Indy Wijngaards

MEASURING WORKER WELL-BEING

An Evaluation of Closed and Open-Ended Survey Questions

THESIS

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Measuring Worker Well-Being

An evaluation of closed and open-ended survey questions

Meten van medewerkerswelzijn

Een beschouwing van gesloten en open vragenlijst vragen

Thesis

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General introduction

1.1. WORKER WELL-BEING: A HOT TOPIC

Worker well-being is a hot topic in organizations. A 2018 study of 250 UK organizations showed that 45% had a general well-being strategy in place, and that 84% of the ones that did not were planning to install one within the next three years (REBA, 2018). Likewise, the Chartered Institute of Personnel and Development (CIPD) revealed that in 2017 55% of the surveyed UK executives had worker well-being on their strategic agendas and in 2018 this percentage had risen to 61% (CIPD, 2019). PricewaterhouseCoopers' Health and Well-being Touchstone Surveys (2019, 2020) demonstrated that present-day organizations typically offer a wide range of well-being programs to help workers with specific aspects of their well-being, e.g., employee assistance programs, resiliency programs, weight management, fitness challenges, smoking cessation, stress management, mediation resources and financial coaching. Perhaps unsurprisingly, the current workplace wellness market is worth more than $45 billion and is projected to grow in the decades to come (Allied Market Research, 2020; Global Wellness Institute, 2016). As an illustration, Fidelity Investments and National Business Group on Health's 10th Annual Health and Well-being Survey estimated the average per-worker expenditure on health and well-being to be $762 in 2019 (Fidelity investments, 2019).

The interest in worker well-being is also widespread in the scientific community. A multitude of scholars have concentrated on the definition and measurement of worker well-being (Page & Vella-Brodrick, 2009; Sonnentag, 2015). Others have worked on mapping its determinants, including management practices (e.g., leadership style, Inceoglu et al., 2018; pay, Judge et al., 2010; job design, Wegman et al., 2018; restructuring, De Jong et al., 2016), sociodemographic factors (e.g., age, Ng & Feldman, 2010; employment contract, Wilkin, 2013) and personality (Bruk-Lee et al., 2009). Again others focused on the development and evaluation of interventions that promote worker well-being (Briner & Walshe, 2015; Nielsen, Randall, et al., 2010). As an illustration, the academic literature on job satisfaction dates back more than a century and has developed into a wide range of subfields (Judge et al., 2017), counting more than 60 distinct job satisfaction measures (Hora et al., 2018).

Numerous instrumental reasons support the popularity of worker well-being in organizations and academia. A myriad of studies have linked worker well-being to key performance indicators (Taris & Schaufeli, 2015). For instance, a meta-analysis of available evidence showed that satisfaction with the company is favorably related to objective measures of organizational and individual productivity, customer loyalty and staff turnover (Krekel et al., 2019). Longitudinal research revealed that subjective well-being is related to workplace performance and productivity (Bryson et al., 2017; DiMaria et al., 2020). Experimental research demonstrated that the relationship between worker well-being and productivity is, in fact, causal in nature. For example, a laboratory study reported that a happiness intervention resulted in a 12% increase in productivity (Oswald et al., 2015). A more recent quasi-experiment among call center workers in a large UK telecommunications firm showed that workers make around 13% more sales in weeks where they report being happy compared to weeks when they report being unhappy (Bellet et al., 2020).

Besides instrumental reasons to pursue worker well-being, there is a pertinent moral imperative for it (Guest, 2017). Among the many things that might be thought to be good in themselves, human well-being is perhaps the one object most highly regarded as such (Aristotle, 340 C.E.; Kraut, 2009; Mill, 1859; Raz, 1986; Sidgwick, 1874). The moral case for protecting worker well-being is strengthened by the great challenges that characterize today's workplaces, e.g., market globalization, rapid technological innovation, work intensification and increased job uncertainty, and the toll these challenges can take on the well-being of workers (Barley et al., 2017; World Bank, 2018). The coronavirus disease 2019 (COVID-19) pandemic presented a new set of demands that also put well-being in jeopardy, e.g., social isolation, issues with work-life balance and the fear of unemployment (Collings et al., 2021; Kniffin et al., 2020). Indeed, research by Qualtrics and SAP in the early days of the pandemic showed that, of the 2700 employees surveyed, 75% felt more socially isolated and 53% reported greater emotional exhaustion (R. Smith, 2020). A global survey fielded between August and September 2020 indicated that 62% of employees consider mental health issues to be a top challenge during the pandemic (McKinsey & Company, 2020).

