed only two daily diary surveys. A total of 51 participants completed at least three daily diary surveys and were retained for analyses. This resulted in 248 total observations (81.05% completion rate for retained participants; 4.86 surveys per person).

Participants were mostly male (70.59%) and White (72.55%; 13.73% Asian; 7.84% Black) with an average age of 40.52 years old (*SD* = 12.84). Regarding highest level of education, 41.18% reported a 2-year college degree (e.g., Associate's), 25.49% reported a high school diploma, and 19.61% reported a 4-year college degree (e.g., Bachelor's). The demographic composition of this sample (primarily White and male, relatively educated, and average age greater than 40) was consistent with reports from other sources, supporting the representativeness of this sample for gig drivers in the United States (Campbell, 2021; Cook et al., 2021; Sellers, 2020). The majority of participants were not currently in school (92.16%) and did not hold jobs outside of gig drivers (66.66%). The average annual household income was $57,800 with 75% of the participants reporting annual household incomes less than $80,000. On average, gig driving contributed 54.28% to the participants' annual household income.

The sample consisted of 44.23% rideshare drivers (e.g., Uber, Lyft), 30.77% food delivery drivers (e.g., GrubHub, Instacart, DoorDash), and 25% drove for both rideshare and food delivery companies. The average job tenure as a gig driver was 2.26 years (*SD* = 1.77). Participants worked as a gig driver for an average of 31.37 hours per week (*SD* = 10.58) and drove 5.22 days per week (*SD* = 1.36). For the daily surveys, the average shift length was 7.18 hours (*SD* = 3.34). Daily surveys were completed about equally on weekdays (53.22%) and weekends (46.77%).

Measures

The measures used for each construct are provided below. Psychological capital was measured in the Wave 1 survey as a between-person measure. The other constructs (i.e., positive interactions with customers, negative interactions with customers, cognitive crafting, work engagement, psychological well-being, job satisfaction) were assessed at the daily level. Following daily diary study best practices, I used shortened versions of established measures when possible to reduce participant fatigue (Beal, 2015; Christensen et al., 2003; Gabriel et al., 2019; Uy et al., 2010). In the daily surveys, the measures were also presented in a randomized sequence each day to minimize order effects. All measures are presented in Appendix B – Appendix I.

Psychological Capital. Psychological capital consisted of *hope*, *resilience*, *optimism*, and *self-efficacy* (Luthans, Youssef, et al., 2007). *Hope* (4 items), *resilience* (3 items), and *optimism* (2 items) will be measured with the Psychological Capital Questionnaire - Short Version (Luthans, Avolio, et al., 2007). Example items for each subscale, respectively, were as follows: "I am meeting the work goals that I have set for myself", "I can get through difficult times at work because I've experienced difficulty before", and "I am optimistic about what will happen to me in the future as it pertains to work". The Cronbach's alphas demonstrated satisfactory internal consistency (α =.83). All items from these subscales were included in the survey. The response scales for all three subscales will be "1 = Strongly disagree" to "7 = Strongly agree".

Self-efficacy was measured with a one-item measure (Matthews et al., 2022). The item is "I feel like I have the skills and abilities to perform well in my job." According to Matthews et al. (2022), this single item measure demonstrated very good content validity, high test-retest reliability, and criterion validity as well as no usability concerns. I chose to use the Matthews et al. (2022) item rather than the Luthans et al. (2007) *self-efficacy* subscale because the items from the Luthans et al. measure did not apply to the context of gig driving. For example, the Luthans et al. items refer to representing one's work area in meetings with management, presenting information to colleagues, and contributing to discussions about the organization's strategy. Therefore, the broader *self-efficacy* item by Matthews et al. was better suited for this sample. The response scale for this item will be "1 = Strongly disagree" to "7 = Strongly agree". Psychological capital will be only measured in Wave 1 and Wave 2. In both waves, the prompt included, "Thinking about the last two weeks". As previously discussed, psychological capital will be considered a between-person variable.

Positive Interactions with Customers. Positive interactions with customers was operationalized with a list of seven positive interpersonal events that may occur between the gig driver and customers. As a list of these types of interactions in the gig work context does not currently exist, I adapted a list from prior studies (Starkey et al., 2019) and interviews collected in earlier data collection (mentioned in Chapter 2). The positive interactions included 1) provided emotional support to a customer, 2) shared a laugh with a customer, 3) helped a customer, 4) made a difference in a customer's life, 5) shared knowledge with a customer, 6) a customer was nice to me, 7) a customer thanked me. In the daily survey, the prompt for these items was "The following statements describe situations that may occur in your interaction with customers. Please think over your work today and indicate the frequency that your customers treated you in the following ways during today's work:". The response scale was "0 = Never", "1 = A few times", "2 = Half of the times", "3 = A majority of the time," and "4 = All the time" (Wang et al., 2011).

In the daily survey, participants also responded to an open text item. The item stated, "Please tell us about the MOST positive interaction you had with a customer today using at least a few sentences." Including open-text items helped identify any fraudulent or careless responders. Additionally, this item was developed for this study to capture more context about the types of positive interactions gig drivers experience with customers.

Negative Interactions with Customers. Negative interactions with customers were measured with items from Dormann and Zapf's (2004) customer-related social stressors scale. To accommodate the brief nature of daily diary surveys, I used two items per subdimension: *disproportionate customer expectations* (e.g., "a customer demanded special treatment."), *customer verbal aggression* (e.g., "a customer shouted at me") , *ambiguous customer expectations* (e.g., “a customer’s instructions complicated my work”), and *disliked customers* (e.g., “I had to work with unpleasant customers”), for a total of eight items for this measure. The two items were selected based on the highest factor loadings for each subscale and relevance to the gig driving context (Dormann & Zapf, 2004; Dudenhöffer & Dormann, 2015). This approach is consistent with prior studies that have shortened the scale and eliminated items that were irrelevant to the occupational context to better serve daily diary studies and specific work groups (Wang et al., 2011; Yang et al., 2020). As noted by Wang et al. (2011), Cronbach’s alphas are not necessary for this measure since the scale assesses distinct behaviors experienced daily by workers. In the daily survey, the prompt for these items was “The following statements describe situations that may occur in your interaction with customers. Please think over your work today and indicate the frequency that your customers treated you in the following ways during today’s work:”, and the response scale was “0 = Never”, “1 = A few times”, “2 = Half of the times”, “3 = A majority of the time,” and “4 = All the time” (Wang et al., 2011).

In the daily survey, participants also responded to an open text item. The item stated, “Please tell us about the MOST negative interaction you had with a customer today using at least a few sentences.” This qualitative item helped identify responders that may be fraudulent or careless. This item was also used to gain more context about the types of negative interactions gig drivers experience with customers.

Cognitive Job Crafting. *Cognitive crafting* was measured with five items from the Job Crafting Questionnaire (Slemp & Vella-Brodrick, 2013). Example items asked about the extent to which participants “remind yourself of the importance of your work for the broader community”, “think about the ways in which your work positively impacts your life”, and “reflect on the role your job has for your overall well-being”. This scale was presented to participants twice in each daily survey to assess cognitive crafting in response to positive interactions with customers (“When I had positive interactions with customers today”) and negative interactions with customers (“When I had negative interactions with customers today”). Both scales demonstrated satisfactory internal consistent (cognitive crafting positive interactions α = .91; cognitive crafting negative interactions α = .93). Participants responded on a scale from “1 = Strongly disagree” to “7 = Strongly agree”[5].

Work Engagement. Work engagement was measured with three item Utrecht Work Engagement Scale (W. B. Schaufeli et al., 2019). This ultra-short work engagement scale (UWES-3) assesses each dimension with one item: *vigor* (“I felt bursting with energy”), *dedication* (“I was enthusiastic about my job”), and *absorption* (“I was immersed in my work”). The UWES-3 has demonstrated sufficient internal consistency (α = .77-.85 in Schaufeli et al., 2019; α = .85 in this dissertation) and has been found to be as valid, reliable, and usable as the often-used UWES-9 (Schaufeli et al., 2019). The short nature of this version of the UWES was optimal for the daily diary design of this dissertation. In the daily survey, these items began with the prompt,

[5] In the original Slemp and Vella-Brodrick (2013) article, the Job Crafting Questionnaire uses a frequency-based response scale (“1 = hardly ever “to “6 = very often”). Because this dissertation uses a daily diary survey and asks participants about cognitive crafting in response to interactions with customers, I decided to use an agreement-based response scale instead. Other studies using this job crafting measure in daily diary designs have also taken this approach (Geldenhuys et al., 2021).

“Thinking about how I felt during work today”. Respondents answered the items on a scale from “1 = Strongly disagree” to “7 = Strongly agree”.

Work-related Psychological Well-being. Work-related psychological well-being was measured with the shortened version of Ryff’s (1989) Psychological Well-being Scale. The shortened version assessed one item per dimension and has been used in other daily diary study designs (Culbertson et al., 2010). This scale has demonstrated adequate internal consistency ($\alpha = .82$). Example items include “Thinking now about my work today, I feel positive about myself and the events that happened at work today” (*self-acceptance*) and “Thinking now about my work today, my work challenged me and made me grow as a person” *(personal growth*). Participants responded on a scale from “1 = Strongly disagree” to “7 = Strongly agree”.

Job Satisfaction. Job satisfaction was measured with a one-item measure from Matthews et al. (2022). Single item measures of job satisfaction have been found to be valid and reliable assessments of the construct (Fisher et al., 2016; Matthews et al., 2022; Nagy, 2002). Job satisfaction was measured with the item, “Thinking now about your work today, how satisfied are you with your job?” The response scale ranged from “1 = Extremely dissatisfied” to “7 = Extremely satisfied”.

Day and Time. In addition to the measures listed above, I also captured a few additional variables to be considerate of the nonstandard nature of gig driving. Gig drivers are not expected to work traditionally scheduled hours (e.g., 9am - 5pm, Monday - Friday). Thus, the days in which they work and their start/end time on a workday vary. Following recommendations for daily diary studies of nonstandard workers (Gabriel et al., 2019), I created a variable for *day of the week* based on data automatically captured by Qualtrics. I also included an item at the beginning of each daily survey for participants to enter their work start time and end time for the day. Using the information participants provide, I was able to create a *length of shift* variable and *time of shift* (i.e., morning, afternoon, evening, and/or overnight).

Analysis

Participants were retained for analysis if they completed the Wave 1 survey and at least three daily surveys ($N = 52$) so that within-person variation could be properly modeled and to adequately capture gig drivers' lived experiences (Gabriel et al., 2021; Rosen et al., 2016; Weiss & Rupp, 2011). I checked for obvious cases of careless responding, scams/bots, and outliners and remove them from the data to be analyzed as necessary ($N = 2{,}598$ from registration survey; $N = 5$ from Wave 1; $N = 0$ from daily surveys). For any measures with negatively worded items, I reverse coded these items prior to analysis. I calculated Cronbach's alpha values for each scale when applicable (e.g., not necessary for one-item scales like job satisfaction) as well as means, standard deviations, and correlations. Then, I used multilevel path analysis, multi-group path analysis, and generalized linear models to test the hypothesized relations. The daily variables - positive interactions with customers, negative interactions with customers, cognitive crafting, work engagement, psychological well-being, job satisfaction – were considered as Level-1 variables (i.e., repeated daily assessments that are expected to vary within individuals). Psychological capital was considered a Level-2 variable (e.g., Wave

1 assessment that was expected to vary between individuals). The R Markdown syntax for the analyses is provided in Appendix J.

CHAPTER EIGHT

RESULTS

Descriptives and Correlations

Table 1 presents the means, standard deviations, and the Cronbach's alphas for the study variables as well as the correlations among the study variables. Prior to testing the hypothesized relationships, I examined the correlations among the study variables. Following Gabriel et al. (2021), I used the within-person correlations for the Level-1 variables (daily positive customer interactions, daily negative customer interactions, both daily cognitive crafting variables, daily work engagement, daily work-related psychological well-being, daily job satisfaction). I aggregated the Level-1 variables to Level-2 to test the correlations with psychological capital. Overall, the correlation results were significant and in the expected direction.

Daily positive customer interactions were negatively associated with daily negative customer interactions (r = -.19, p < .001) and positively related to the other daily variables (cognitive crafting, r = .27, p < .001; work engagement, r = .26, p < .001; work-related psychological well-being, r = .26, p < .001; job satisfaction, r = .33, p < .001). The relationship between aggregated daily positive customer interactions and psychological capital was positive and marginally significant (r = .27, p = .060).

Daily negative customer interactions were significantly correlated and in the expected direction with work-related psychological well-being (r = -.14, p = .04) and job satisfaction (r = -.22, p < .001). The correlation between daily negative customer interactions and daily work engagement was negative but non-significant (r = -.07, p =

.27), and the correlation between the aggregated daily negative customer interactions and psychological capital was negative and non-significant ($r = -.05$, $p = .75$). Interestingly, the relationship between daily negative customer interactions and daily cognitive crafting was significant and in the opposite direction than expected ($r = -.14$, $p = .01$).

The daily cognitive crafting variables were positively correlated with each other ($r = .43$, $p < .001$). Daily cognitive crafting (positive events) was positively correlated with daily work engagement ($r = .26$, $p < .001$), daily work-related psychological well-being ($r = .30$, $p < .001$), and daily job satisfaction ($r = .30$, $p < .001$). Daily cognitive crafting (negative events) was also positively related to these variables, respectively ($r = .21$, $p < .001$; $r = .16$, $p = .02$; $r = .21$, $p < .001$). Both aggregated daily cognitive crafting variables were positively and significantly related to psychological capital (for positive, $r = .36$, $p = .009$; for negative, $r = .28$, $p = .048$).

Daily work engagement was positively correlated with both daily outcome variables (work-related psychological well-being, $r = .34$, $p < .001$; job satisfaction, $r = .57$, $p < .001$). Aggregated daily work engagement was positively correlated with psychological capital ($r = .63$, $p < .001$). Lastly, the daily outcome variables were positively correlated with each other ($r = .39$, $p < .001$). The aggregated daily outcome variables were also positively correlated with psychological capital (for work-related psychological well-being, $r = .62$, $p < .001$; $r = .63$, $p < .001$).

Multilevel Path Analysis

For *Hypotheses 1-13*, I used multilevel path analysis in R Studio 4.2.0 (e.g., *nlme*, *multilevel, lavaan*) to account for the nested nature of my data (i.e., days nested within participants). I first confirmed that multilevel analysis was appropriate by partitioning variance in Level-1 constructs for within-person variability. Results (see Table 2) demonstrated that within-person variance ranged from .51 to 1.03 supporting multilevel analyses. Notably, the percentage of total variance within-person for the outcome variables - work-related psychological well-being and job satisfaction – were 65.37% and 41.07%, respectively, supporting my within-person focus.

I then conducted a multilevel confirmatory factor analysis (CFA). I modeled positive interactions with customers, negative interactions with customers, cognitive crafting, work engagement, psychological well-being, job satisfaction at Level-1 (i.e., repeated daily assessments that are expected to vary within individuals). I followed best practices (Gabriel et al., 2021; Hofmann et al., 2000; Ohly et al., 2010; Scott et al., 2010) to person-mean center Level-1 constructs (i.e., the means of each daily construct across days for each individual). Using person-mean centering removes between-person variance in the Level-1 variables which better analyzes the within-person relationship by removing effects attributable to between-person factors. Person-mean centering also focuses the analysis on fluctuations among the Level-1 relationships relative to each participant's individual mean day-to-day. To evaluate the fit of the CFA model, I examined global fit testing (e.g., examining approximate fit indices) and local fit testing (e.g., examining residual covariance matrices). The CFA results indicated overall acceptable fit (χ 2 (8) = 29.42, $p < .001$, CFI = .91, RMSEA = .11, SRMR = .06, and BIC = 2351.62). Although the CFI was slightly lower than Hu and Bentler's (1999) proposed criterion of .95, a CFI greater than .90 is still considered acceptable fit (Bentler & Bonett, 1980; Marsh et al., 2004).

Next, in the multi-level path analysis, I modeled all Level-1 regressions as random and modeled control variables (e.g., day of the week, length of shift, time of shift) as fixed to reduce issues with model complexity (Gabriel et al., 2020, 2021). Additionally, the well-being outcomes (job satisfaction and work-related psychological well-being) were allowed to covary with each other (Gabriel et al., 2020). The model was clustered by participant ID. The results are summarized in Figure 2 and Table 3.