1.2. THE PROMISE OF SURVEY MEASUREMENT TO IMPROVE WORKER WELL-BEING

With worker well-being getting higher on the agendas of organizations and scholars, the interest for assessing worker well-being and its drivers and consequences in organizations is spiking. Surveys have always been the most popular instrument for assessing worker well-being (Gerrad & Hyland, 2020; Jarden & Jarden, 2017). As an illustration, the Engagement Institute reported that over 80% of the organizations worldwide survey their workers regularly (Ray et al., 2013). A survey of 414 HR professionals in 2019 revealed that surveys are the most popular tool for measuring employee engagement and 72% of large US organizations administer one annually (hr.com, 2019). Besides administering annual surveys, more and more organizations are using pulse surveys – frequent, short surveys to capture fluctuations in job attitudes over time (Mayo, 2016; Welbourne, 2016). In support of this, the study by hr.com demonstrated that 36% of organizations measure employee engagement using pulse surveys and that 21% do so at least every quarter.

The widespread acceptance of survey instruments is not without reason: They are relatively easy to administer and hold great potential for advancing worker well-being in organizations (Jarden & Jarden, 2017; Nielsen, Randall, et al., 2010). On a general level, administering a survey signals that an organization cares about its workers and can, in turn, improve their morale (Jarden & Jarden, 2017). However, the greatest value of survey instruments lies in the data they produce. Data about worker well-being, work experiences, preferences and complaints contains information that organizations can use to make evidence-based decisions about improving worker well-being in the organization (Briner & Walshe, 2015). Below, several functions of worker well-being surveys are listed, and examples are provided.

(1) Survey data can be used as a diagnostic tool to spot individual workers or groups of workers that are suffering from low well-being or to identify aspects of well-being that need attention. For example, Sutton et al. (2016) used a corporate survey administered in a European financial services organization to show that workers and team leaders had significantly lower well-being than workers higher up in the organizational hierarchy. In addition, the survey revealed that not all components of worker well-being were at risk; only sleep problems emerged as a pertinent concern across all levels of the organization.

(2) Survey data can help advance the understanding of what factors drive well-being. For example, De Neve et al. (2018) analyzed survey data from workers nested in thousands of organizations worldwide and found that importance rankings of workplace quality indicators differed across subgroups in the working population. For example, the perceived usefulness of work turned out to be a significantly more important predictor of job satisfaction for highly educated workers than for lowly educated workers.

(3) Survey data can pinpoint to the cause and possible solutions to certain well-being problems in an organization. For example, Nielsen et al. (2014) used a tailored survey to uncover specific well-being problems in a postal service organization and to obtain input for interventions to address them. An analysis of the survey data showed that problems associated with the unrealistic computer-generated delivery routes were easily solved by hanging up a board in the sorting room that workers could use to fine-tune the preplanned route layout.

(4) Survey data can help in the evaluation of organizational interventions. For example, Randall et al. (2009) illustrated how surveys can be used to evaluate a team working intervention and can provide insight into the reasons that drive an interventions' success or failure. They found that the intervention had a positive effect on worker well-being, especially in teams with managers that had a positive attitude towards the intervention and good social cohesion.

1.3. THE PRINCIPLES OF RIGOROUS MEASUREMENT OF WORKER WELL-BEING

A prerequisite for an effective worker well-being survey is the rigorous measurement of the concept of worker well-being *itself*. After all, data-driven insights on well-being problems, outcomes and interventions will be biased and, thus, of limited value for evidence-based decision making, if data on the concept of worker well-being is unreliable or incomplete. Three principles of rigorous worker well-being measurement are (i) the examination of a broad selection of worker well-being constructs (or variables), (ii) the use of valid closed survey questions and (iii) the consideration of open-ended survey questions.

1.3.1. The examination of a broad selection of worker well-being constructs

A comprehensive selection of constructs is essential for the identification of well-being problems in the workforce and the selection and evaluation of interventions to resolve such problems (P. Y. Chen & Cooper, 2014; F. R. Goodman et al., 2020). With worker well-being being a multifaceted phenomenon[1], the constructs that fall under its conceptual umbrella can differ in the direction and magnitude of their relationships with other variables (Briner & Walshe, 2015; Grant et al., 2007). A variable can, for instance, be positively related to one well-being construct, but negatively related or not at all related to another. Consequently, the adoption of a narrow operationalization of worker well-being (e.g., measuring just one well-being variable) may lead to overgeneralized claims about favorable, unfavorable or nonexistent effects of particular variables on worker well-being in general.

There are numerous studies that illustrate this point. Kushlev and Dunn (2015), for example, showed that an intervention aimed at improving email use had a direct effect on daily stress levels at work, but not on daily and weekly levels of positive and negative affect, social connectedness, sleep quality and meaningfulness. Coffeng et al. (2014) revealed that an office refurbishment had an effect on workers' perceived absorption at work but not on their enthusiasm and energy in the workplace. Guerci et al. (2019) showed that pay-for-performance can improve workers' psychological well-being, but deplete relational well-being. The authors also demonstrated that job enrichment may lead to higher psychological well-being in the short term but may deter physical well-

1 For example, contemporary models of worker well-being include general constructs such as life satisfaction (Erdogan et al., 2012; Ilies et al., 2007), fluctuant constructs such as job affect (Beal & Ghandour, 2011; Ilies & Judge, 2004) and state work engagement (Breevaart et al., 2012), and constructs with alternative philosophical underpinnings such as eudaimonic well-being at work (Kożusznik et al., 2019; Page & Vella-Brodrick, 2009) and flow (Moneta, 2012, 2017).

being in the long term. Halbesleben (2011) evidenced that, under certain conditions, high levels of work engagement are positively associated with work-family conflict and poor family satisfaction.

1.3.2. The use of valid closed question survey measures

Once a comprehensive set of well-being constructs is selected, it is key to select valid survey instruments to measure them and verify the quality of the survey data when it has been collected (Arthur Jr et al., 2020; Flake & Fried, 2020). Doing this allows a researcher to maximize the likelihood that a measure contains a limited amount of measurement error and captures the well-being construct that (s)he aims to measure. Scholars have developed a vast array of closed survey questions to measure worker well-being constructs (Jarden & Jarden, 2017) and statistical techniques for psychometric validation of the collected survey data (e.g., internal consistency, test-retest reliability, factor structure, measurement invariance, Borsboom et al., 2004; Zickar, 2020). Most validated closed question measures comprise multiple items because single-item measures are of limited value for measuring multidimensional constructs and often deemed unreliable because internal consistency and reliability cannot be estimated (G. G. Fisher et al., 2016; Nunnally & Bernstein, 1994). For example, Breevaart et al. (2012) showed that the 9-item Utrecht Work Engagement Scale (Schaufeli et al., 2006) measuring dispositional work engagement can be validly used to measure daily work engagement by customizing the item stem (i.e. using 'today' instead of 'in general'). Drawing from validity statistics from 79 samples, Kinicki et al. (2002) showed that the 72-item Job Descriptive Index (P. C. Smith et al., 1969) has reasonable psychometric properties. Using a similar research design, Bowling and Hammond (2008) showed that the 4-item Michigan Organizational Assessment Job Satisfaction Subscale (Cammann et al., 1979) is a reliable and construct-valid measure of job satisfaction.

There are examples abound of why both careful selection of a measure and the validation of survey data is important to ensure the validity of research findings. Below, two examples for each aspect are provided. Concerning the selection of measures, an accumulating body of research has shown that the full version of the Maslach Burnout Inventory (Maslach & Jackson, 1981) should not be used to scan for burnout in a workforce, as the 'exhaustion' and 'cynicism' subscales capture burnout and the 'lack of professional efficacy' subscale does not (Qiao & Schaufeli, 2011). Another strand of research has demonstrated that overall job satisfaction is better measured using a general measure of job satisfaction (e.g., "How satisfied are you with your job as a whole?") rather than a composite of job facet measures (e.g., "How satisfied are you with your relationships at work?") because the aggregation of job facet satisfaction scores into an overall scores is problematic (Dalal, 2012; Ferratt, 1981; Ironson et al., 1989; Mikes & Hulin, 1968; Quinn & Mangione, 1973; for counterevidence, see Bowling & Zelazny, 2021).

Concerning the validation of survey data, a study of burnout among professors by Fernet et al. (2004) illustrated that it is essential to check the item-level descriptive statistics and internal consistency of a scale. They showed that two items in the Maslach Burnout Inventory's exhaustion subscale (i.e., "Working with people directly puts too much stress on me" and "Working with people all day is really a strain for me") had extremely low means in their sample and attenuated the scales' internal consistency. The authors concluded that most respondents perceived these items to be irrelevant and decided to drop the items. A methodological study by Kam and Meyer (2015) offered an illustration of why it is important to check for response styles in survey data. Using a shortened version of the Illinois Job Satisfaction Index (Chernyshenko et al., 2003; Credé et al., 2009), the authors revealed that two response styles (i.e., careless responding and acquiescence) can lead to bias in factor analytical results and can affect bivariate correlations. For example, the correlation between job satisfaction and organizational citizenship behavior was 0.38 for careful respondents and 0.51 for careless respondents.

1.3.3. The consideration of open-ended survey questions

Open-ended survey questions have the promise of increasing the rigor of worker well-being surveys and are increasingly used to measure worker well-being constructs, especially job satisfaction (e.g., Borg & Zuell, 2012; Gilles et al., 2017; Poncheri et al., 2008). First, administering both kinds of questions facilitates triangulation of methods (Turner et al., 2017). As careless responding could introduce bias in closed question scales (Meade & Craig, 2012; for examples for well-being, see Espinoza et al., 2018; Kam & Meyer, 2015), and open-ended questions force respondents into a more intensive and therefore arguably more careful form of cognitive processing (Krosnick, 1999), textual measures could be used to cross-validate closed survey questions or as an additional data source for hypothesis testing (Mossholder et al., 1995; Taber, 1991).

Second, textual data can be leveraged to obtain a more holistic perspective on the construct of study in particular contexts (Jick, 1979; Turner et al., 2017). For example, the responses can be used to assess when, why and how a construct is manifested and unravel the psychological processes that influence the self-report responses to closed survey questions (Edwards, 2008; Spector & Pindek, 2016). For example, Gilles et al.'s (2017) textual analysis of open survey comments from healthcare workers showed that certain issues were common across all professional groups (e.g., tight scheduling), while others were more group-specific (e.g., lack of skill recognition for administrative workers).