Hypothesis 1 and *Hypothesis 2* proposed that daily negative customer interactions and daily positive customer interactions would positively relate to daily cognitive crafting, respectively. The results indicated that the relationship between daily negative customer interactions and daily cognitive crafting was negative and marginally significant ($\gamma = -.03$, $p = .056$), contradicting the expected direction in *Hypothesis 1*. The path from daily positive customer interactions and daily cognitive crafting was significant and positive as expected ($\gamma = .03$, $p = .006$), supporting *Hypothesis 2.*

Hypotheses 3a and *3b* proposed that the daily cognitive crafting variables would be positively associated with daily work engagement. *Hypothesis 3a* was not supported for negative customer interactions ($\gamma = .05$, $p = .351$); however, *Hypothesis 3b* was supported for positive interactions, $\gamma = .18$, $p = .020$. *Hypothesis 4* and *Hypothesis 5* proposed that daily cognitive crafting would mediate the relationships between daily positive customer interactions and daily negative customer interactions with daily work engagement, respectively. The indirect effect for positive customer interactions was marginally significant (*Hypothesis 4,* $\gamma = .01$, $p = .096$). The indirect for negative customer interactions was not significant (*Hypothesis 5,* $\gamma = -.00$, $p = .358$), failing to support these hypotheses.

Hypothesis 6 proposed that daily positive customer interactions were positively related to daily work-related psychological well-being. This path was marginally significant ($\gamma = .02$, $p = .093$) but failed to support *Hypothesis 6. Hypothesis 7* proposed that daily negative customer interactions were negatively related to daily work-related psychological well-being. This path also failed to support *Hypothesis 7* ($\gamma = -.02$, $p = .186$).

Hypothesis 8 and *Hypothesis 9* proposed that daily job satisfaction would be positively related to daily positive customer interactions and negatively related to daily negative customer interactions, respectively. The path from daily positive customer interactions to daily job satisfaction was significant and supported *Hypothesis 8* ($\gamma = .05$, $p = .024$). the path from daily negative customer interactions was marginally significant ($\gamma = -.05$, $p = .066$), failing to support *Hypothesis 9*.

Hypotheses 10 and *Hypothesis 11* proposed the serial mediation effects from daily positive customer interactions to daily work-related psychological well-being (*Hypothesis 10)* and job satisfaction (*Hypothesis 11)* through daily cognitive crafting and daily work engagement. The indirect effects were not significant for either outcome ($\gamma = .00$, $p = .125$; $\gamma = .01$, $p = .125$, respectively). *Hypothesis 12* and *Hypothesis 13* proposed the serial mediation effects from daily negative customer interactions to daily work-related psychological well-being (*Hypothesis 12*) and job satisfaction (*Hypothesis 13)* through daily cognitive crafting and daily work engagement. The indirect effects were not significant for either outcome (γ = -.00, p = .350; γ = -.00, p = .374, respectively).

Moderation Analyses

For *Hypotheses 14-17*, I also used R Studio 4.2.0 for linear mixed-effect models (e.g., *lme4*) and multi-group path analysis (e.g., *lavaan*) to examine psychological capital as a between-person moderator of the proposed within-person relationships.

For *Hypothesis 14* and *Hypothesis 15,* I used the *lmer* function to account for the daily repeated surveys (Level 1) being nested within individuals (Level 2). These hypotheses tested psychological capital (Level 2) as a moderator of the daily customer interactions (Level 1) and daily cognitive crafting variables while controlling for day, length of shift, and time of shift. I person-mean centered the Level 1 variables and grand-mean centered the Level-2 variables. I also specified a random intercept for participant ID so that the intercept could vary across participants while the effects of the predictors remained fixed across participant IDs to account for the clustered nature of the data. For significant interaction terms, I tested simple slopes using one standard deviation below and below the mean.

Hypothesis 14 proposed that psychological capital would moderate the relationship between daily negative customer interactions with daily cognitive crafting such that gig drivers with higher levels of psychological capital would be more likely to engage in daily cognitive crafting than those with lower psychological capital when faced with more daily negative interactions with customers. The results indicated that the main effect of psychological capital was positive and significant (γ = .46, p = .01). The main effect of daily negative customer interactions was not significant ($\gamma = .01$, $p = .66$). The interaction effect was significant ($\gamma = .09$, $p < .001$), and the simple slopes supported *Hypothesis 14*. Simple slopes were plotted in Figure 3. The results indicated that at the low level of psychological capital, the slope was negative ($\gamma = -.07$, $p < .001$), whereas the slope was positive ($\gamma = .09$, $p = .045$) at the high level of psychological capital.

Hypothesis 15 proposed that psychological capital would moderate the relationship between daily positive customer interactions with daily cognitive crafting such that gig drivers with higher levels of psychological capital would be more likely to engage in daily cognitive crafting than those with lower levels psychological capital when faced with less daily positive customers interactions. The results indicated that the main effects of psychological capital and daily positive customer interactions on daily cognitive crafting were positive and significant ($\gamma = .04$, $p = .01$; $\gamma = .55$, $p < .001$, respectively). The interaction effect was significant ($\gamma = -.07$, $p < .001$). The simple slopes are plotted in Figure 4 and did not align with the expectations of *Hypothesis 15*. The simple slopes analysis revealed that at the high level of psychological capital, the slope is not significant ($\gamma = .04$, $p = .58$); however, at the low level of psychological capital and mean level of psychological capital, the slopes were positive and significant ($\gamma = .09$, $p < .001$; $\gamma = .04$, $p = .0$, respectively).

For the final two hypotheses (*Hypothesis 16* and *Hypothesis 17*), I used multi-group path analysis to test for moderated mediation. The psychological capital variable was dichotomized into the "high psychological capital" or "low psychological capital" group following median-split procedure (Carraher & Buckley, 1996; Dawson & Richter, 2006; Dikkers et al., 2007; Farth et al., 1998; Hayes & Matthes, 2009; Lechner & Rammstedt, 2015). Per best practices, the I first fit the "unconstrained" model in which all parameters were free to vary. Then, I fit the "constrained" model that fixed both intercepts and path coefficients in each group to be the same. Both models included the control variables (day, length of shift, and time of shift). A chi-square difference test was conducted to test whether the path coefficients among the daily variables differed significantly in the "high psychological capital" versus "low psychological capital" groups.

The fit indices for the unconstrained model were satisfactory, χ 2 (12) = 25.58, p = .012, CFI = .94, RMSEA = .10, SRMR = .04, and BIC = 2478.27. The constrained model also fit the data well, χ 2 (17) = 29.39, p = .031, CFI = .95, RMSEA = .08, SRMR = .05, and BIC = 2455.18. The chi-square difference test indicated no significant difference between the two models, $\Delta\chi^2(5) = 3.15$, $p = .678$. These results suggest that the daily path coefficients did not differ significantly across levels of psychological capital and fail to support moderated mediation for *Hypothesis 16* and *Hypothesis 17*.

Supplemental Analyses

Based on questions from my dissertation committee during my dissertation proposal, I tested additional moderation analyses by examining the interaction effects of economic dependence, need for meaning, and perceived control over interactions. Following the analysis approach used for *Hypotheses 14 – 17*, I used R Studio 4.2.0 for both linear mixed-effect models and multi-group path analysis to examine the three suggested between-person moderators. All Level-1 predictors were within-person centered, and Level-2 moderators were grand-mean centered. For the multi-group path analyses, median-split procedure was used to create "low" and "high" level groups for the moderator.

Economic Dependence

Economic dependence reflects economic vulnerability due to the need for one's job in order to meet living expenses (Brief et al., 1997; Greenhalgh & Rosenblatt, 1984, 2010). I measured economic dependence with the Economic Dependency Scale (Brief et al., 1997). The internal consistency of the measure was satisfactory, $\alpha = .89$. Example items included, "I really need every dollar I make from my job" and "If I lost even one week's pay, I would have a difficult time making ends meet". Participants responded on a scale from "1 = Strongly disagree" to "7 = Strongly agree".

The linear mixed-model analysis tested economic dependence as a between-person moderator of two models: a) daily positive customer interactions and daily cognitive crafting and b) daily negative customer interactions and daily cognitive crafting. For the first model, the main effect of daily positive customer interactions on daily cognitive crafting was significant ($\gamma = .06$, $p < .001$), but the main effect of economic dependence was not significant ($\gamma = -.01$, $p = .949$). The interaction term was also not significant ($\gamma = .01$, $p = .420$). For the second model, the main effect of daily negative customer interactions on daily cognitive crafting was significant ($\gamma = -.04$, $p = .021$), but the main effect of economic dependence was not significant ($\gamma = -.00$, $p = .992$). The interaction term was marginally significant ($\gamma = .03$ $p = .095$).

For the multi-group path analysis, the fit indices for the unconstrained model were satisfactory, χ 2 (16) = 38.39, p = .001, CFI = .91, RMSEA = .12, SRMR = .06, and BIC = 2373.35. The constrained model also fit the data well, χ 2 (21) = 44.94, p = .002, CFI = .90, RMSEA = .10, SRMR = .06, and BIC = 2353.12. The chi-square difference test indicated no significant difference between the two models, $\Delta\chi^2(5) = 5.31$, $p = .379$.

Need for Meaning

While the desire for meaning is considered to be a universal instinct (Frankl, 2014; Lysova et al., 2019), individuals are expected to differ in their *need* for meaning (Schlegel & Hicks, 2017). I measured this construct with the Need for Meaning subscale from the Meaning in Life scale (Zhang et al., 2018). I adapted the construct to the work context by replacing the word “life” in each item. The items included: “I think a job without meaning is pointless”, “I need to seek meaning in my work”, and “I need to believe that my life is meaningful”. The Cronbach’s alpha was .69, which is just below generally accepted satisfactory thresholds.

The linear mixed-model analysis tested need for meaning as a between-person moderator of the daily positive customer interactions model and the daily negative customer interactions model. The main effects of daily positive customer interactions (γ = .06, p < .001) and need for meaning (γ = .42, p = .949) on daily cognitive crafting were significant. The interaction term was also not significant (γ = .01, p < .001). The main effect of daily negative customer interactions on daily cognitive crafting was significant (γ = -.03, p = .046), and the main effect of need for meaning was significant (γ = .42, p < .001). The interaction effect was not significant (γ = -.00 p = .870).

For the multi-group path analysis, the fit indices for the unconstrained model were satisfactory, χ 2 (16) = 38.00, p = .002, CFI = .91, RMSEA = .11, SRMR = .06, and BIC = 2434.84. The constrained model did not fit the data very well with CFI being less than .90, χ 2 (21) = 50.87, p < .001, CFI = .88, RMSEA = .12, SRMR = .07, and BIC = 2420.93. The chi-square difference test indicated a marginally significant difference between the two models, $\Delta\chi^2(5) = 10.74$, $p = .057$.

Perceived Control Over Customer Interactions

Lastly, I tested gig drivers' perceived control over customer interactions as a between-person moderator. This construct was measured with single item developed for this study based on feedback from a dissertation committee member. The item asked, "To what extent can you control whether your interactions with your customers are positive or negative?" Participants responded to the following scale: "1 = Not at all", "2 = Very little", "3 = Somewhat", and "4 = To a great extent".

The linear mixed-model analysis tested perceived control over customer interactions as a between-person moderator of the daily positive customer interactions model and the daily negative customer interactions model. The main effect of daily positive customer interactions on daily cognitive crafting was significant ($\gamma = .06$, $p < .001$), but the main effect of perceived control over customer interactions was not significant ($\gamma = .40$, $p = .137$). The interaction term was marginally significant ($\gamma = -.04$, $p = .063$). For the second model, the main effects of daily negative customer interactions ($\gamma = .01$, $p = .768$) and perceived control over customer interactions ($\gamma = .39$, $p = .147$) on daily cognitive crafting were not significant. The interaction term was significant ($\gamma = .14$, $p = .002$).

Because the interaction term was significant, I conducted simple slopes analysis for the daily negative customer interactions model. At high levels of perceived control over customer interactions, the slope was positive and significant ($\gamma = .10$, $p = .030$). At low levels of perceived control over customer interactions, the slope was negative and significant ($\gamma = -.08$, $p < .001$). The simple slopes are plotted in Figure 5.

For the multi-group path analysis, the fit indices for the unconstrained model were satisfactory, χ 2 (16) = 37.12, p = .002, CFI = .92, RMSEA = .11, SRMR = .05, and BIC = 2387.48. The constrained model did not fit the data very well with CFI being less than .90, χ 2 (21) = 51.53, p < .001, CFI = .89, RMSEA = .12, SRMR = .06, and BIC = 2375.11. The chi-square difference test indicated a marginally significant difference between the two models, $\Delta\chi^2(5) = 9.72$, $p = .084$.

CHAPTER NINE

DISCUSSION

With the everchanging nature of work and growth of precarious work arrangements such as gig driving, organizational psychologists should consider factors that promote and hinder these workers' well-being. In response to calls for research on cognitive crafting (Melo et al., 2021; Rudolph et al., 2017; Tims et al., 2021; Zhang & Parker, 2019), I employed mixed-methods data collection to test cognitive crafting as an avenue for gig drivers to derive meaning in their work and experience work-related well-being in light of customer interactions. Additionally, this study used a daily diary design to capture how the proposed paths unfold on a daily basis as gig drivers encounter various types of customer interactions and how these processes differ based on individual differences in gig drivers.

Summary of Findings

The results of this study were expected to demonstrate that gig drivers engage in daily cognitive crafting as a sensemaking mechanism and motivational process following daily customer interactions. That is, daily positive and negative interactions with customers were hypothesized to be positively, indirectly related to gig drivers' daily work-related psychological well-being and daily job satisfaction through the serial mediation of daily cognitive crafting and daily work engagement. Even though daily negative customers interactions were expected to have negative direct effects on daily job satisfaction and daily work-related psychological well-being, daily cognitive crafting was expected to redirect this relationship to lead to positive outcomes. Furthermore, these indirect effects were expected to be moderated by psychological capital such that gig drivers with higher levels of psychological experience are more likely to engage in daily cognitive crafting and experience its subsequent benefits. All of the hypothesized relationships were expected to hold even when controlling for day, length of shift, and time of shift to account for the nonstandard nature of gig driving.

The data fit the hypothesized model well, but there was mixed support for the hypothesized relationship. The first two hypotheses predicted positive relationships between daily customer interactions with daily cognitive crafting. The path for *Hypothesis 1* was marginally significant but in the opposite direction, failing to support *Hypothesis 1*. That is, daily negative customer interactions were negatively associated with daily cognitive crafting, contradicting expectations in *Hypothesis 1* as well as prior interpersonal sensemaking models (Vuori et al. 2012). *Hypothesis 2* was supported such that daily positive customer interactions were positively related to daily cognitive crafting. While these results aligned with *Hypothesis 2*, they actually counter expectations in existing interpersonal sensemaking models (e.g., Vuori et al., 2012; Wrzesniewski et al., 2003) which will be discussed in more detail in the next section.

Hypothesis 3a and *3b* predicted that daily cognitive crafting would be positively associated with daily work engagement. For cognitive crafting (positive), the path was significant and supported *Hypothesis 3a*. However, the path for cognitive crafting (negative) was not significant, failing to support *Hypothesis 3b*. The next set of hypotheses (*Hypothesis 4 and Hypothesis 5*) expected that daily cognitive crafting would mediate the relationships between daily positive/negative customer interactions and daily work engagement, respectively. The indirect effect was significant to support *Hypothesis 4*; daily cognitive crafting mediated the relationship between daily positive customer interactions and daily work engagement. The indirect effect was not significant for the daily negative customer interactions path, failing to support *Hy Hypothesis 5*.

Hypotheses 6 – 9 captured the direct effects of the predictors (daily positive customer interaction and daily negative customers interactions) on the outcome variables (daily work-related psychological well-being and daily job satisfaction). Daily positive customer interactions were positively associated with daily job satisfaction, supporting *Hypothesis 8*. The paths from daily positive customer interactions to daily work-related psychological well-being and from daily negative customer interactions to daily job satisfaction were marginally significant but failed to support *Hypothesis 6* and *Hypothesis 9*, respectively. Daily negative customer interactions were not significantly associated with daily work-related psychological well-being and did not support *Hypothesis 7*.

Hypotheses 10 – 13 tested daily cognitive crafting and daily work engagement serially mediating the relationships between the predictors (daily positive customer interaction and daily negative customers interactions) on the outcome variables (daily work-related psychological well-being and daily job satisfaction). None of the indirect effects calculating the serial mediation effects were significant. Thus, the results failed to support *Hypotheses 10 – 13*, and the relationships between daily customer interactions and daily work-related well-being could not be explained through daily cognitive crafting and daily work engagement.

The last four hypotheses examined the moderating effect of psychological capital as a between-person factor on the daily variables. *Hypothesis 14* predicted that psychological capital moderated the relationship between daily negative customer interactions and daily cognitive crafting. In support of *Hypothesis 14*, the interaction effect was significant such that gig drivers with high levels of psychological capital engaged in more daily cognitive crafting (positive relationship), whereas gig drivers with low levels of psychological capital engaged in less daily cognitive crafting (negative relationship). *Hypothesis 15* was not supported. Although psychological capital moderated the relationship between daily positive customer interactions and daily cognitive crafting, the simple slopes did not align with expectations. For gig drivers with low psychological capital, the relationship was significant and positive; however, for gig drivers with high psychological capital, the relationship was not significant. The moderated serial mediation effects proposed in *Hypothesis 16* and *Hypothesis 17* compared the serial mediation model for participants with high levels of psychological capital to participants with low levels of psychological capital. The results failed to support these hypotheses.