1.4. THE CHALLENGES OF RIGOROUS WORKER WELL-BEING MEASUREMENT

The rigorous measurement of worker well-being thus ideally consists of the wide selection of worker well-being constructs, the administration of both validated closed and open-ended survey questions and the judicious analysis of the survey data. Yet, scholars and practitioners concerned with well-being assessment in organizations, such as experts from consultancy firms, in-house organizational behavior specialists and human resource (HR) professionals, do not seem to invariably adhere to the principles of rigorous worker well-being measurement. As an illustration, practitioners often focus on a narrow selection of well-being constructs, e.g., job satisfaction and engagement (Saks & Gruman, 2014), use idiosyncratic, single-item measures, and rarely engage in measure validation (Jarden & Jarden, 2017; Spence, 2015). Systematic literature reviews suggest that, despite the advances in the conceptualization of worker well-being, many scholars also study a limited set of (mostly work-related) well-being constructs and traditionally use cross-sectional designs to collect survey data (e.g., Erdogan et al., 2012; Inceoglu et al., 2018; Mäkikangas et al., 2016). Both practitioners and scholars often include one or two open-ended survey questions, but rarely use the textual data they produce for the construction and validation of measures or systematic qualitative analyses (Borg & Zuell, 2012).

Two challenges may explain this trend. The first issue relates to the practical challenges of rigorous worker well-being measurement in organizations. Due to a fear of high opportunity costs, backlash from workers and low-quality data, organizations are rarely keen to participate in studies that put a heavy burden on the time of workers, e.g., studies with intensive repeated measurement and studies using lengthy batteries of questions (Lapierre et al., 2018). As a result, scholars and practitioners are forced to make their surveys as time-efficient as possible. It should be noted that the worries of organizations are not unjustified. Scientific research shows that workers are regularly disinclined to complete surveys (i.e., average response rate in organizational studies = 52.3%; Anseel et al., 2010). Lengthy surveys can lead to more careless responding (Bowling et al., 2020; Eisele et al., 2020; Gibson & Bowling, 2019) and nonresponse (Yan et al., 2011), especially among workers with negative job attitudes (Fauth et al., 2013; Mueller et al., 2011; Rogelberg et al., 2000, 2003). Following workers over time with repeated measurements will inevitably lead to attrition (Ployhart & Vandenberg, 2010). As an illustration, in a ten-year study of burnout of primary healthcare physicians, Schaufeli et al. (2011) invited a random sample of 801 physicians for a survey. Of the physicians in the sampling frame, 567 provided a valid response in the first survey wave, 299 in the second wave and 165 in the third wave. Yaldiz et al.'s (2018) longitudinal study on the determinants of stress in US public works departments started off with a sampling frame of 520 workers. In the end, 348 workers filled out the first survey and 243 completed the 12-month follow-up survey.

The second challenge relates to technical challenges of rigorous worker well-being measurement. Academic researchers are theory-minded (Aguinis & Vandenberg, 2014) and trained in psychological methods, such as test construction, research design, multiple regression analysis, analysis of variance and basic psychometric analyses (Aiken et al., 2008). This background allows them to leverage theory to identify the relevant well-being constructs, to select well-established closed question measures to capture them, and to evaluate the data's validity once it has been collected. However, research shows that many scholars still find it difficult to navigate the "conceptual jungle" (Mäkikangas et al., 2016, p. 62) that characterizes the worker well-being literature and to identify the most suitable constructs and measures (F. R. Goodman et al., 2020; Zheng et al., 2015). Due to lack of professional training, many scholars are not comfortable with deploying statistical techniques required for constructing textual measures (Kobayashi et al., 2017) and struggle with the rapid developments in advanced research methodology (Aguinis et al., 2018; Aiken et al., 2008). Such technical challenges seem even more pertinent for practitioners. In contrast to scholars, practitioners often do not have access to scientific literature (e.g., recent evidence on the measurement of worker well-being, measure validation practices and textual measure creation), are not adequately trained to process such content, or both (Briner et al., 2009; C. Gill, 2018; Rynes, 2012). Additionally, even though an increasing number of practitioners is comfortable with performing basic statistical analyses of numerical data (e.g., creating a dashboard with descriptive data), most practitioners have received little to no training in statistics whatsoever (Angrave et al., 2016; Marler & Boudreau, 2017; Rynes & Bartunek, 2017).

1.5. RESEARCH OBJECTIVES

In summary, despite the widespread interest in measuring worker well-being using surveys, many scholars and practitioners are currently not following the principles of rigorous worker well-being measurement, e.g., operationalizing worker well-being as narrow concept, not using scientific literature to select of a closed question survey measure, forgetting to validate survey data once collected and ignoring textual data from open-ended survey questions. Here above, it was argued that this trend can be explained by two challenges: (1) practical challenges in organizations and (2) technical challenges for scholars and, in specific, practitioners.

These challenges have several consequences. First, technical challenges, such as a difficulty navigating scientific literature and the lack of access thereto, make it difficult for scholars and practitioners to grasp the full breath of the concept of worker well-being and consider all relevant constructs that could fall under its conceptual umbrella. Second, the practical challenges in organizations, such as the disinclination to administer time-inefficient surveys in the workforce, may complicate the study of a wide array of constructs and incentivize scholars and practitioners to focus on a small selection of constructs. Third, these practical challenges also disincentivize scholars and practitioners to administer psychometrically sound, but lengthy survey scales and do intensive longitudinal research. On top of that, technical challenges hamper the identification of the most appropriate closed question survey measures and the validation of survey data. Fourth, technical challenges lead to the low perceived value and the neglect of open-ended survey question data.

The central aim of this thesis is to offer scholars and practitioners guidance on how to deal with the practical and technical challenges of rigorous worker well-being surveys. These efforts hopefully contribute to the promotion of worker well-being survey research that is both rigorous and realistic. I do this by providing both conceptual and practical guidance. First, I develop a conceptual framework of worker well-being and an accessible synthesis of established as well as more innovative survey instruments that could be used for measuring worker well-being reliably and validly. Beyond conceptual guidance in the operationalization of worker well-being, I describe the most important approaches for validating well-being data and creating textual measures from responses to open-ended questions. Second, I demonstrate how these recommendations can be applied in practical research contexts and reflect on the challenges that I have come across in doing this empirical work.

Notably, this thesis does not intend to provide a definitive conceptual model of worker well-being, a gold standard measure for capturing it or an exhaustive list of best practices for measure construction and validation. Attempting this would be ostentatious because every research context is different, and the literature of worker well-being is scattered and continuously expanding. Instead, this thesis offers practitioners a thorough introduction to the science of worker well-being measurement, evidence that highlights the importance of rigorous measurement and examples on how methodological rigor can realistically be improved in organizations. This thesis offers scholars and practitioners a roadmap to navigate the ever-expanding literature on worker well-being and a primer to the construction of textual survey measures from open-ended survey questions.

This thesis is organized around four research questions:
(1) How can the concept of worker well-being be defined and operationalized into constructs?
(2) Which worker well-being constructs should be focused on in a survey?

(3) What kind of closed survey questions are suitable for measuring worker well-being constructs in organizations?
(4) How can open-ended survey questions contribute to measuring worker-well-being in organizations?

1.6. THESIS OUTLINE

This thesis consists of six substantive chapters, preceded by this introduction chapter and concluded with a discussion chapter. **Chapter 2** provides the theoretical foundation for addressing the first three research questions of this thesis, explaining what worker well-being is, how worker well-being constructs can be measured, and how a worker well-being measure should be selected. To maximize the relevance to practitioners, scientific terminology is explained as much as possible in this chapter.

Chapters 3 to 5 report on three studies that were conducted in a diverse set of organizations in the Netherlands. The chapters address the first three research questions by providing an empirical showcase of survey measurement using closed questions. For example, how were well-being constructs selected? Which measures were chosen and why? What techniques were used to validate the well-being measure? It should be noted that these chapters do *not* provide a conclusive answer to the research questions. As suggested in the previous sections, the choice of appropriate well-being variables and suitable instruments to measure them is a complex task and depends on a large range of factors, e.g., the research question at hand and acceptable survey duration. The chapters thus serve as case studies that illustrate the scientific study of worker well-being.

Chapter 3 provides an overview of the antecedents of momentary happiness at work for truck drivers. Drawing upon job demands-resources theory (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001), this study predicts that five job resources and five job demands influence momentary happiness at work. These assumptions are tested based on daily survey data and the results from a baseline questionnaire.

Chapter 4 details a study conducted in the healthcare sector in the midst of the COVID-19 pandemic. This study examines the relationship between cognitive job crafting and work engagement (e.g., Buonocore et al., 2020; Vuori et al., 2012; Wrzesniewski et al., 2003), and hypothesizes that cognitive job crafting has a stronger effect on work engagement for workers working from home than those working in the hospital. A cross-sectional survey is used to test this hypothesis.

Chapter 5 describes the effectiveness of an organizational intervention that stimulated workers to check their email only three times a day. Using literature on work interruptions (Puranik et al., 2020; Sonnentag et al., 2018; Ten Brummelhuis et al., 2012) and email management strategies (Jerejian et al., 2013; Kushlev & Dunn, 2015; Mark et al., 2016), it predicts that the intervention reduces email interruptions and emotional exhaustion and improves work engagement. Survey data from remote workers in the financial services industry collected across five waves is used to test these effects.

Chapters 6 and 7 report on two studies that demonstrate the added value of open-ended survey questions for investigating worker well-being and therefore primarily relate to the fourth research question. As the studies measure multiple well-being variables and use validated instruments for measurement, they are also used to address the other research questions.