Implications of findings

Despite the mixed support for the hypotheses, this dissertation's results offer implications for both theory and practice.

Theoretical Implications

Cognitive crafting as a sensemaking mechanism. Researchers have recently suggested that cognitive crafting may be best conceived as a sensemaking strategy (Melo et al., 2020); however, this approach to cognitive crafting has not received adequate attention. This dissertation provided insight into cognitive crafting as a bottom-up, meaning-making strategy by pulling from existing models of interpersonal sensemaking (Vuori et al., 2012; Wrzesniewski et al., 2003) and bridging them with COR theory (Hobfoll, 1989; 2018). The results generated interesting findings regarding daily cognitive crafting as a sensemaking mechanism for daily customer interactions. As expected based on the qualitative data results (Chapter 2), the daily diary study supported that the positive and negative interactions gig drivers experienced with customers on a daily basis influenced their work experiences. The results specific to the relationships between cognitive crafting and daily customer interactions contradicted expectations based on prior literature (e.g., Vuori et al., 2012).

In contradiction to my dissertation's hypothesis (*Hypothesis 1*) and prior interpersonal sensemaking models (Vuori et al., 2012; Wrzesniewski et al., 2003), daily negative customer interactions were negatively related to daily cognitive crafting. That is, on days when gig drivers experienced more negative interactions with customers, they reported engaging in less cognitive crafting that day. Extant models of interpersonal sensemaking suggest a positive relationship between these constructs such that gig drivers would perceive negative customer interactions as a threat or loss of work meaningfulness and be motivated to cognitive craft (e.g., remind themselves of the significance of their work) as a meaning-making strategy to protect this resource (Vuori et al., 2012). Contrarily, this dissertation's daily diary results reflect that gig drivers were less likely to cognitive craft when experiencing negative customer interactions.

While the model in this dissertation focused on approach cognitive crafting based on rationale from prior interpersonal sensemaking models (Vuori et al., 2012), one potential explanation for this unexpected finding is that work stressors such as customer mistreatment provoke avoidance cognitive crafting rather than approach cognitive crafting. Drawing from COR theory, approach cognitive crafting through meaning-making can be argued to require resources from gig drivers; yet, these resources may have been compromised by negative interactions with customers (Hobfoll, 2002; Koopmann et al., 2015; Yang et al., 2020). Thus, gig driver may not have sufficient resources to engage in approach cognitive crafting and must engage in avoidance cognitive crafting instead as a less resource-taxing strategy.

Avoidance cognitive crafting is the cognitive shift away from negative aspects of one's job and includes withdrawal crafting (i.e., "the systematic removal of oneself, either mentally or physically, from a person, situation, or event through changes to one's job", Bruning & Campion, 2018, p. 508), avoidance resources crafting (i.e., "reframing one's job to avoid or diminish aspects of the job that lack resources", Zhang & Parker, 2019, p. 131), and avoidance demands crafting (i.e., "reframing one's job to avoid the experience of demands", Zhang & Parker, 2019, p. 131). It is possible that gig drivers psychologically withdraw by intentionally diverting thoughts about negative customer interactions or reshaping their perceptions of their job to minimize their felt responsibility for dealing with unpleasant customers (e.g., my job as a gig driver is to safely deliver a passenger from point A to point B, and my job is not to go above and beyond to ensure their satisfaction beyond my basic job duties). If gig drivers withdraw in the context of negative customer interactions, they may be less likely to engage in the intentional meaning-making efforts presumed by the approach cognitive crafting measured in this study. Future research should explore the role of avoidance cognitive crafting as a strategy employed by gig drivers to manage work stressors such as negative customer interactions.

Another potential explanation for the unexpected negative relationship between daily negative customer interaction and daily cognitive crafting is that the nature of this relationship may vary based on individual differences. The extant literature suggests that individual differences such as global self-esteem (Amarnani et al., 2019), core self-evaluations (Chi et al., 2016), recovery self-efficacy (Yang et al., 2020), and trait resilience (Yang et al., 2020) moderate the outcomes of customer mistreatment. In this dissertation, I tested psychological capital (e.g., resilience, hope, optimism, self-efficacy) as a between-person moderator of the daily negative customer interactions – daily cognitive crafting relationship (*Hypothesis 14*). The results (Figure 3) showed that the relationship between daily negative customer interactions and daily cognitive crafting differed for gig drivers with high levels of psychological capital versus low levels of psychological capital. Daily negative customer interactions were positively related to daily cognitive crafting for gig drivers with greater psychological capital (consistent with *Hypothesis 1* and prior literature), and the relationship was negative for gig drivers with lower psychological capital (contradicting *Hypothesis 1* and prior literature).

The nature of psychological capital's interaction effect for daily negative customer interactions and daily cognitive crafting provides a valuable contribution to the literature (and to the dissertation's results) about the importance of considering individual differences. This interesting finding reveals that relationships modeled in the interpersonal sensemaking theories proposed by Vuori et al. (2012) and Wrzesniewski et al. (2003) do not universally apply to all workers. Rather, in line with COR theory (Hobfoll, 1989, 2018), workers with greater resources (in this case, psychological capital resources) are better positioned to invest in future resources gains (meaning-making techniques through cognitive crafting) to protect the meaningfulness of their work when encountering negative customer interactions. Prior qualitative work also supports that workers with greater psychological capital were better able to engage in meaning-making techniques when facing job demands than the workers that lacked psychological capital (Buonocore et al., 2022). On the other hand, per COR theory, workers with fewer psychological capital resources are more prone to resource loss and may employ avoidance cognitive crafting strategies instead to withdraw to preserve resources since they do not have the resources to engage in resource-building strategies like approach cognitive crafting.

The supplemental analyses provide some insight into other relevant individual differences. Economic dependence and need for meaning did not moderate the proposed relationships. However, perceived control over customer interactions moderated the relationship between daily negative customer interactions and daily cognitive crafting, following a similar pattern to the psychological capital interaction. Future research should consider other individual differences that may influence cognitive crafting as an interpersonal sensemaking process for gig drivers.

For example, future researchers may examine prosocial motivation – the desire to benefit others (Liao et al., 2022) - as an individual difference influencing this relationship such that gig drivers with greater prosocial motivation may be more inclined to engage in meaning-making techniques like approach cognitive crafting when faced with negative customer interactions to compensate for this desire compared to gig drivers with less prosocial motivation. As another example, personality characteristics such as extroversion or introversion may influence the relationship between customer interactions and cognitive crafting. Perhaps extroverted gig drivers value interpersonal interactions more and would be more included to cognitively craft in light of negative customer interactions to make sense of the poor interaction, whereas introverted gig drivers may not be as impacted with the interactions with customers. Using a sample of undergraduate students with customer-facing jobs, Goussinsky (2011) found that extroverted participants who faced higher levels of customer aggression experienced lower job satisfaction and greater emotional dissonance than those who reported being lower in extroversion or less frequent encounters with customer aggression. Future research considering additional individual differences will better disentangle the customer interaction – cognitive crafting relationship.

The findings for the relationship between daily positive customer interactions and daily cognitive crafting (*Hypothesis 2*) also challenge the assumptions of interpersonal sensemaking model theory (Vuori et al., 2012). Vuori et al. (2012) posed that workers' positive interactions in their job signify that their work is meaningful so they will engage in less meaning-making strategies such as cognitive crafting (i.e., meaning-making strategies are not necessary). However, I proposed that daily positive customer interactions would be positively related to daily cognitive crafting which was supported in this dissertation's results. These results echo one of the basic tenets of COR theory (Hobfoll, 1989, 2018) that individuals are motivated to retain and foster resources such as meaningfulness. The positive customer interactions reflected the meaningfulness of gig drivers' work (e.g., receiving gratitude from customers), and gig drivers were motivated to cognitively craft foster this resource. For example, consistent with COR theory, gig drivers may use cognitive crafting to bolster their reservoir of meaningfulness resources, creating a resource caravan to better manage future threats of resource loss in negative customer interactions.

Again, the psychological capital moderator results provide additional insight into this relationship between daily positive customer interactions and daily cognitive crafting. The results indicated that positive relationship only held true for gig drivers with low or average (i.e., mean) levels of psychological; the relationship was not significant for gig drivers with high levels of psychological capital. These findings countered my hypothesis (*Hypothesis 15*) that predicted the high level of psychological capital gig drivers to have a stronger, positive relationship than the low-level group. One potential explanation is that, in line with interpersonal sensemaking models (Vuori et al., 2012; Wrzesniewski et al., 2003), gig drivers with high levels of psychological capital may possess adequate resources that it is not necessary for them to cognitive craft to elevate the meaningfulness from their positive customer interactions because they are satisfied with this resource. For example, gig drivers with high psychological capital who experience positive customer interactions may already feel optimistic about their work (e.g., looks on the positive side of things) and hopeful that they are meeting their goals (e.g., the goal of benefitting others through their work) and are less inclined to cognitive crafting to intentionally bolster the perceived significance of their work.

On the other hand, gig drivers with low levels of psychological capital may rely more heavily on positive customer interactions as relational resources to drive cognitive crafting as a meaning-making strategy than gig drivers with high psychological capital. COR theory suggests that individuals who lack resources are less capable of resource gain (Hobfoll, 1989; 2018). Thus, individuals who lack resources may need to be more intentional in investing their resources (e.g., through cognitive crafting) to promote gains. That is, when gig drivers lack psychological capital resources and experience positive customer interactions, they may be more intentional in thinking about how these positive customer interactions reflect the meaningfulness of their work and engage in cognitive crafting as a meaning-making technique to foster this resource. Ultimately my dissertation's findings on the relationships between daily customer interactions, daily cognitive crafting, and psychological capital indicate that there is not a one-size-fits all approach for interpersonal sensemaking theories and it is importance to consider individual differences when examining cognitive crafting as meaning-making strategy.

Cognitive crafting as a motivational process. The second role of cognitive crafting in this dissertation model was as a motivational process. That is, daily cognitive crafting was expected to promote daily work engagement as employing this meaning-making strategy should better position gig drivers to be motivated and engaged in their work. Interestingly, the findings for the daily cognitive crafting and daily work engagement relationship in this dissertation differed for daily cognitive crafting in the positive customer interactions path versus the negative customer interactions path. As previously stated, I intentionally delineated the positive versus negative customer interactions paths in the model by including two measures of cognitive crafting – cognitive crafting when reflecting on positive customer interactions (*Hypothesis 3a*) and cognitive crafting when reflecting on negative customer interactions (*Hypothesis 3b*). The relationship daily cognitive crafting when reflecting on positive customer interactions and daily work engagement was significant, whereas the other path was not.

These conflicting results may be understood through the findings of *Hypothesis 1* (daily negative customer interactions negatively related to daily cognitive crafting) and *Hypothesis 2* (daily positive customer interactions positively related to daily cognitive crafting). Daily negative customer interactions seemed to invoke withdrawal rather than meaning-making through daily cognitive crafting, thus if gig drivers reflect on negative customer interactions when cognitive crafting, they may be unable to initiate this motivational process to promote work engagement. Rather, daily cognitive crafting when thinking about positive customer interactions could prompt the motivational process as gig drivers feel energized when they think about how the positive customer interactions reflect the contribution and significant of their work. As a result of cognitive crafting this meaningfulness, gig drivers are more likely to experience vigor, dedication, and absorption in their work. Prior work on cognitive crafting and work engagement has not measured cognitive crafting in relation to work events (Costantini, 2022; Jutengren et al., 2020; Letona-Ibañez et al., 2019; Nguyen et al., 2019; Pimenta de Devotto et al., 2020; Sakuraya et al., 2020). Yet, the differing findings framing the daily cognitive crafting measure for the positive customer interactions versus negative customer interactions paths indicates the importance in considering the context of cognitive crafting and intentionally capturing the context in construct measurement.

Although the wording of the two daily cognitive crafting measures captured the connection of cognitive crafting and the valence of customer interactions, I more explicitly tested these relationships in *Hypothesis 4* and *Hypothesis 5* by proposing that daily cognitive crafting would mediate the relationship between the respective type of customer interaction and daily work engagement. The indirect effect of daily positive customer interactions on daily work engagement through daily cognitive crafting was marginally significant, and although this ultimately failed to support *Hypothesis 4*, it provides some backing for the rationale for *Hypothesis 3a.* Perhaps unsurprisingly based on the other results, daily cognitive crafting when reflecting on negative customer interactions did not mediate the relationship between daily negative customer interactions and daily work engagement, further supporting the potential for a withdrawal response to negative customer interactions.

Worker well-being outcomes. The final component of my dissertation model tested the relationships between daily customer interactions, daily cognitive crafting, and daily work engagement with worker well-being. Specifically, I considered two types of worker well-being (Sinclair et al., 2022). This dissertation included both worker eudaimonic well-being (work-related psychological well-being) and hedonic well-being (job satisfaction) as outcomes of the model.

First, I will discuss the direct effects. Regarding hedonic well-being (job satisfaction, *Hypothesis 8*), gig drivers who experienced more daily positive customer interactions were more likely to positively evaluate their job at the end of the day. In line with prior work (Kriffin-Peterson et al., 2012), it is likely that positive customer interactions elicit positive emotions that elevate the pleasure gig drivers derive from their job. These findings contribute to the limited literature on positive customer interactions as a relational resource that boosts hedonic well-being (Kiffin-Peterson et al., 2012; Zimmerman et al., 2011) and extends prior work by supporting these relationships at the daily level.

However, the negative relationship between daily negative customer interactions and daily job satisfaction (*Hypothesis 9*) was only marginally significant. This only marginally significant finding was surprising as it was expected a similar rationale (i.e., negative customer interactions induce negative emotions and poorer evaluations of one's job). For example, the stressor-emotion model (Fox & Spector, 2006) poses that stressors at work such as interpersonal conflict provokes negative emotions and has been supported in a daily diary design that found that frontline service workers who experienced daily customer mistreatment reported greater daily negative emotions (Chi et al., 2016). It is possible that perhaps the intensity or nature of the negative customer interaction influences gig drivers' perceptions of job satisfaction. Examining the daily negative customer interactions at the item-level indicates that the most reported negative interactions related to gig drivers experiencing difficulties in making arrangements with customers ($M = 1.72$, $SD = 1.09$) or customers demanding special treatment ($M = 1.70$, $SD = .95$), and the least reported negative customer interactions were the more intense types of mistreatment (customer verbal aggression) such as gig drivers being shouted at ($M = 1.54$, $SD = 1.06$) or verbally attacked by customers ($M = 1.53$, $SD = .88$).

While interpersonal conflict in general should elicit negative emotions per the stressor-emotion model, certain negative customer interactions may be considered less of a threat to resources – such as the one's most commonly experienced in this dissertation's sample – and induce negative emotions but not enough to tip the scale to job dissatisfaction (i.e., a negative relationship). Future researchers should further explore how the different types of negative customer interactions differentially relate to hedonic well-being outcomes by considering both frequency and intensity. It is also possible that this path from daily customer negative interactions and daily job satisfaction ($p = .066$) would become significant with more statistical power, thus future researcher should replicate the proposed model in larger samples.

For eudaimonic well-being (work-related psychological well-being, *Hypothesis 6* and *Hypothesis 7*), the path from daily positive customer interactions to daily work-related psychological well-being was only marginally significant, and the path from daily negative customer interactions to daily work-related psychological well-being was not significant. Although I expected that the influence of customer interactions would be similar for both hedonic and eudaimonic indicators of well-being, the findings suggest that is not the case. One explanation is that daily positive and negative customer interactions may have more proximal effects on hedonic well-being as the extent to which gig drivers experience these interactions influences their daily evaluations of the job as pleasurable or not (with this more so being the case for positive customer interactions based on the results for *Hypothesis 8*). However, these daily customer interactions may have less of an impact on how gig drivers evaluate the deeper meaning of their job captured by eudaimonic well-being. It should be noted that prior work has found a significant, negative relationship between customer mistreatment and Ryff's psychological well-being (Gordon et al., 2021; Sood & Kour, 2022). These prior studies were only cross-sectional and did not take into account the relationship over time or within-person, thus the daily diary design used in this dissertation provides a more nuanced insight into the relationship between customer interactions and work-related psychological well-being.

Beyond the direct effects of daily customer interactions on worker well-being, I also tested a serial mediation model that connected daily positive and negative customer interactions with daily job satisfaction and daily work-related psychological well-being *through* daily cognitive crafting and daily work engagement. I also tested psychological capital as a between-person moderator of the serial mediation model that would demonstrate greater worker well-being outcomes for gig drivers with high levels of psychological capital compared to those with low levels of psychological capital. None of these hypotheses were supported in the full model.