Chapter 6 describes a study on the potential of open-ended and semi-open-ended survey questions for measuring worker's job satisfaction. The study elaborates on the various approaches for inferring sentiment from textual data and the types of measurement error in text-based measures. In addition, it formulates a range of hypotheses relating to the construct validity of text-based measures. The hypotheses are tested based on cross-sectional and time-lagged data from a sample of crowd-sourced English-speaking workers.

Chapter 7 builds on the previous chapter by zooming in on the promise of semi-open-ended survey questions in the study of job satisfaction. It elaborates on how computer-aided sentiment analysis based on dictionaries works. Using the sampling procedure from Chapter 6, we replicate the analyses conducted in the previous chapter and conduct various qualitative analyses to show the complementary value of semi-open-ended questions.

Chapter 8 summarizes the findings in relation to the research questions of this thesis and provides a general discussion of these findings, a critical reflection on the strengths and limitations of this thesis, and a summary of implications for scholars and practitioners in organizations. It ends with a general conclusion.

Notably, this thesis comprises published articles and submitted manuscripts in peer-reviewed scientific journals. As such, the chapters can be read independently, and some content of the chapters may overlap. All chapters were developed in collaboration with co-authors. In all chapters, I was responsible for conceptualization of the research idea and the writing of the initial draft. My co-authors were responsible for reviewing and editing. In all chapters but Chapter 4, I conducted the empirical analyses used for hypothesis testing.

In several instances, the code and the data used for constructing measures, validating these measures and hypothesis testing can be found in the Online Supplementary

Materials to the published article versions of the chapters. These resources can be used by practitioners as inspiration and starting point for their own analyses and by scholars to replicate the results that are presented in this thesis.

2

What is worker well-being, and how it should be measured

Based on paper: Wijngaards, I., King, O.C., Burger, M.J., & Van Exel, N.J.A. (2021). What is worker well-being, and how it should be measured. *Applied Research in Quality of Life*, 1-38.

2.1. INTRODUCTION

> "What we measure affects what we do; and if our measurements are flawed, decisions may be distorted."
>
> \- Stiglitz et al. (2009, p. 7)

In light of changes in the conditions and nature of work, along with wider appreciation of the importance of social responsibility, organizations and consultancy firms have taken a serious interest in worker well-being (Scott & Spievack, 2019). Indeed, an article in *Forbes* magazine on the human resources (HR) trends of 2020 suggests that worker well-being should be HR's top priority, explaining, "Many companies concerned about the future of work focus on the massive disruption of jobs, automation, and workforce demographics. All of this is important but as HR leaders we need to start with making worker wellbeing a priority in 2020!" (Meister, 2020). A lot of buzz surrounds worker well-being.

Numerous good reasons support widespread interest in worker well-being. The *Forbes* article highlights the purported role of worker well-being in workforce resilience and healthy organizational culture. Indeed, worker well-being may be an indicator of organizational ethics (Giacalone & Promislo, 2010), and it has been found to predict other key indicators of organizational performance (Salas et al., 2017; Taris & Schaufeli, 2015), such as productivity (Bellet et al., 2019; Oswald et al., 2015), absenteeism (Kuoppala et al., 2008), job performance (Judge et al., 2001a) and voluntary turnover (Judge, 1993; Wright & Bonett, 2007; Wright & Cropanzano, 1998). In addition to all of these ways in which worker well-being may be instrumentally valuable for advancing organizational objectives, worker well-being has great intrinsic value. Among the many things that might be thought to be good in themselves, human well-being is perhaps the one object most highly regarded as such (Aristotle, 340 C.E.; Mill, 1859; Raz, 1986; Sidgwick, 1874). In sum, for many different reasons, the well-being of workers (and anyone else) is well worth pursuing.

Not only is there great interest in worker well-being by practitioners in organizations, academic researchers have also been paying much attention to the subject matter (P. Y. Chen & Cooper, 2014; Zheng et al., 2015). Over many decades, a rich and mature field of research has emerged, with thousands of psychological studies that conceptually and empirically study worker well-being constructs such as job satisfaction (Judge et al., 2017) and engagement (Macey & Schneider, 2008; Purcell, 2014). More recently, researchers from outside the psychological sciences have started to embrace the topic, including economics (Bellet et al., 2019; Bryson et al., 2013; Golden & Wiens-Tuers, 2006; Oswald et al., 2015), information systems (Gelbard et al., 2018; Jung & Suh, 2019) and machine learning (Lawanot et al., 2019; LiKamWa et al., 2013). However, buzz about worker well-being, enthusiasm for new programs to promote it and interest to research it have not been accompanied by universal enthusiasm for scientific measurement on the work floor. Hence, there remains a gap between the buzz surrounding worker well-being and the science needed to support it. However, pushes to research and influence worker well-being without careful scientific measurement may be ineffective (Bartels et al., 2019). Even worse, these endeavors may be genuinely problematic: If researchers conceptualize or measure worker well-being inadequately, a scientific study may impede rather than advance the science that surrounds it (Podsakoff et al., 2016). If an organization touts purported improvements in well-being when, in fact, there has been no real improvement, it amounts to a case of "ethics washing" (Bietti, 2020; Wagner, 2018), and may hide the need for actual meaningful improvement.