Given that pieces of the model produce significant results, this dissertation is still encouraging that gig drivers cognitively craft as a way to make sense of their customer interactions and, in some cases, may motivate gig drivers to be more engaged in their job. Future researchers should continue to explore the role(s) that cognitive crafting plays in shaping gig drivers' perceptions of well-being. For example, perhaps the distinction between approach cognitive crafting and avoidance crafting should be incorporated into the model to potentially more accurately capture cognitive crafting in the context of positive customer interactions (relational resources) versus negative customer interactions (relational demands). Similar to other worker well-being models like the Job Demands-Resources model (JD-R model; Bakker & Demerouti, 2017; Demerouti et al., 2001), it is possible that there are dual pathways. Perhaps there is a *motivational pathway* in which daily positive customer interactions promote approach daily cognitive crafting (e.g., meaning-making strategy) in an effort to elevate these positive experiences. These positive experiences signify the greater meaning of gig drivers' work which is motivating and boosts daily worker well-being. And perhaps there is a *preservation pathway* in which daily negative customer interactions provoke avoidance daily cognitive (e.g., mentally withdrawing and distancing) as a way to prevent strain (e.g., burnout, emotional exhaustion) and preserve daily worker well-being. This type of model would also be an interesting way to consider cognitive crafting into a JD-R-like model and encourage efforts to integrate cognitive into the predominant job crafting framework (Costantini, 2022; Melo et al., 2021; Tims & Bakker, 2010).

Practical Implications

My dissertation also has practical implications. For example, the results support that psychological capital is a key resource that can positively alter the relationship between negative customer interactions and cognitive crafting when gig drivers have high levels of psychological capital. This finding aligns with conceptual work that has suggested psychological capital is of particular importance to gig workers (Kauffeld & Spurk, 2022; Keith et al., 2020). Psychological capital has been found to be a trainable resource in which interventions can significant increase workers' psychological capital (Dello Russo & Stoykova, 2015; Luthans et al., 2008, 2010; Salanova & Ortega-Maldona, 2019). Even web-based psychological capital interventions have been found to be successful (Luthans et al., 2008) which would be particularly relevant given the nature of gig driving (e.g., no home-base office, limited interactions with employer). To enhance gig drivers' psychological capital, gig driver employers (e.g., Uber, Lyft, Instacart) should consider offering web-based psychological capital intervention training for their workers.

With that being said, I recognize that there may be challenges in gaining support from gig driver employers to promote such training. As noted in my interviews with gig drivers, gig drivers often receive minimal resources from their employers. Organizational psychology scholars who focus on nonstandard workers such as gig drivers must be creative in identifying nonstandard ways to connect with these workers.

Another avenue would be to find alternative ways to distribute web-based psychological capital training that may better suit the nature of gig driving. For example, the web-based training could be advertised through gig driver Reddit threads and Facebook groups (similar to the approaches I used for dissertation recruitment) or pushed out by advocates in the gig driver community such as the Rideshare Guy.

Limitations

This dissertation is not without limitations. First, while this study uses a daily diary design to assess how the proposed relationships vary day-to-day, the participants still had to engage in some extent of recall to respond questions about the positive and negative interactions they had with customers and how these interactions influenced their cognitive crafting. To examine the relationship more closely between specific events and cognitive crafting, an experience sampling method (i.e., ESM) study design would be beneficial. However, due to the nature of gig driving (e.g., driving and often being on the road), an ESM design that required participants to complete the survey immediately after reporting a positive or negative event would be potentially dangerous. This expectation would potentially place expectations on the participants to complete the survey while driving (e.g., dangerous and in violation the law in most states) or to temporarily stop driving/taking orders to safely complete the survey (e.g., participants would miss out on income and maybe damage their ride/order acceptance rating on the phone application).

Second, this study relied on self-report data for all measures which can be susceptible to common method bias, social desirability, and faking (Paulhus, 2017). However, self-report data was the most feasible and relevant method of data collection to assess gig drivers' perceptions of their interactions with customers, cognitive crafting, work engagement, and well-being. Additionally, person-centering the Level 1 variables decreased concerns that the results will be influenced by individual response tendencies (Bryk & Raudenbush, 2002). Future studies may include other-report outcomes to supplement self-report data (e.g., customer reviews and ratings through the ride-hailing/food delivery app).

Lastly, this dissertation and prior related data collection demonstrated the challenges associated with recruiting gig drivers to participate in surveys. By leveraging social media groups and online communities, I recruited an adequate number of participants for this study (Level-2 $N = 51$, Level-1 $N = 248$). Although I was not able to recruit my original goal of 75 participants due to the recruitment hurdles, prior daily diary studies have published with similar samples at levels 1 and 2 (Yang et al., 2020). Additionally, it was not possible to measure how many gig drivers view the posted survey but opt to not participate and if there are differences between gig drivers who choose to participate or not (e.g., perhaps participants are more engaged in their gig driving job than drivers who do not take the time to participate). Recruiting broadly through various online platforms, hard copies of flyers, and the participant pool from the pre-survey hopefully helped mitigate some of these concerns by not restricting recruitment to a specific platform that may attract certain types of people (e.g., Reddit). Even with the potential limitations of this study, this dissertation contributes to the organizational psychology literature and provides a basis for future research.

Directions for Future Research

My dissertation will set the groundwork for several avenues of future research in addition to the ones mentioned throughout the discussion. First, future researchers should test the efficacy of the cognitive crafting process when faced with other job demands and job resources. For example, findings from the interviews in the prior data collection identified gig drivers' demands (e.g., economic stress, physical demands) and resources (e.g., flexibility) that were not focused on in this dissertation. Second, future researchers should examine how the influence of cognitive crafting extends to other positive (e.g., performance) and negative (e.g., stress) outcomes for gig drivers beyond the outcomes included in this study. Third, similar models as proposed in this dissertation should be considered for other gig worker profiles and precarious work arrangements to investigate how cognitive crafting promotes well-being in these work groups that may be susceptible to less inherent meaningfulness.

Fourth, future researchers should consider how other types of job crafting (e.g., skill crafting, task crafting, relational crafting) manifest in the context of gig driving. My interviews with gig drivers identified that gig drivers also engage in skill crafting (e.g., Instacart drivers learned new ways to more efficiently collect, organize, and deliver grocery orders), task crafting (e.g., intentionally driving during certain times or in certain locations to maximize profits, managing multiple gig driving apps), and relational crafting (e.g., searching for communities of gig drivers through online platforms like Reddit or Facebook). Conducting additional qualitative and quantitative studies would provide more insight into the various ways in which gig drivers job crafting and how job crafting influences their work experiences. Lastly, future researchers should develop cognitive crafting interventions (and other types of job crafting) to train gig drivers how to more effectively engage in cognitive crafting to reap its benefits.

Conclusion

In conclusion, despite the focus on the negative aspects of working as a gig driver in the extant literature, this dissertation highlights that gig drivers can craft the meaningfulness to their work and can experience positive outcomes in this job. This is the first study, to my knowledge, that examines the influence of cognitive crafting in promoting gig drivers' well-being. This dissertation opens the door for future research to explore how gig drivers can employ meaning-making strategies such as cognitive crafting to productively make sense of both positive and negative customer interactions and enhance their work-related well-being.

APPENDICES

Appendix A

The Hypothesized Model

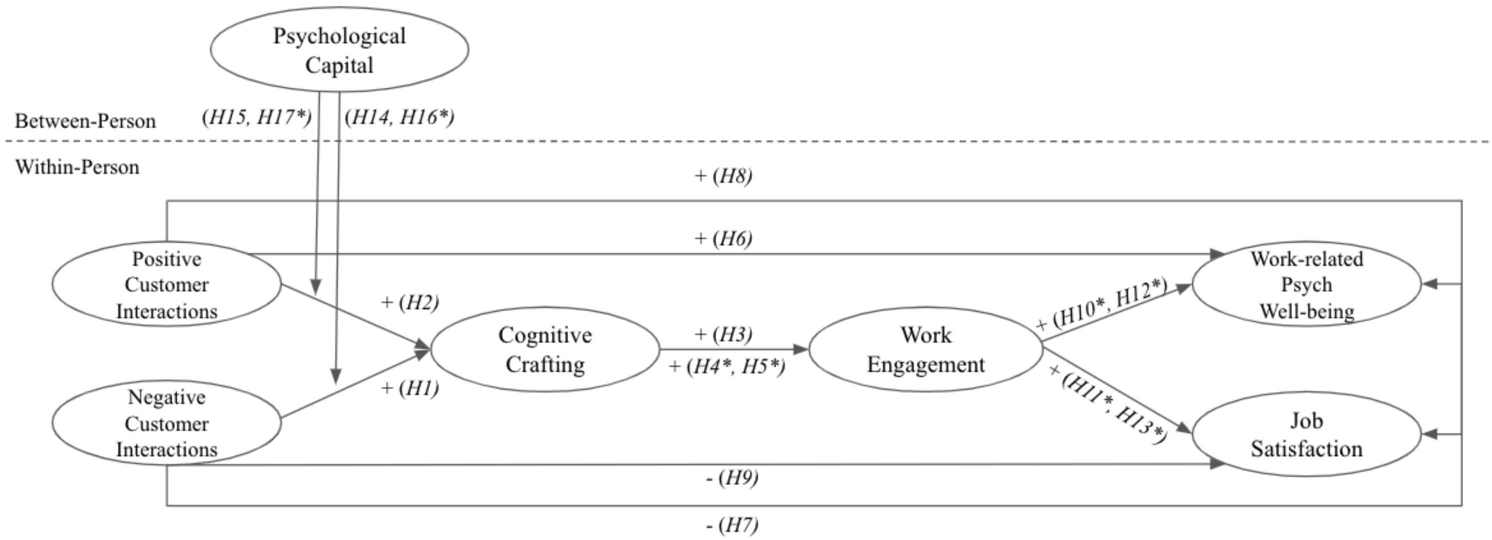


Figure 1. Hypothesized model.

Notes: + = hypothesized positive path, - = hypothesized negative path, * = indirect effect

Appendix B

Measure of Psychological Capital

"Thinking about the last two weeks, please indicate the extent to which you agree or disagree with the following statements."

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

1. If I should find myself in a jam at work, I could think of many ways to get out of it.
2. Right now, I see myself as being pretty successful at work.
3. I can think of many ways to reach my current work goals.
4. At this time, I am meeting the work goals that I have set for myself.
5. I can be "on my own" so to speak, at work if I have to.
6. I usually take stressful things at work in stride.
7. I can get through difficult times at work because I've experienced difficulty before.
8. I always look on the bright side of things regarding my job.
9. I am optimistic about what will happen to me in the future as it pertains to work.

10. I feel like I have the skills and abilities to perform well in my job.

Note: Psychological capital was measured in Wave 1 and Wave 2.

Appendix C

Measure of Positive Interactions with Customers

"The following statements describe situations that may occur in your interaction with customers. Please think over your work today and indicate the frequency that your customers treated you in the following ways during today's work."

0 = Never

1 = A few times

2 = Half of the times

3 = A majority of the time

4 = All the time

1. Provided emotional support to a customer
2. Shared a laugh with a customer
3. Helped a customer
4. A customer was nice to me
5. A customer thanked me
6. Made a difference in a customer's life
7. Shared knowledge with a customer

Note: Positive customer interactions were measured in the daily survey.

Appendix D

Measure of Negative Interactions with Customers

"The following statements describe situations that may occur in your interaction with customers. Please think over your work today and indicate the frequency that your customers treated you in the following ways during today's work."

0 = Never

1 = A few times

2 = Half of the times

3 = A majority of the time

4 = All the time

1. A customer demanded special treatment.
2. A customer did not understand that we have to comply with certain rules.
3. A customer shouted at me.
4. A customer personally attacked me verbally.
5. I had to work with hostile customers.
6. I had to work with unpleasant customers.
7. It was difficult to make arrangements with customers.
8. A customer's instructions complicated my work.

Note: Negative customer interactions were measured in the daily survey.

Appendix E

Measure of Cognitive Crafting – Positive Customer Interactions

"Please indicate the extent to which you agree or disagree with the following statements when thinking about the positive interactions you had with customers today."

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

"When I had positive interactions with customers today, I…"

1. Thought about how my job gives my life purpose.
2. Reminded myself about the significance my work has for the success of the organization.
3. Reminded myself of the importance of my work for the broader community.
4. Thought about the ways in which my work positively impacts my life.
5. Reflected on the role my job has for my overall wellbeing

Note: Cognitive crafting – positive customer interactions – was measured in the daily survey.

Appendix F

Measure of Cognitive Crafting – Negative Customer Interactions

"Please indicate the extent to which you agree or disagree with the following statements when thinking about the negative interactions you had with customers today."

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

"When I had negative interactions with customers today, I…"

1. Thought about how my job gives my life purpose.
2. Reminded myself about the significance my work has for the success of the organization.
3. Reminded myself of the importance of my work for the broader community.
4. Thought about the ways in which my work positively impacts my life.
5. Reflected on the role my job has for my overall wellbeing

Note: Cognitive crafting – negative customer interactions – was measured in the daily survey.

Appendix G

Measure of Work Engagement

"Please indicate how much the following statements applied to your job today."

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

1. I feel bursting with energy.
2. I was enthusiastic about my job.
3. I was immersed in my work.

Note: Work engagement was measured in the daily survey.

Appendix H

Measure of Work-related Psychological Well-being

““Thinking about work today, please indicate the extent to which you agree or disagree with the following statements.”

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

1. I feel positive about myself and the events that happened at work.
2. I had positive and satisfying relations with those at work.
3. Social pressures and the expectations of others made me act and think in certain ways at work.
4. I had difficulty managing my daily affairs and controlling events at work.
5. I did not have a sense of purpose and meaning in my work.
6. My work challenged me and made me grow as a person.

Note: Work-related psychological well-being was measured in the daily survey.

Appendix I

Measure of Job Satisfaction

““Thinking about work today, please indicate the extent to which you are satisfied with your job.”

1 = Extremely dissatisfied

2 = Dissatisfied

3 = Slightly Dissatisfied

4 = Neither Satisfied nor Dissatisfied

5 = Slightly Satisfied

6 = Satisfied

7 = Extremely Satisfied

1. Thinking now about your work today, how satisfied are you with your job?

Note: Job satisfaction was measured in the daily survey.

Appendix J

R Markdown Code

```
---
title: "GPW Dissertation Analyses (Final)"
author: "GPW"
date: "`r Sys.Date()`"
output:
  word_document:
   toc: true
   toc_depth: 3
   number_sections: true
editor_options:
  chunk_output_type: console
---
```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)
```
Loading Packages
```{r}
library(dplyr) # lots of uses
library(mice) # data missingness
library(VIM) # data imputation
```
```

````
library(misty) # item.reverse

library(ggplot2) # ggplot2

library(apaTables) # correlation table

library(bmlm) # centering variables

library(psych) # describe

library(lme4) # for null models and lmer

library(lmerTest) # for null models - not sure if I need this + lme4 but I usually load both

library(nlme) #for lmer

library(effects)  # for plots

library(lavaan) # for mlm

library(correlation) # for multilevel correlation

library(bruceR) # for group mean center check

library(sjPlot) # for plotting models

library(interactions) # for interaction plot

library(jtools) # for summ

```

# Import Data

```{r}

# Import Wave 1 data

wave1 <- read.csv("~/GPW Dissertation/Wave 1 Diss Data (3-22 - final).csv")

wave1 <- wave1[-(60:118),]

View(wave1)
````

dim(wave1) # Should be 59 by 330

Import daily data

daily<- read.csv("~/GPW Dissertation/Daily Diss Data (03-22 - final).csv",

comment.char="#")

View(daily)

dim(daily) # Should be 259 by 103

Rename variables to Participant ID

daily$PartID <- as.factor(daily$RecipientFirstName)

wave1$PartID <- as.factor(wave1$RecipientFirstName)

Survey day as.factor()

daily$Survey.Day <- as.factor(daily$Survey.Day)

dim(wave1) # should be 59 X 331

dim(daily) # should be 259 X 104

```

# Missingness

```{r}

# At least three responses were required for analyses.

```
Check the number of cases with only one response
daily %>%
  group_by(PartID) %>%
  tally() %>%
  filter(n == 1)

Check the number of cases with only two responses
daily %>%
  group_by(PartID) %>%
  tally() %>%
  filter(n == 2)

Remove Participant IDs with < 3 responses
daily_2 <- daily %>%
  filter(!PartID %in% c("91","117","128","24","58","61","159"))

wave1 <- wave1 %>%
  filter(!PartID %in% c("91","117","128","24","58","61","159","109"))

daily_2 %>%
  group_by(PartID) %>%
  tally() %>%
```

```
  filter(n >= 3)

dim(daily_2) # should be 248 X 104
dim(wave1)  # should be 51 X 331

# Combine to check patterns of missingness
checkmiss.d <- select(daily_2,PartID, Platform.Daily,Shift, Day, Survey.Day,
Total.Days, Time.of.Shift, PosInt.Daily_1, PosInt.Daily_2, PosInt.Daily_3,
PosInt.Daily_4, PosInt.Daily_5, PosInt.Daily_6, PosInt.Daily_7,NegInteractions_1,
NegInteractions_2, NegInteractions_3, NegInteractions_4, NegInteractions_5,
NegInteractions_6, NegInteractions_7, NegInteractions_8,
CC_Positive.Daily_1,CC_Positive.Daily_2,CC_Positive.Daily_3,CC_Positive.Daily_4,C
C_Positive.Daily_5,CC_,CC_Negative_1,CC_Negative_2,CC_Negative_4,CC_Negative
_5,CC_Negative_6, WE.Daily_1, WE.Daily_2, WE.Daily_3,Well.being_1,
Well.being_2,Well.being_3,
Well.being_4,Well.being_5,Well.being_6,JobSat.Daily,Meaningfulness.Daily_1,OverallI
nt.Daily_1)
dim(checkmiss.d) # should be 248 by 50

# Check missingness in daily
are.missing.d <- rowSums(is.na(checkmiss.d))
are.missing.d
```

```
checkmiss.d <- cbind.data.frame(checkmiss.d, are.missing.d)
less.miss.d <- as.data.frame(subset(checkmiss.d, are.missing.d<2))
summary(complete.cases(less.miss.d))
dim(less.miss.d) # should be 223 X 51

md.pattern(less.miss.d[,-c(1:7)], rotate.names=T)

daily.miss <- aggr(less.miss.d[,-c(1:7)], col=c(4,"pink"), numbers=T,
        sortVars=TRUE, labels=names(less.miss.d),
        cex.axis=.5, gap=2,
        ylab=c("Proportion of Missingness","Pattern of Missingness"))

# Impute data
daily.impute <- mice(less.miss.d[,-c(1:7)], m=20, maxit=20, seed=9173, print=FALSE)
#removed first flow columns (PartID, Platform.Daily, Shift, Day, Survey.Day)
plot(daily.impute)
sample(1:20, 1, replace=TRUE) # generate random number and update below
daily.impute9<- complete(daily.impute, 9)
daily.impute9 <- cbind(less.miss.d[,1:7], daily.impute9)
dim(daily.impute9) # should be 223 X 51

# Check missingness in wave 1 psychological capital items
```

```
PsyCap.items <- wave1 %>%
dplyr::select(PsyCap_1,PsyCap_2,PsyCap_3,PsyCap_4,PsyCap_5,PsyCap_7,PsyCap_8,P
syCap_9,PsyCap_10,PsyCap_11)

wave1.items <-
dplyr::select(wave1,PartID,PsyCap_1,PsyCap_2,PsyCap_3,PsyCap_4,PsyCap_5,PsyCap
_7,PsyCap_8,PsyCap_9,PsyCap_10,PsyCap_11,EconDependence_1,EconDependence_2,
EconDependence_3,EconDependence_4,EconDependence_5,EconDependence_6,Needfo
rMeaning_1,NeedforMeaning_2,NeedforMeaning_3,Control)

are.missing.w1 <- rowSums(is.na(PsyCap.items))
are.missing.w1
PsyCap.items <- cbind.data.frame(PsyCap.items, are.missing.w1)
less.miss.w1 <- subset(PsyCap.items, are.missing.w1<2)
summary(complete.cases(less.miss.w1))

w1.miss <- aggr(less.miss.w1, col=c(4,"pink"), numbers=T,
        sortVars=TRUE, labels=names(less.miss.w1),
        cex.axis=.5, gap=2,
        ylab=c("Proportion of Missingness","Pattern of Missingness"))
```

```
w1.impute <- mice(less.miss.w1.all, m=20, maxit=20, seed=9173, print=FALSE)

plot(w1.impute)

w1.impute$method

plot(w1.impute)

w1.impute4 <- complete(w1.impute, 4)


# Check the dissertation items


# PsyCap

PsyCap.items <- as.data.frame(apply(PsyCap.items, 2, as.numeric))

PsyCap.all <- apply(PsyCap.items, MARGIN = 1, sum)

sjPlot::tab_itemscale(PsyCap.items)


# EconDep

EconDep.items <- w1.impute4 %>%

dplyr::select(EconDependence_1,EconDependence_2,EconDependence_3,EconDepende
nce_4,EconDependence_5,EconDependence_6)

EconDep.items  <- as.data.frame(apply(EconDep.items , 2, as.numeric))

EconDep.all <- apply(EconDep.items, MARGIN = 1, sum)

sjPlot::tab_itemscale(EconDep.items)


# Need for meaning
```

```
NFM.items <- w1.impute4 %>%
  dplyr::select(NeedforMeaning_1,NeedforMeaning_2,NeedforMeaning_3)
NFM.items  <- as.data.frame(apply(NFM.items , 2, as.numeric))
NFM.all <- apply(NFM.items, MARGIN = 1, sum)
sjPlot::tab_itemscale(NFM.items)

# Positive Interactions (daily)
PosInt.d.items <- daily.impute9 %>%
  dplyr::select(PosInt.Daily_1, PosInt.Daily_2, PosInt.Daily_3, PosInt.Daily_4,
PosInt.Daily_5, PosInt.Daily_6, PosInt.Daily_7)
PosInt.d.items <- as.data.frame(apply(PosInt.d.items, 2, as.numeric))
PosInt.d.all <- apply(PosInt.d.items, MARGIN = 1, sum)
sjPlot::tab_itemscale(PosInt.d.items)

# Negative Interactions (daily)
NegInt.d.items <- daily.impute9 %>%
  dplyr::select(NegInteractions_1, NegInteractions_2, NegInteractions_3,
NegInteractions_4, NegInteractions_5, NegInteractions_6, NegInteractions_7,
NegInteractions_8)
NegInt.d.items <- as.data.frame(apply(NegInt.d.items, 2, as.numeric))
NegInt.d.all <- apply(NegInt.d.items, MARGIN = 1, sum)
sjPlot::tab_itemscale(NegInt.d.items)
```

```
# Cognitive Crafting (pos - daily)
CC.Pos.d.items <- daily.impute9 %>%

dplyr::select(CC_Positive.Daily_1,CC_Positive.Daily_2,CC_Positive.Daily_3,CC_Positi
ve.Daily_4,CC_Positive.Daily_5)
CC.Pos.d.items <- as.data.frame(apply(CC.Pos.d.items, 2, as.numeric))
CC.Pos.d.all <- apply(CC.Pos.d.items, MARGIN = 1, sum)
sjPlot::tab_itemscale(CC.Pos.d.items)

# Cognitive Crafting (neg - daily)
CC.Neg.d.items <- daily.impute9 %>%

dplyr::select(CC_Negative_1,CC_Negative_2,CC_Negative_4,CC_Negative_5,CC_Nega
tive_6)
CC.Neg.d.items <- as.data.frame(apply(CC.Neg.d.items, 2, as.numeric))
CC.Neg.d.all <- apply(CC.Neg.d.items, MARGIN = 1, sum)
sjPlot::tab_itemscale(CC.Neg.d.items)

# Work Engagement (daily)
WE.d.items <- daily.impute9 %>%
  dplyr::select(WE.Daily_1, WE.Daily_2, WE.Daily_3)
```

````
WE.d.items <- as.data.frame(apply(WE.d.items, 2, as.numeric))

WE.d.all <- apply(WE.d.items, MARGIN = 1, sum)

sjPlot::tab_itemscale(WE.d.items)


# Wellbeing (daily)

Wellbeing.d.items <- daily.impute9 %>%

  dplyr::select(Well.being_1, Well.being_2,Well.being_3,

Well.being_4,Well.being_5,Well.being_6)

Wellbeing.d.items <- as.data.frame(apply(Wellbeing.d.items, 2, as.numeric))

wellbeing.d.all <- apply(Wellbeing.d.items, MARGIN = 1, sum)

sjPlot::tab_itemscale(Wellbeing.d.items)


# Job Satisfaction (daily)

JobSat.d.item <- daily.impute9$JobSat.Daily


```

# Sample Demographics


```{r}

# Analyze demographic variables. Most of these variables were captured in the Wave 1

data, except for the average daily shift length and frequency of day of week
````

```
# Age
describe(wave1$Age)


# Gender
## 1 = female, 2 = male, 3 = non-binary/third gender, 4 = prefer not to say, 5 = other
table(wave1$Gender)
prop.table(table(wave1$Gender))


# Race/Ethnicity
## 1 = American Indian or Alaskan Native, 2 = Asian, 3 = Black or African American, 4
= Native Hawaiin or other Pacific Islander, 5 = White, 6 = Hispanic, 7 = Prefer not to
say, 8 = other
table(wave1$Race.Ethnicity)
prop.table(table(wave1$Race.Ethnicity))


# Education
## 1 = did not finish high school, 2 = high school diploma or GED, 3 = 2 year college, 4
= 4 year college, 5 = Master's degree, 6 = PhD or other advanced professional degree
table(wave1$Education)
prop.table(table(wave1$Education))


# Current Student
```

```
## 1 = high school, 2 = college (undergrad), 3 = graduate school, 4 = I am not in school
table(wave1$School)
prop.table(table(wave1$School))

# Household Income
## 5 = 50,000-59,999, 6 = $60,000-69,999
describe(wave1$Income)
summary(wave1$Income) # 8  = $80,000-89,999
table(wave1$Income)
prop.table(table(wave1$Income))

# Gig Driving of Income % of Household
describe(wave1$Income._1)

# Average Hours
wave1$AvgHours <- (wave1$Hours_1 + wave1$Hours_2)/2
describe(wave1$AvgHours)

# Tenure
describe(wave1$Tenure)

# Days per Week
```

```
describe(wave1$Days.Per.Week)
table(wave1$Days.Per.Week)
prop.table(table(wave1$Days.Per.Week))

# Time of Week (1 = weekdays only, 2 = weekends only, 3 = both)
table(wave1$Weekday)
prop.table(table(wave1$Weekday))

# Gig Driving Type (1 = Food delivery, 2 = Amazon flex, 3 = Ride-hailing, 4 = Other)
table(wave1$Driving.Type)
prop.table(table(wave1$Driving.Type))

# Voluntary (0 = I can stop anytime I want, 10 = I could NOT stop even if I wanted to)
describe(wave1$Voluntary_1)
summary(wave1$Voluntary_1)
table(wave1$Voluntary_1)
prop.table(table(wave1$Voluntary_1))

# Reasons for working as a gig driver
describe(wave1$Reason_1) # financial dependence
describe(wave1$Reason_2) # flexibility
describe(wave1$Reason_3) # between jobs
```

```
describe(wave1$Reason_4) # lucrative

describe(wave1$Reason_5) # passion

describe(wave1$Reason_6) # independence

describe(wave1$Reason_7) # career

describe(wave1$Reason_8) # casual spending money

describe(wave1$Reason_9) # lack of qualifications

describe(wave1$Reason_10) # disability

describe(wave1$Reason_11) # only option

describe(wave1$Reason_12) # other


# Non-Gig Driving Job

## 1 = no, 2 = yes

table(wave1$Non.Gig.Jobs)

prop.table(table(wave1$Non.Gig.Jobs))


# Daily Shift Lengths

describe(daily_2$Shift)


# Daily Days

table(daily_2$Day)

prop.table(table(daily_2$Day))
```

````
# Daily shift time

table(daily_2$Time.of.Shift)

prop.table(table(daily_2$Time.of.Shift))

```


# Create Scales

```{r}

# Create scales for dissertation variables.

## Psychological capital in the Wave 1 data.


wave1 <- wave1 %>%

  mutate(PsyCap = (PsyCap_1 + PsyCap_2 + PsyCap_3 + PsyCap_4 + PsyCap_5 +

PsyCap_7 + PsyCap_8 + PsyCap_9 + PsyCap_10 + PsyCap_11)/10)


dim(wave1) # Should be 51 by 333


## Reverse code needed items

daily.impute9$Well.being_3.R <- item.reverse(daily.impute9$Well.being_3, min = 1,

max = 7)

daily.impute9$Well.being_4.R <- item.reverse(daily.impute9$Well.being_4, min = 1,

max = 7)
````

```
daily.impute9$Well.being_5.R <- item.reverse(daily.impute9$Well.being_5, min = 1,
max = 7)

dim(daily.impute9) # Should be 223 by 54

## Positive interactions, negative interactions, cognitive crafting (pos), cognitive crafting
(neg), work engagement, psychological well-being, and job satisfaction in the daily data.

daily.impute9 <- daily.impute9 %>%
  mutate(PosInt.d = (PosInt.Daily_1 + PosInt.Daily_2 +  PosInt.Daily_3 + PosInt.Daily_4
+ PosInt.Daily_5 + PosInt.Daily_6 + PosInt.Daily_7)/7,
        CC.Pos.d = (CC_Positive.Daily_1 + CC_Positive.Daily_2 + CC_Positive.Daily_3 +
CC_Positive.Daily_4 + CC_Positive.Daily_5) /5,
        Wellbeing.d = (Well.being_1 +
Well.being_2 +Well.being_3.R + Well.being_4.R + Well.being_5.R +Well.being_6)/6,
       NegInt.d = (NegInteractions_1 +  NegInteractions_2 + NegInteractions_3 +
NegInteractions_4 + NegInteractions_5 + NegInteractions_6 + NegInteractions_7 +
NegInteractions_8)/8,
       CC.Neg.d = (CC_Negative_1 +  CC_Negative_2 + CC_Negative_4 +
CC_Negative_5 + CC_Negative_6 /5,
       WE.d = (WE.Daily_1 + WE.Daily_2 + WE.Daily_3)/3,
       JobSat.d = (JobSat.Daily))
```

````
daily.impute9 <- daily.impute9 %>%
  mutate(PosInt.sum = (PosInt.Daily_1 +  PosInt.Daily_2 + PosInt.Daily_3 +
PosInt.Daily_4 + PosInt.Daily_5 + PosInt.Daily_6 + PosInt.Daily_7),
         NegInt.sum = (NegInteractions_1 + NegInteractions_2 + NegInteractions_3 +
NegInteractions_4 + NegInteractions_5 + NegInteractions_6 + NegInteractions_7 +
NegInteractions_8))

dim(daily.impute9) # should be 223 by 63
```
# Scale Descriptives
```{r}

describe(wave1$PsyCap)
describe(daily.impute9$PosInt.d)
describe(daily.impute9$NegInt.d)
describe(daily.impute9$CC.Pos.d)
describe(daily.impute9$CC.Neg.d)
describe(daily.impute9$WE.d)
describe(daily.impute9$Wellbeing.d)
describe(daily.impute9$JobSat.d)
describe(daily.impute9$PosInt.sum)
````

```
describe(daily.impute9$NegInt.sum)



ggplot(data=wave1, aes(x=PsyCap)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Psychological Capital")

ggplot(data=daily.impute9, aes(x=PosInt.sum)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Positive Interactions (daily)")

ggplot(data=daily.impute9, aes(x=NegInt.sum)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Negative Interactions (daily)")

ggplot(data=daily.impute9, aes(x=PosInt.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Positive Interactions (avg daily)")

ggplot(data=daily.impute9, aes(x=NegInt.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Negative Interactions (avg daily)")
```

```
ggplot(data=daily.impute9, aes(x=CC.Pos.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Cognitive Crafting (pos - daily)")

ggplot(data=daily.impute9, aes(x=CC.Neg.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Cognitive Crafting (neg - daily)")

ggplot(data=daily.impute9, aes(x=WE.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Work Engagement (daily)")

ggplot(data=daily.impute9, aes(x= Wellbeing.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Psychological Wellbeing (daily)")

ggplot(data=daily.impute9, aes(x=JobSat.d)) +
  geom_histogram(fill="white", color="black",bins=10) +
  labs(x = "Job Satisfaction (daily)")
```

~~~
# seems to be some skewed data (e.g., positive skew in daily negative interactions) but
can use the MLR estimator in my multilevel mediation model to account for non-normal
data.
```
# Create Dissertation File


```{r}
# Dissertation variables from Wave 1
diss.wave1 <- select(wave1, PartID, PsyCap, Age, Gender, Race.Ethnicity, Education,
School, Voluntary_1, Driving.Type,)


# Dissertation variables from Daily
diss.daily <- select(daily.impute9, PartID, PosInt.d, PosInt.sum, NegInt.d, NegInt.sum,
CC.Pos.d, CC.Neg.d, WE.d, Wellbeing.d, JobSat.d, Platform.Daily,
Meaningfulness.Daily_1, OverallInt.Daily_1,Shift, Day, Survey.Day, Shift,Time.of.Shift)


# Merge files with scales needed for dissertation analyses
## What happens to participant IDs in wave 1 that do not have cases in daily
diss.data <- merge(diss.wave1, diss.daily, by="PartID")
dim(diss.data) # Should be 223 by 25
View(diss.data)
~~~

diss.all <- merge(wave1, daily.impute9, by="PartID")

diss.data2 <- merge(w1.impute4,diss.daily, by="PartID")

```

# Center Variables

```{r}

# Person-center level 1 variables

diss.data <- isolate(diss.data, by = "PartID",

                    value = c("PosInt.sum", "NegInt.sum",

"PosInt.d","NegInt.d","CC.Pos.d","CC.Neg.d","WE.d"), which = "within")

diss.data <- isolate(diss.data, by = "PartID",

                    value = c("Wellbeing.d","JobSat.d"), which = "within")

centered <- group_mean_center(diss.data, c("PosInt.sum", "NegInt.sum",

"PosInt.d","NegInt.d","CC.Pos.d","CC.Neg.d","WE.d"), by ="PartID",

add.suffix="_centered2")