We believe that the gap between the burgeoning psychological science of worker well-being and the buzz around it in other domains is caused by the complexity of worker well-being itself and the vast array of approaches to measuring it, combined with the variety of goals stakeholders may have for studying it. For many, it can be difficult to choose, let alone confidently justify, the selection of a particular research strategy for studying worker well-being. The primary goal of this paper is to help close the gap by offering a conceptual overview of the science of worker well-being and practical guidance for leveraging it in light of the particular objectives motivating the study of worker well-being.

This work will be useful for researchers of various stripes. First and foremost, this work will be relevant for research practitioners in organizations and academics outside psychological sciences. After all, it is not straightforward to move from intuitions about the need to pay more attention to worker well-being to adequate conceptualization and rigorous measurement. Insufficient scientific rigor prevents policy and research initiatives from being as relevant as they could be. In addition, even experienced psychological researchers who have been administrating well-being surveys – currently still the preferred instrument for measuring well-being (Nave et al., 2008) – for years may benefit from a synthesis of conceptual approaches and an enlargement of their inventory of approaches to measurement. As most psychologists are trained primarily in classic psychological methods (Aiken et al., 2008), a foray outside their comfort zone that updates them on the methodological developments across other fields may prove useful. Inspiration to use new, innovative measures helps researchers to address calls for increased attention to the construction of better well-being measures (Brulé & Maggino, 2017; Diener, 2012; Schneider & Schimmack, 2009) and facilitates collaborative interdisciplinary research.

We build on prior work that offers direction through "the conceptual jungle that currently characterizes the employee wellbeing literature" (Mäkikangas et al., 2016, p. 62). For example, Johnson et al. (2018) and Zheng et al. (2015) offered conceptual overviews on employee well-being and provide a handful of examples of validated survey instruments that can be readily used. Focusing on particular well-being constructs, other academics have reviewed existing traditional survey measures (Cooke et al., 2016; Roscoe, 2009; Schaufeli & Bakker, 2010; Van Saane et al., 2003; Veenhoven, 2017), non-survey measures (Luhmann, 2017; Rossouw & Greyling, 2020), or both (Diener, 1994, 2012). Going beyond both disciplinary and construct borders, other academics have concentrated on the promise of certain devices (e.g., wearable devices, Chaffin et al., 2017; Eatough, Shockley, & Yu, 2016), and measure categories for measurement of psychological constructs in general (Ganster et al., 2017; Luciano et al., 2017). A commonality among these works is that they each have a focus on specific instruments or constructs. Such specificity is both a blessing and a curse. It is helpful for researchers wanting an overview of the state-of-the-science of a particular instrument (e.g., the use of physiological measures in organizational science) or construct (e.g., survey measures of job satisfaction), but of limited use for readers interested in the bigger picture. In our work, we therefore offer a comprehensive field guide, which we hope will have broad appeal. Notably, in its broad scope, our work is not meant as an exhaustive overview, but rather as illustrative synthesis that maps the lay of the land and directs researchers to more specialized research. We structure our synthesis around three research questions:

(1) What is worker well-being?
(2) How can worker well-being be measured?
(3) How should a worker well-being measure be selected?

We will address the first question by offering a rationale about how to think about the concept of worker well-being and proposing a construct taxonomy that researchers can draw from to operationalize the concept of worker well-being. In doing so, we intend to disentangle the conceptual jungle that we find in the current literature. The second question will be addressed by creating an illustrative overview of measures for ten constructs that fall under the conceptual umbrella of worker well-being: life satisfaction, dispositional affect, moods, emotions, psychological well-being, job satisfaction, dispositional job affect, job moods, job emotions and work engagement. Looking beyond disciplinary borders, we will show that innovative, non-survey measures show promise for measuring worker well-being and, thereby, hopefully inspire researchers to enrich their methodological toolbox. The third question will be answered by reviewing different conceptual, methodological, practical and ethical considerations for selecting a measure and doing so in ways that are responsive to the motivations driving researchers and practitioners to take an interest in worker well-being. These considerations are summarized into a checklist.