View(diss.data)

View(centered)

# Grand mean center level 2 variable

diss.data <- isolate(diss.data, by = "PartID", value = c("PsyCap"), which = "between")

````
diss.data <- isolate(diss.data, by = "PartID", value = c("CC.Pos.d","CC.Neg.d"), which = "between") # not sure if I need this but added for one of my full model attempts

# Spot check centered variables
head(dplyr::select(diss.data, PartID, PsyCap_cb, CC.Pos.d_cw, WE.d_cw, CC.Pos.d_cb))

dim(diss.data) # Should be X by 35 (may be less if remove the CC.Pos.d and CC.Neg.d between)
```
# Correlations
```{r}

# Create APA formatted correlation matrix with level 1 variables (within-person centered)

diss.correlations <- diss.data %>%
  dplyr::select(PosInt.sum_cw, NegInt.sum_cw, CC.Pos.d_cw, CC.Neg.d_cw, WE.d_cw, Wellbeing.d_cw, JobSat.d_cw)

apa.cor.table(diss.correlations, filename="Dissertation Correlation Table.doc")
````

```
# exact p values
corr.test(select(diss.data,PosInt.sum_cw, NegInt.sum_cw, CC.Pos.d_cw, CC.Neg.d_cw,
WE.d_cw, Wellbeing.d_cw, JobSat.d_cw))

## aggregate level 1 to level 2 for correlations with psycap
agg <-
aggregate(diss.data[,(which(colnames(diss.data)=="PosInt.sum")):(which(colnames(diss.
data)=="JobSat.d"))],list(diss.data$PartID),mean)
View(agg)
agg$PartID <- agg$Group.1
agg2 <- merge(wave1,agg,by="PartID")

diss.correlations5 <- agg2 %>%
  dplyr::select(PosInt.sum, NegInt.sum, CC.Pos.d, CC.Neg.d, WE.d, Wellbeing.d,
JobSat.d, PsyCap)

apa.cor.table(diss.correlations5)

# exact p values
corr.test(select(agg2,PosInt.sum, NegInt.sum, CC.Pos.d, CC.Neg.d, WE.d, Wellbeing.d,
JobSat.d, PsyCap))
```

~~~~
# ICCs
## Confirm that within-person variability justifies multilevel analyses
```{r}
library(multilevel) # for ICCs - disables select() function in dplyr - not sure if there is a fix for this so I wait to load this package when it is necessary

# Calculate ICC1 and ICC2

# Daily positive customer interactions
multilevel.icc(diss.data$PosInt.sum, cluster = diss.data$PartID,type=1)
multilevel.icc(diss.data$PosInt.sum, cluster = as.numeric(diss.data$PartID),type=2)

PosInt.fit0 <- lme(PosInt.sum ~ 1, random = ~1|PartID,
                   data=diss.data,
                   na.action=na.exclude)
summary(PosInt.fit0)
VarCorr(PosInt.fit0) # double checked that the ICC1s using int/(resid+int) as the multilevel.icc function

# Daily negative customer interactions
multilevel.icc(diss.data$NegInt.sum, cluster = diss.data$PartID,type=1)
~~~~

```
multilevel.icc(diss.data$NegInt.sum, cluster = as.numeric(diss.data$PartID),type=2)

NegInt.fit0 <- lme(NegInt.sum ~ 1, random = ~1|PartID,
                   data=diss.data,
                   na.action=na.exclude)
summary(NegInt.fit0)
VarCorr(NegInt.fit0) # double checked that the ICC1s using int/(resid+int) as the
multilevel.icc function

# Daily cognitive crafting (positive)
multilevel.icc(diss.data$CC.Pos.d, cluster = diss.data$PartID,type=1)
multilevel.icc(diss.data$CC.Pos.d, cluster = as.numeric(diss.data$PartID),type=2)

CC.Pos.fit0 <- lme(CC.Pos.d ~ 1, random = ~1|PartID,
                   data=diss.data,
                   na.action=na.exclude)
summary(CC.Pos.fit0)
VarCorr(CC.Pos.fit0) # double checked that the ICC1s using int/(resid+int) as the
multilevel.icc function

# Daily cognitive crafting (negative)
multilevel.icc(diss.data$CC.Neg.d, cluster = diss.data$PartID,type=1)
```

```
multilevel.icc(diss.data$CC.Neg.d, cluster = as.numeric(diss.data$PartID),type=2)


CC.Neg.fit0 <- lme(CC.Neg.d ~ 1, random = ~1|PartID,
                   data=diss.data,
                   na.action=na.exclude)
summary(CC.Neg.fit0)
VarCorr(CC.Neg.fit0)


# Daily work engagement
multilevel.icc(diss.data$WE.d, cluster = diss.data$PartID,type=1)
multilevel.icc(diss.data$WE.d, cluster = as.numeric(diss.data$PartID),type=2)


WE.fit0 <- lme(WE.d ~ 1, random = ~1|PartID,
               data=diss.data,
               na.action=na.exclude)
summary(WE.fit0)
VarCorr(WE.fit0)


# Daily psychological well-being
multilevel.icc(diss.data$Wellbeing.d, cluster = diss.data$PartID,type=1)
multilevel.icc(diss.data$Wellbeing.d, cluster = as.numeric(diss.data$PartID),type=2)
```

````
Wellbeing.fit0 <- lme(Wellbeing.d ~ 1, random = ~1|PartID,
                 data=diss.data,
                 na.action=na.exclude)
summary(Wellbeing.fit0)
VarCorr(Wellbeing.fit0)


# Daily job satisfaction
multilevel.icc(diss.data$JobSat.d, cluster = diss.data$PartID,type=1)
multilevel.icc(diss.data$JobSat.d, cluster = as.numeric(diss.data$PartID),type=2)


JobSat.fit0 <- lme(JobSat.d ~ 1, random = ~1|PartID,
                 data=diss.data,
                 na.action=na.exclude)
summary(JobSat.fit0)
VarCorr(JobSat.fit0)
```
# One-Way Random Effects ANOVAs
```{r}
# Daily cognitive crafting (positive)
null.aov.CCPos.d <- aov(CC.Pos.d ~ PartID, diss.data)
summary(null.aov.CCPos.d)
````

```
# Daily cognitive crafting (negative)
null.aov.CCNeg.d <- aov(CC.Neg.d ~ PartID, diss.data)
summary(null.aov.CCNeg.d)

# Daily work engagement
null.aov.WE.d <- aov(WE.d ~ PartID, diss.data)
summary(null.aov.WE.d)

# Daily psychological well-being
null.aov.Wellbeing.d <- aov(Wellbeing.d ~ PartID, diss.data)
summary(null.aov.Wellbeing.d)
ICC2(null.aov.Wellbeing.d) # double check consistency with ICC2s calculated in last
block

# Daily job satisfaction
null.aov.JobSat.d <- aov(JobSat.d ~ PartID, diss.data)
summary(null.aov.JobSat.d)
ICC2(null.aov.JobSat.d) # double check consistency with ICC2s calculated in last block

## Compare nested models

# Daily cognitive crafting (positive)
```

````
int.mod.CCpos <- gls(CC.Pos.d ~ 1, diss.data)

anova(int.mod.CCpos, null.aov.CCPos.d)


# Daily cognitive crafting (negative)

int.mod.CCneg <- gls(CC.Neg.d ~ 1, diss.data)

anova(int.mod.CCneg, null.aov.CCNeg.d)


# Daily work engagement

int.mod.WE <- gls(WE.d ~ 1, diss.data)

anova(int.mod.WE, null.aov.WE.d)


# Daily psychological well-being

int.mod.Wellbeing <- gls(Wellbeing.d ~ 1, diss.data)

anova(int.mod.Wellbeing,null.aov.Wellbeing.d)


# Daily job satisfaction

int.mod.JobSat <- gls(JobSat.d ~ 1, diss.data)

anova(int.mod.JobSat, null.aov.JobSat.d)

```

# Add in Survey.Day

```{r}

# lme fit models
````

```
# Daily cognitive crafting (positive)
lmefit.CCpos <- lme(CC.Pos.d ~ Survey.Day, random = ~1|PartID,
                    data = diss.data,
                    na.action = na.omit)
summary(lmefit.CCpos)
anova(lmefit.CCpos)


# Daily cognitive crafting (negative)
lmefit.CCneg <- lme(CC.Neg.d ~ Survey.Day, random = ~1|PartID,
                    data = diss.data,
                    na.action = na.omit)
summary(lmefit.CCneg)
anova(lmefit.CCneg)


# Daily work engagement
lmefit.WE <- lme(WE.d ~ Survey.Day, random = ~1|PartID,
                    data = diss.data,
                    na.action = na.omit)
summary(lmefit.WE)
anova(lmefit.WE)
```

```
# Daily psychological well-being
lmefit.Wellbeing <- lme(Wellbeing.d ~ Survey.Day, random = ~1|PartID,
                        data = diss.data,
                        na.action = na.omit)
summary(lmefit.Wellbeing)
anova(lmefit.Wellbeing)

# Daily job satisfaction
lmefit.JobSat <- lme(JobSat.d ~ Survey.Day, random = ~1|PartID,
                     data = diss.data,
                     na.action = na.omit)
summary(lmefit.JobSat)
anova(lmefit.JobSat)

# Plot effects
# Daily positive customer interactions
plot(predictorEffects(lmefit.CCpos, ~Survey.Day),
     xlab = "Day",
     ylab = "Cognitive Crafting (positive interaction)",
     main = "Cognitive Crafting (positive interaction) over Time")

plot(lmefit.CCpos, PartID ~ resid(.), abline = 0)
```

```
# Daily cognitive crafting (positive)
plot(predictorEffects(lmefit.CCpos, ~Survey.Day),
    xlab = "Day",
    ylab = "Cognitive Crafting (positive interaction)",
    main = "Cognitive Crafting (positive interaction) over Time")

plot(lmefit.CCpos, PartID ~ resid(.), abline = 0)

# Daily cognitive crafting (negative)
plot(predictorEffects(lmefit.CCneg, ~Survey.Day),
    xlab = "Day",
    ylab = "Cognitive Crafting (negative interactions)",
    main = "Cognitive Crafting (negative interactions) over Time")

plot(lmefit.CCneg, PartID ~ resid(.), abline = 0)

# Daily work engagement
plot(predictorEffects(lmefit.WE, ~Survey.Day),
    xlab = "Day",
    ylab = "Work Engagement",
    main = "Work Engagement over Time")
```

~~~
plot(lmefit.WE, PartID ~ resid(.), abline = 0)

# Daily psychological well-being
plot(predictorEffects(lmefit.Wellbeing, ~Survey.Day),
    xlab = "Day",
    ylab = "Wellbeing",
    main = "Wellbeing over Time")

plot(lmefit.Wellbeing, PartID ~ resid(.), abline = 0)

# Daily job satisfaction
plot(predictorEffects(lmefit.JobSat, ~Survey.Day),
    xlab = "Day",
    ylab = "Job Satisfaction",
    main = "Job Satisfaction over Time")

plot(lmefit.JobSat, PartID ~ resid(.), abline = 0)
```
# Within-Person Multilevel Path Analysis
## Hypothesis Testing
```{r}
~~~

```
## Within-person path analysis when accounting for cluster="PartID"
## Does not account for covariates – not the hypothesized model yet
model_within1 <- '
  # Direct effects
  Wellbeing.d ~ c1*PosInt.sum_cw + c2*NegInt.sum_cw
  JobSat.d ~ c3*PosInt.sum_cw + c4*NegInt.sum_cw

  # Indirect effects
  CC.Pos.d_cw ~ a11*PosInt.sum_cw
  CC.Neg.d_cw ~ a22*NegInt.sum_cw
  WE.d_cw ~ b11*CC.Pos.d_cw + b12*CC.Neg.d_cw
  Wellbeing.d ~ b2*WE.d_cw
  JobSat.d ~ b4*WE.d_cw

  # Residual variances
  Wellbeing.d ~~ e1*Wellbeing.d
  JobSat.d ~~ e2*JobSat.d
  Wellbeing.d ~~ e3*JobSat.d
  CC.Pos.d_cw ~~ e4*CC.Neg.d_cw + e5*WE.d_cw
  CC.Neg.d_cw ~~ e6*WE.d_cw
```

```
 # Indirect effects Results
 indirect1 := a11*b11
 indirect2 := a22*b12
 indirect3 := a11*b11*b2
 indirect4 := a11*b11*b4
 indirect5 := a22*b12*b2
 indirect6 := a22*b12*b4
 '

#CFA
model.cfa1 <- cfa(model_within1, estimator = "MLR", data=diss.data, cluster="PartID")
summary(model.cfa1, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.cfa1, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr"))
modificationindices(model.cfa1,sort=TRUE)

#Path analysis
model.pa <- sem(model_within1, estimator = "MLR", data=diss.data, cluster = "PartID")
summary(model.pa, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr"))

# add covariates
## Testing the hypothesized model (model_within1c)
```

```
model_within1c <- '
  # Direct effects
  Wellbeing.d ~ c1*PosInt.sum_cw + c2*NegInt.sum_cw + cv1*Shift + cv2*Day +
cv5*Time.of.Shift
  JobSat.d ~ c3*PosInt.sum_cw + c4*NegInt.sum_cw + cv3*Shift + cv4*Day +
c6*Time.of.Shift

  # Indirect effects
  CC.Pos.d_cw ~ a11*PosInt.sum_cw + av1*Shift + av2*Day + av5*Time.of.Shift
  CC.Neg.d_cw ~ a22*NegInt.sum_cw + av3*Shift + av4*Day + av6*Time.of.Shift
  WE.d_cw ~ b11*CC.Pos.d_cw + b12*CC.Neg.d_cw + bv1*Shift + bv2*Day +
av7*Time.of.Shift
  Wellbeing.d ~ b2*WE.d_cw
  JobSat.d ~ b4*WE.d_cw

  # Residual variances
  Wellbeing.d ~~ e1*Wellbeing.d
  JobSat.d ~~ e2*JobSat.d
  Wellbeing.d ~~ e3*JobSat.d
  CC.Pos.d_cw ~~ e4*CC.Neg.d_cw

  # Indirect effects Results
```

```
  indirect1 := a11*b11
  indirect2 := a22*b12
  indirect3 := a11*b11*b2
  indirect4 := a11*b11*b4
  indirect5 := a22*b12*b2
  indirect6 := a22*b12*b4
  '

#CFA
model.cfa1c <- cfa(model_within1c, estimator = "MLR", data=diss.data,
cluster="PartID")
summary(model.cfa1c, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.cfa1c, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr",'bic'))
modificationindices(model.cfa1c,sort=TRUE)

#Path analysis
model.pac <- sem(model_within1c, estimator = "MLR", data=diss.data, cluster =
"PartID")
summary(model.pac, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pac, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr"))
## The results for model.pac correspond with Hypotheses 1-13 of my dissertation
```

````
# PsyCap as Continuous Moderator
## Hypotheses 14 and 15
```{r}
library(tidyverse) # for interaction plot – load when needed because masks other functions

# PsyCap moderating the path from daily negative customer interactions to daily cognitive crafting
## Hypthesis 14
mod.Neg <- lmer(CC.Neg.d ~ NegInt.sum_cw + PsyCap_cb +
NegInt.sum_cw:PsyCap_cb + Day + Time.of.Shift + Shift + (1|PartID), data = diss.data)
summary(mod.Neg)
summ(mod.Neg)
plot_model(mod.Neg, type = "pred", terms = c("NegInt.sum_cw", "PsyCap_cb"))
interact_plot(mod.Neg,
        pred = NegInt.sum_cw,
        modx = PsyCap_cb,
        modx.values = "plus-minus",
        x.label = "Daily Negative Customer Interactions",
        y.label = "Daily Cognitive Crafting",
        modx.labels = c("Low Psychological Capital", "High Psychological Capital")
        ) +
````
````

```
  ylim(0,7)
sim_slopes(mod.Neg, pred = NegInt.sum_cw, modx = PsyCap_cb)
johnson_neyman(mod.Neg, pred = NegInt.sum_cw, modx = PsyCap_cb, alpha = .05)

# PsyCap moderating the path from daily positive customer interactions to daily cognitive
crafting
## Hypothesis 15
mod.Pos <- lmer(CC.Pos.d ~ PosInt.sum_cw + PsyCap_cb + PosInt.sum_cw:PsyCap_cb
+ Day + Time.of.Shift + Shift + (1|PartID), data = diss.data)
summary(mod.Pos)
summ(mod.Pos)
plot_model(mod.Pos, type = "pred", terms = c("PosInt.sum_cw", "PsyCap_cb"))
interact_plot(mod.Pos,
        pred = PosInt.sum_cw,
        modx = PsyCap_cb,
        modx.values = "plus-minus",
        x.label = "Daily Positive Customer Interactions",
        y.label = "Daily Cognitive Crafting",
        modx.labels = c("Low Psychological Capital", "High Psychological Capital")
        ) +
  ylim(0,7)
sim_slopes(mod.Pos, pred = PosInt.sum_cw, modx = PsyCap_cb)
```

johnson_neyman(mod.Pos, pred = PosInt.sum_cw, modx = PsyCap_cb, alpha = .05)

```

# Multi-group Path Analysis (Moderation)

## Hypotheses 15 and 16

```{r}

## model_group accounts for cluster="PartID" and for group="PsyCap" for multi-group comparison

## create grouping variable for PsyCap

describe(diss.data$PsyCap) # median = 5

diss.data <- diss.data %>%

  mutate(Group.Psycap.med = case_when(PsyCap >= 5 ~ "High",

                                      PsyCap < 5 ~ "Low"))

## median split model

model_group.med <- '

  # Direct effects

  Wellbeing.d ~ c("c1a","c1b")*PosInt.sum_cw + c("c2a","c2b")*NegInt.sum_cw + c("cv1a","cv1b")*Shift + c("cv2a","cv2b")*Day + c("cv5a","cv5b")*Time.of.Shift

  JobSat.d ~ c("c3a","c3b")*PosInt.sum_cw + c("c4a","c4b")*NegInt.sum_cw + c("cv3a","cv3b")*Shift + c("cv4a","cv4b")*Day + c("cv6a","cv6b")*Time.of.Shift

```
# Indirect effects
CC.Pos.d_cw ~ c("a11a","a11b")*PosInt.sum_cw + c("av1a","av1b")*Shift +
c("av2a","av2b")*Day + c("av5a","av5b")*Time.of.Shift
CC.Neg.d_cw ~ c("a22a","a22b")*NegInt.sum_cw + c("av3a","av3b")*Shift +
c("av4a","av4b")*Day + c("av6a","av6b")*Time.of.Shift
WE.d_cw ~ c("b11a","b11b")*CC.Pos.d_cw + c("b12a","b12b")*CC.Neg.d_cw +
c("bv1a","bv1b")*Shift + c("bv2a","bv2b")*Day + c("av7a","av7b")*Time.of.Shift
Wellbeing.d ~ c("b2a","b2b")*WE.d_cw
JobSat.d ~ c("b4a","b4b")*WE.d_cw

# Residual variances
Wellbeing.d ~~ c("e1a","e1b")*Wellbeing.d
JobSat.d ~~ c("e2a","e2b")*JobSat.d
Wellbeing.d ~~ c("e3a","e3b")*JobSat.d
CC.Pos.d_cw ~~ c("e4a","e4b")*CC.Neg.d_cw + c("e5a","e5b")*WE.d_cw
CC.Neg.d_cw ~~ c("e6a","e6b")*WE.d_cw

# Indirect effects Results
indirect1a := a11a*b11a
indirect2a := a22a*b12a
indirect3a := a11a*b11a*b2a
```

```
 indirect4a := a11a*b11a*b4a
 indirect5a := a22a*b12a*b2a
 indirect6a := a22a*b12a*b4a

 indirect1b := a11b*b11b
 indirect2b := a22b*b12b
 indirect3b := a11b*b11b*b2b
 indirect4b := a11b*b11b*b4b
 indirect5b := a22b*b12b*b2b
 indirect6b := a22b*b12b*b4b
 '

#CFA free
model.cfa2m <- cfa(model_group.med, estimator = "MLR", data=diss.data,
cluster="PartID",group = "Group.Psycap.med", fixed.x=TRUE)
summary(model.cfa2m, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.cfa2m, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

#Path analysis free
model.pa2m <- sem(model_group.med, estimator = "MLR", data=diss.data, cluster =
"PartID", group = "Group.Psycap.med")
summary(model.pa2m, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
```

~~~
fitmeasures(model.pa2m, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))


#Path analysis constrained
model.pa3m <- sem(model_group.med, estimator = "MLR", data=diss.data, cluster =
"PartID", group = "Group.Psycap.med", group.equal = c("intercepts", "regressions"))
summary(model.pa3m, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa3m, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))


anova(model.pa2m,model.pa3m)
```
# Supplemental analyses – Economic Dependence
```{r}
# Multi-group Path Analysis (Moderation - Economic Dependence)


## model_group accounts for cluster="PartID" and for group="EconDep" for multi-group
comparison


## create grouping variable for Econ
describe(diss.data2$EconDep) #median = 4.83
diss.data2 <- diss.data2 %>%
  mutate(Group.EconDep.med = case_when(EconDep >= 4.83 ~ "High",
                                       EconDep < 4.83 ~ "Low"))
~~~

```
### median split model

model_group.med.econdep<- '

  # Direct effects

  Wellbeing.d ~ c("c1a","c1b")*PosInt.sum_cw + c("c2a","c2b")*NegInt.sum_cw +
c("cv1a","cv1b")*Shift + c("cv2a","cv2b")*Day + c("cv5a","cv5b")*Time.of.Shift

  JobSat.d ~ c("c3a","c3b")*PosInt.sum_cw + c("c4a","c4b")*NegInt.sum_cw +
c("cv3a","cv3b")*Shift + c("cv4a","cv4b")*Day + c("cv6a","cv6b")*Time.of.Shift


  # Indirect effects

  CC.Pos.d_cw ~ c("a11a","a11b")*PosInt.sum_cw + c("av1a","av1b")*Shift +
c("av2a","av2b")*Day + c("av5a","av5b")*Time.of.Shift

  CC.Neg.d_cw ~ c("a22a","a22b")*NegInt.sum_cw + c("av3a","av3b")*Shift +
c("av4a","av4b")*Day + c("av6a","av6b")*Time.of.Shift

  WE.d_cw ~ c("b11a","b11b")*CC.Pos.d_cw + c("b12a","b12b")*CC.Neg.d_cw +
c("bv1a","bv1b")*Shift + c("bv2a","bv2b")*Day + c("av7a","av7b")*Time.of.Shift

  Wellbeing.d ~ c("b2a","b2b")*WE.d_cw

  JobSat.d ~ c("b4a","b4b")*WE.d_cw


  # Residual variances

  Wellbeing.d ~~ c("e1a","e1b")*Wellbeing.d

  JobSat.d ~~ c("e2a","e2b")*JobSat.d
```

```
  Wellbeing.d ~~ c("e3a","e3b")*JobSat.d
  CC.Pos.d_cw ~~ c("e4a","e4b")*CC.Neg.d_cw

  # Indirect effects Results
  indirect1a := a11a*b11a
  indirect2a := a22a*b12a
  indirect3a := a11a*b11a*b2a
  indirect4a := a11a*b11a*b4a
  indirect5a := a22a*b12a*b2a
  indirect6a := a22a*b12a*b4a

  indirect1b := a11b*b11b
  indirect2b := a22b*b12b
  indirect3b := a11b*b11b*b2b
  indirect4b := a11b*b11b*b4b
  indirect5b := a22b*b12b*b2b
  indirect6b := a22b*b12b*b4b
  '

#CFA free
model.cfa2m.ed <- cfa(model_group.med.econdep, estimator = "MLR", data=diss.data2,
cluster="PartID",group = "Group.EconDep.med", fixed.x=TRUE)
```

```
summary(model.cfa2m.ed, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)

fitmeasures(model.cfa2m.ed, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))


#Path analysis free

model.pa2m.ed <- sem(model_group.med.econdep, estimator = "MLR", data=diss.data2,
cluster = "PartID", group = "Group.EconDep.med")

summary(model.pa2m.ed, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)

fitmeasures(model.pa2m.ed, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))


#Path analysis constrained

model.pa3m.ed <- sem(model_group.med.econdep, estimator = "MLR", data=diss.data2,
cluster = "PartID", group = "Group.EconDep.med", group.equal = c("intercepts",
"regressions"))

summary(model.pa3m.ed, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)

fitmeasures(model.pa3m.ed, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))


anova(model.pa2m.ed,model.pa3m.ed)


# Continuous Moderator

mod.Pos.ed <- lmer(CC.Pos.d ~ PosInt.sum_cw + EconDep_cb +
PosInt.sum_cw:EconDep_cb + Day + Time.of.Shift + Shift + (1|PartID), data =
diss.data2)
```

~~~
summary(mod.Pos.ed)
summm(mod.Pos.ed)


mod.Neg.ed <- lmer(CC.Pos.d ~ NegInt.sum_cw + EconDep_cb +
NegInt.sum_cw:EconDep_cb + Day + Time.of.Shift + Shift + (1|PartID), data =
diss.data2)
summary(mod.Neg.ed)
summ(mod.Neg.ed)
```


# Supplemental Analyses – Need for meaning
```{r}
# Multi-group Path Analysis (Moderation - Need for meaning)
## model_group accounts for cluster="PartID" and for group="NeedforMeaning" for
multi-group comparison


## create grouping variable for Econ
describe(diss.data2$NeedforMeaning) #median = 4.33
diss.data2 <- diss.data2 %>%
  mutate(Group.NFM.med = case_when(NeedforMeaning >= 4.33 ~ "High",
                                  NeedforMeaning < 4.33 ~ "Low"))
### median split model
~~~

```
model_group.med.nfm<- '
  # Direct effects
  Wellbeing.d ~ c("c1a","c1b")*PosInt.sum_cw + c("c2a","c2b")*NegInt.sum_cw +
c("cv1a","cv1b")*Shift + c("cv2a","cv2b")*Day + c("cv5a","cv5b")*Time.of.Shift
  JobSat.d ~ c("c3a","c3b")*PosInt.sum_cw + c("c4a","c4b")*NegInt.sum_cw +
c("cv3a","cv3b")*Shift + c("cv4a","cv4b")*Day + c("cv6a","cv6b")*Time.of.Shift
  # Indirect effects
  CC.Pos.d_cw ~ c("a11a","a11b")*PosInt.sum_cw + c("av1a","av1b")*Shift +
c("av2a","av2b")*Day + c("av5a","av5b")*Time.of.Shift
  CC.Neg.d_cw ~ c("a22a","a22b")*NegInt.sum_cw + c("av3a","av3b")*Shift +
c("av4a","av4b")*Day + c("av6a","av6b")*Time.of.Shift
  WE.d_cw ~ c("b11a","b11b")*CC.Pos.d_cw + c("b12a","b12b")*CC.Neg.d_cw +
c("bv1a","bv1b")*Shift + c("bv2a","bv2b")*Day + c("av7a","av7b")*Time.of.Shift
  Wellbeing.d ~ c("b2a","b2b")*WE.d_cw
  JobSat.d ~ c("b4a","b4b")*WE.d_cw
  # Residual variances
  Wellbeing.d ~~ c("e1a","e1b")*Wellbeing.d
  JobSat.d ~~ c("e2a","e2b")*JobSat.d
  Wellbeing.d ~~ c("e3a","e3b")*JobSat.d
  CC.Pos.d_cw ~~ c("e4a","e4b")*CC.Neg.d_cw
  # Indirect effects Results
  indirect1a := a11a*b11a
```

```
  indirect2a := a22a*b12a
  indirect3a := a11a*b11a*b2a
  indirect4a := a11a*b11a*b4a
  indirect5a := a22a*b12a*b2a
  indirect6a := a22a*b12a*b4a

  indirect1b := a11b*b11b
  indirect2b := a22b*b12b
  indirect3b := a11b*b11b*b2b
  indirect4b := a11b*b11b*b4b
  indirect5b := a22b*b12b*b2b
  indirect6b := a22b*b12b*b4b
  '
#CFA free
model.cfa2m.nfm <- cfa(model_group.med.nfm, estimator = "MLR", data=diss.data2,
cluster="PartID",group = "Group.NFM.med", fixed.x=TRUE)
summary(model.cfa2m.nfm, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.cfa2m.nfm, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

#Path analysis free
model.pa2m.nfm <- sem(model_group.med.nfm, estimator = "MLR", data=diss.data2,
cluster = "PartID", group = "Group.NFM.med")
```

```
summary(model.pa2m.nfm, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa2m.nfm, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

#Path analysis constrained
model.pa3m.nfm <- sem(model_group.med.nfm, estimator = "MLR", data=diss.data2,
cluster = "PartID", group = "Group.NFM.med", group.equal = c("intercepts",
"regressions"))
summary(model.pa3m.nfm, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa3m.nfm, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))
modificationindices(model.pa3m.nfm, sort = TRUE)

anova(model.pa2m.nfm,model.pa3m.nfm)

# Continuous Moderator

mod.Pos.nfm <- lmer(CC.Pos.d ~ PosInt.sum_cw + NeedforMeaning_cb +
PosInt.sum_cw:NeedforMeaning_cb + Day + Time.of.Shift + Shift + (1|PartID), data =
diss.data2)
summary(mod.Pos.nfm)
summ(mod.Pos.nfm)
```

````
mod.Neg.nfm <- lmer(CC.Pos.d ~ NegInt.sum_cw + NeedforMeaning_cb +
NegInt.sum_cw:NeedforMeaning_cb + Day + Time.of.Shift + Shift + (1|PartID), data =
diss.data2)
summary(mod.Neg.nfm)
summ(mod.Neg.nfm)
```
# Supplemental Analyses – Perceived Control

```{r}
# Multi-group Path Analysis (Moderation - Control)

## model_group accounts for cluster="PartID" and for group="Control" for multi-group
comparison

## create grouping variable for Control
describe(diss.data2$Control) #median = 3
diss.data2 <- diss.data2 %>%
  mutate(Group.C.med = case_when(Control >= 3 ~ "High",
                                 Control < 3 ~ "Low"))

### median split model
model_group.med.c<- '
````

```
# Direct effects
Wellbeing.d ~ c("c1a","c1b")*PosInt.sum_cw + c("c2a","c2b")*NegInt.sum_cw +
c("cv1a","cv1b")*Shift + c("cv2a","cv2b")*Day + c("cv5a","cv5b")*Time.of.Shift
JobSat.d ~ c("c3a","c3b")*PosInt.sum_cw + c("c4a","c4b")*NegInt.sum_cw +
c("cv3a","cv3b")*Shift + c("cv4a","cv4b")*Day + c("cv6a","cv6b")*Time.of.Shift

# Indirect effects
CC.Pos.d_cw ~ c("a11a","a11b")*PosInt.sum_cw + c("av1a","av1b")*Shift +
c("av2a","av2b")*Day + c("av5a","av5b")*Time.of.Shift
CC.Neg.d_cw ~ c("a22a","a22b")*NegInt.sum_cw + c("av3a","av3b")*Shift +
c("av4a","av4b")*Day + c("av6a","av6b")*Time.of.Shift
WE.d_cw ~ c("b11a","b11b")*CC.Pos.d_cw + c("b12a","b12b")*CC.Neg.d_cw +
c("bv1a","bv1b")*Shift + c("bv2a","bv2b")*Day + c("av7a","av7b")*Time.of.Shift
Wellbeing.d ~ c("b2a","b2b")*WE.d_cw
JobSat.d ~ c("b4a","b4b")*WE.d_cw

# Residual variances
Wellbeing.d ~~ c("e1a","e1b")*Wellbeing.d
JobSat.d ~~ c("e2a","e2b")*JobSat.d
Wellbeing.d ~~ c("e3a","e3b")*JobSat.d
CC.Pos.d_cw ~~ c("e4a","e4b")*CC.Neg.d_cw
```

```
 # Indirect effects Results
 indirect1a := a11a*b11a
 indirect2a := a22a*b12a
 indirect3a := a11a*b11a*b2a
 indirect4a := a11a*b11a*b4a
 indirect5a := a22a*b12a*b2a
 indirect6a := a22a*b12a*b4a

 indirect1b := a11b*b11b
 indirect2b := a22b*b12b
 indirect3b := a11b*b11b*b2b
 indirect4b := a11b*b11b*b4b
 indirect5b := a22b*b12b*b2b
 indirect6b := a22b*b12b*b4b
 '
#CFA free
model.cfa2m.c <- cfa(model_group.med.c, estimator = "MLR", data=diss.data2,
cluster="PartID",group = "Group.C.med", fixed.x=TRUE)
summary(model.cfa2m.c, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.cfa2m.c, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

#Path analysis free
```

```
model.pa2m.c <- sem(model_group.med.c, estimator = "MLR", data=diss.data2, cluster =
"PartID", group = "Group.C.med")
summary(model.pa2m.c, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa2m.c, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

#Path analysis constrained
model.pa3m.c <- sem(model_group.med.c, estimator = "MLR", data=diss.data2, cluster =
"PartID", group = "Group.C.med", group.equal = c("intercepts", "regressions"))
summary(model.pa3m.c, ci=TRUE, fit.measures=T, standardized=T, rsquare=T)
fitmeasures(model.pa3m.c, c("chisq", "df", "pvalue", "cfi", "rmsea", "srmr","bic"))

anova(model.pa2m.c,model.pa3m.c)

# Continuous Moderator

mod.Pos.c <- lmer(CC.Pos.d ~ PosInt.sum_cw + Control_cb +
PosInt.sum_cw:Control_cb + Day + Time.of.Shift + Shift + (1|PartID), data = diss.data2)
summary(mod.Pos.c)
summ(mod.Pos.c)

mod.Neg.c <- lmer(CC.Pos.d ~ NegInt.sum_cw + Control_cb +
NegInt.sum_cw:Control_cb + Day + Time.of.Shift + Shift + (1|PartID), data = diss.data2)
```

```
summary(mod.Neg.c)

summm(mod.Neg.c)

interact_plot(mod.Neg.c,

        pred = NegInt.sum_cw,

        modx = Control_cb,

        modx.values = "plus-minus",

        x.label = "Daily Negative Customer Interactions",

        y.label = "Daily Cognitive Crafting",

        legend.main = "Perceived Control over Customer Interactions",

        main.title = "Moderating Effects of Perceived Control",

        modx.labels = c("Low Perceived Control", "High Perceived Control")

        ) +

  ylim(0,7) +

  xlim(-5,5)

sim_slopes(mod.Neg.c, pred = NegInt.sum_cw, modx = Control_cb)
```
```
```

Appendix K

Tables

Table 1

Means, standard deviations, and correlations.

Variable	M	SD	1	2	3	4	5	6	7
			Level-1 variables						
1. Positive customer interactions	18.96	6.80							
2. Negative customer interactions	13.11	6.92	-.19***						
3. Cognitive crafting (positive)	4.73	1.29	.27***	-.15*					
4. Cognitive crafting (negative)	4.29	1.43	.25***	-.14*	.43***				
5. Work engagement	3.39	.90	.26***	-.07	.26***	.21***			
6. Work-related psychological well-being	4.62	.87	.28***	-.14*	.30***	.16*	.34***		
7. Job satisfaction	5.09	1.43	.33***	-.22***	.30***	.21***	.57***	.39***	
			Level-2 variable						
8. Psychological capital	5.23	.89	.27•	-.05	.40**	.31*	.63***	.62***	.63***

Note. M and SD are used to represent mean and standard deviation, respectively. Level-1 $N = 248$. Level-2 $N = 51$. Correlations among Level-1 variables reflect within-person centered correlations. Level-1 variables were aggregated to Level-2 to calculate correlations with psychological capital. $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2
Variance Decomposition for Within-Person Variables

Variable	Within-person Variance (σ^2)	Between-person Variance (τ)	Percentage of total variance within-person
Positive Customer Interactions	35.20	12.18	74.29%
Negative Customer Interactions	37.19	9.12	80.31%
Cognitive Crafting (Positive Interactions)	1.26	0.37	77.30%
Cognitive Crafting (Negative Interactions)	1.32	0.69	65.67%
Work Engagement	0.59	0.22	73.00%
Psychological Well-being	0.51	0.27	65.37%
Job Satisfaction	0.84	1.21	41.07%

Note. Percentage of total variance within-person was calculated as the following: $\sigma^2/(\sigma^2 + \tau)$. Estimates are based on the total Level-1 sample size (n = 248). Sum scale scores were used for positive customer interactions and negative customer interactions. Mean scale scores were used for the remaining variables.

Table 3

Results of Within-Person Path Analysis

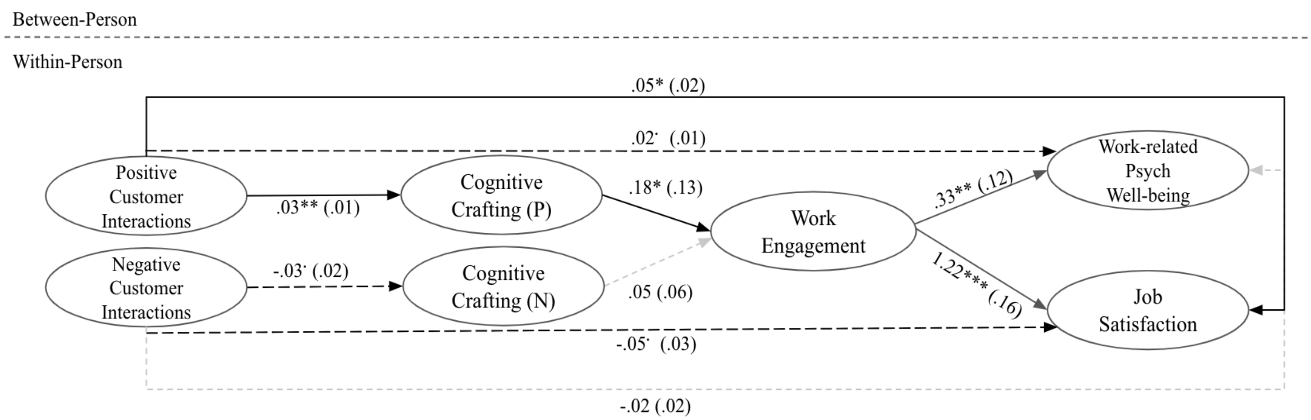
Variables	Cognitive crafting (positive interactions)		Cognitive crafting (negative interactions)		Work engagement		Job satisfaction		Psychological well-being	
	γ	*SE*	γ	*SE*	γ	*SE*	γ	*SE*	γ	*SE*
Intercepts	-.04	(.17)	-.06	(.28)	-.02	(.15)	5.04***	(.66)	4.64***	(.44)
Level-1 predictors and control variables										
Day of the week	-.01	(.02)	-.01	(.03)	.02	(.02)	-.00	(.04)	.04	(.03)
Length of Shift	.01	(.01)	.01	(.01)	.00	(.01)	.02	(.04)	-.06*	(.03)
Time of Shift	.03	(.07)	-.03	(.08)	-.03	(.05)	-.03	(.20)	.11	(.12)
Positive customer interactions	.03**	(.01)	--	--	--	--	.05*	(.01)	.02•	(.01)
Negative customer interactions	--	--	-.03•	(.02)	--	--	-.05•	(.03)	-.02	(.02)
Cognitive crafting (positive)	--	--	--	--	.18*	(.08)	--	--	--	--
Cognitive crafting (negative)	--	--	--	--	.05	(.06)	--	--	--	--
Work engagement	--	--	--	--	--	--	1.22***	(.16)	.33**	(.12)
Residual variance at Level-1	.22	(.05)	.45	(.14)	.16	(.03)	1.69	(.30)	.64	(.10)
Pseudo R^2	.04		.02		.08		.16		.15	

Note. Level-1 N =*248.* Clustered by participant ID (N = 51). Person-mean centered variables were used for Level-1 predictors. • p < .10. * p < .05. ** p < .01. *** p < .001. -- indicates path was not included in the within-person path analysis.

Appendix L

Within-Person Multilevel Path Analysis Results

Figure 2. Within-person Multilevel Path Analysis Results

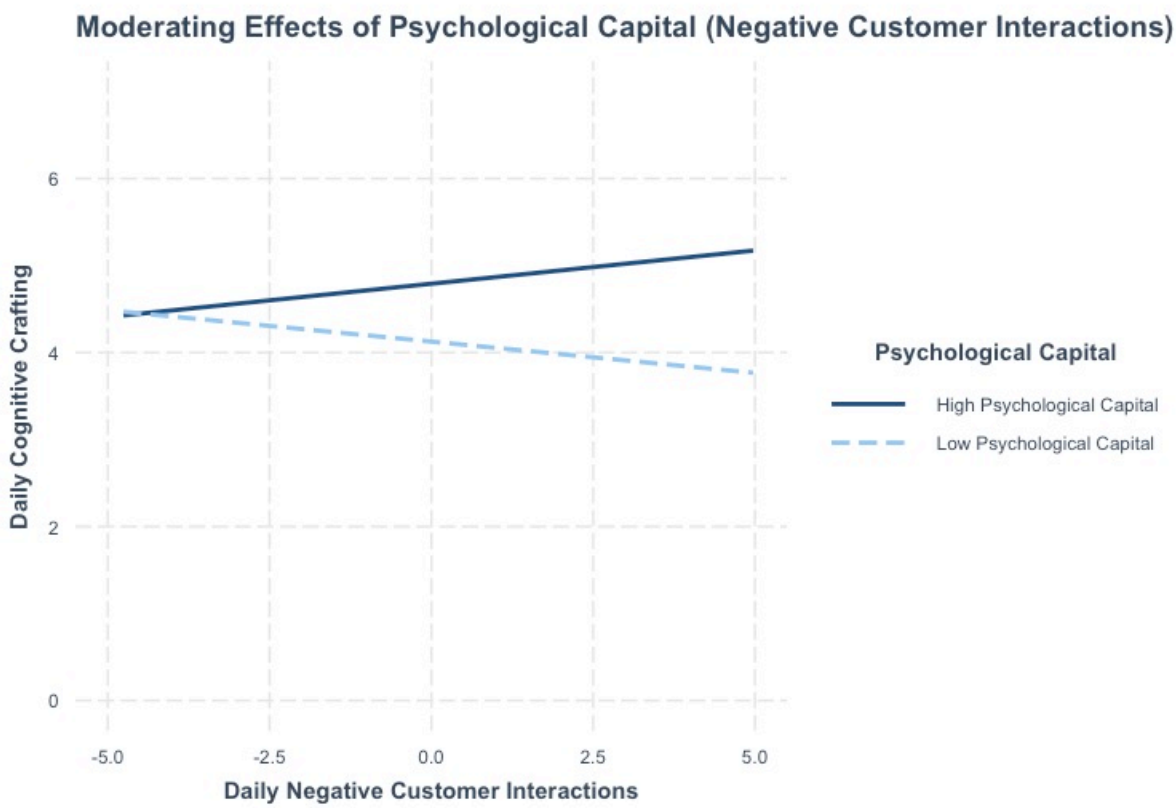


Notes. Level-1 $N = 248$. Clustered by participant ID (N = 51). Person-mean centered variables were used for Level-1 predictors. Standard errors are in parentheses. $^{\bullet}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Appendix M

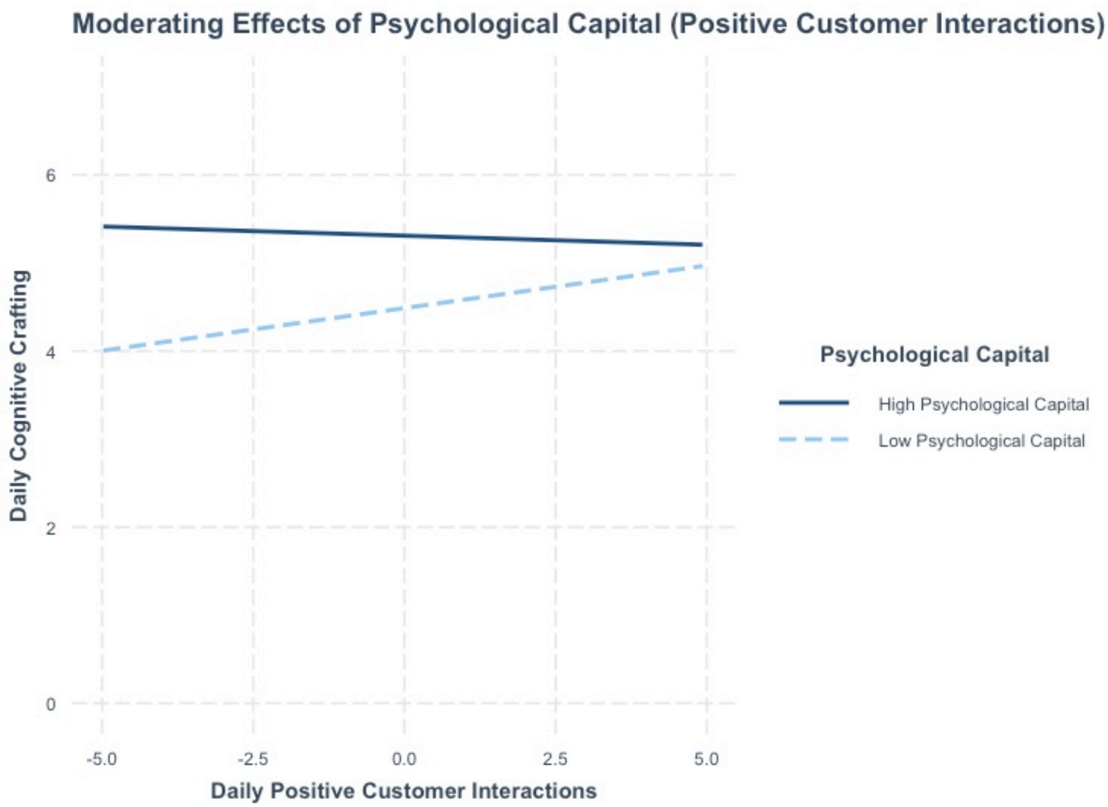
Interaction Plots

Figure 3. Interaction effect of daily negative customer interactions and psychological capital on daily cognitive crafting.



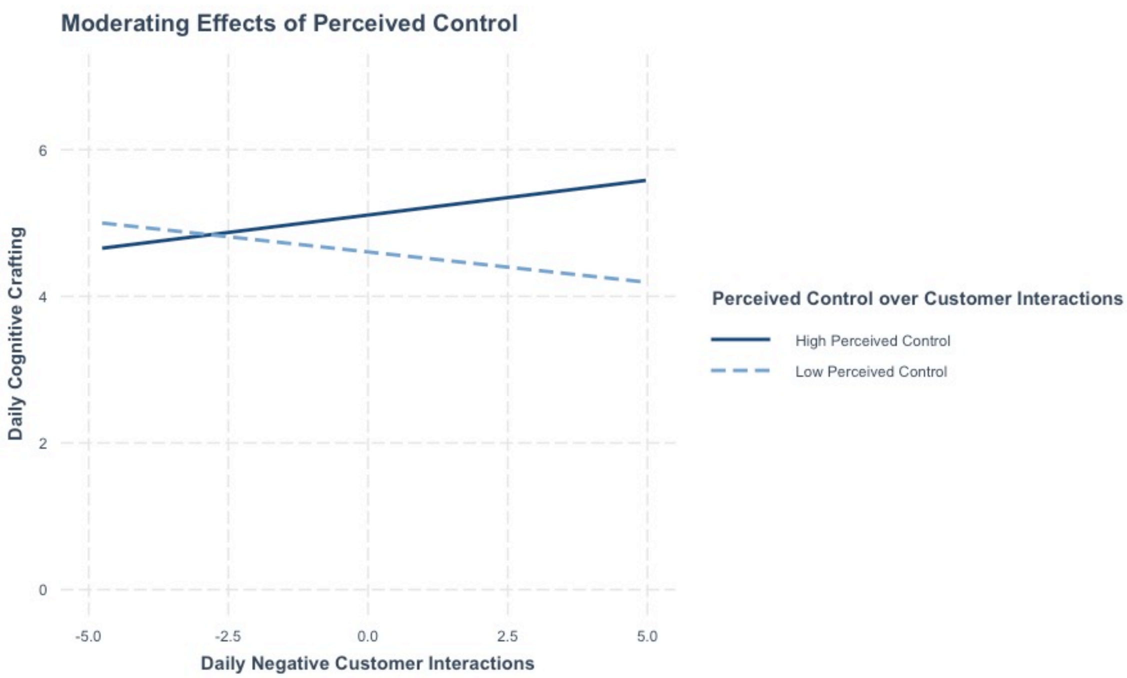
Note. The daily negative customer interactions variable was person-mean centered. The psychological capital variable was grand-mean centered.

Figure 4. Interaction effect of daily positive customer interactions and psychological capital on daily cognitive crafting.



Note. The daily positive customer interactions variable was person-mean centered. The psychological capital variable was grand-mean centered.

Figure 5. Interaction effect of daily negative customer interactions and perceived control over customer interactions on daily cognitive crafting.



Note. The daily negative customer interactions variable was person-mean centered. Perceived control over customer interactions was grand-mean centered.

‘

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