2.2. WHAT IS WORKER WELL-BEING?

2.2.1. Worker well-being and related concepts

We assume that *worker well-being*, at the most inclusive level, comes down to the general well-being of working people. To ensure clear conceptual boundaries, it is useful to differentiate worker well-being from concepts that relate to it. Worker well-being differs from *employee well-being*, as not all working people are employed by organizations, e.g., volunteers, independent contractors, executives and business owners. Even though most well-being constructs are relevant for both employees and non-employed working people, there may be some exceptions. For instance, the construct of *satisfaction with pay* will be inapplicable to volunteers. *Satisfaction with co-workers* and *satisfaction with supervisor* will likely be irrelevant concepts for independent contractors. Worker well-being differs from *work-specific well-being*, as constructs falling under that conceptual umbrella have their origin and application distinctively within the work context. For example, the construct of *satisfaction with colleagues* has its origin in the work context. Work-specific well-being's manifestation can be within and outside the work context, e.g., a worker can feel content about social relationships at work at the dinner table or before going to bed too, which can impact other parts of worker well-being. Worker well-being differs also from *well-being at work*, as this concept merely concerns the experience or state of well-being in the work setting or when working. Notably, the source of well-being at work can be unrelated to work. Workers could, for instance, be contemplating fights with their spouses or reliving a fun weekend while being at work. Finally, worker well-being differs from *general individual-level well-being*, as, in contrast to general individual-level well-being, it pertains specifically to the lives and experiences of working people.

2.2.2. A taxonomy of worker well-being constructs

Many constructs have been proposed to operationalize the concept of worker well-being. We propose a theory-driven construct taxonomy that can be used to categorize constructs and map construct boundaries. We have drawn on eight other conceptual works on worker well-being (i.e. C. D. Fisher, 2014; Ilies et al., 2007; S. Johnson et al., 2018; Page & Vella-Brodrick, 2009; Taris & Schaufeli, 2015; Warr, 2012; Warr & Nielsen, 2018;

Zheng et al., 2015) to do this.[2] We constructed our taxonomy along four dimensions: (i) philosophical foundation, (ii) temporal stability, (iii) scope and (iv) valence.[3]

First, researchers have been adopting different *philosophical foundations* for conceptualizing well-being (Forgeard et al., 2011; Kashdan et al., 2008) and worker well-being (Taris & Schaufeli, 2015). Among the most prevalent are the philosophical traditions of hedonia and eudaimonia (Linley et al., 2009; Ryan & Deci, 2001). The hedonic approach regards well-being as the subjective experience of happiness (Diener et al., 1999; Veenhoven, 2000); the eudaimonic approach focuses on the realization of human potential (Ryff, 1989b; Ryff & Keyes, 1995). The classification of constructs on the hedonic and eudaimonic continuum is not an easy task because the different philosophical traditions are partially overlapping (C. D. Fisher, 2014; Waterman, 2008) and also empirically related (Linley et al., 2009; Pancheva et al., 2020). We categorize a construct as eudaimonic, if intrinsic motivation, activation, purpose and meaningfulness are at its core (Ryan & Deci, 2001). However, it is important that researchers acknowledge that a eudaimonic construct often contains a hedonic component.

Second, a classification can be made based on constructs' *temporal stability* (S. Johnson et al., 2018; Mäkikangas et al., 2016). Well-being researchers have developed state-like and trait-like well-being constructs (C. D. Fisher, 2014). State-like constructs are characterized by high variability over time due to high state variance, whereas trait-like constructs are characterized by greater stability over time (Schimmack et al., 2010). Some state-like constructs are truly momentary and last for a few minutes at most, while others remain somewhat stable (Kashdan et al., 2008). Some traits are inherited and are unlikely to change over a lifetime, while others are subject to some change over months or years (S. Johnson et al., 2018).

Third, two levels of *scope* of worker well-being constructs can be distinguished: context-free and domain-specific constructs (Ilies et al., 2007). Context-free constructs concern the worker's life and experience in general, whereas domain-specific well-being constructs concern well-being within particular life domains (e.g., work, leisure, health,

2 For reasons of parsimony, we were not able to incorporate all theoretical debates and nuances within the social sciences (Huta & Waterman, 2014; Rojas, 2017; Warr & Nielsen, 2018) and philosophy of well-being (e.g., Brey, 2012; Parfit, 1984) in our categorization of well-being constructs.

3 Readers interested in the ethics of worker well-being may wonder why we have not considered the capability approach to well-being (Robeyns, 2005). The reason, in short, is that we are addressing readers who are interested in well-being outcomes, in contrast to the general capabilities that support those outcomes. Although capabilities (and their distribution) have been held to be fundamentally important for justice (Nussbaum, 2011), and thus central to politics and public policy, we are more concerned with the effects of conditions and policies of work and employment. Hence, we focus on well-being, as a lived outcome, rather than the capability for living well (cf. Veenhoven, 2000).

finance). Context-free and domain-specific (especially work-specific) constructs capture the bigger picture and subtleties of worker well-being, respectively (Page & Vella-Brodrick, 2009).

Fourth, the *valence* of a construct can be considered. Some constructs are indicators of ill-being or the absence of well-being (e.g., burnout, negative affect), whereas others are indicators of well-being (e.g., engagement, positive affect). Intuitively, the realization of constructs with positive valence is desirable, while the realization of those with negative valence is undesirable.

To illustrate, we describe eight worker well-being constructs that together span the breath of the taxonomy.[4] In light of its broad scope and alignment with our understanding of worker well-being, we build on Page and Vella-Brodrick's (2009) Framework of Employee Mental Health. It revolves around three concepts: subjective well-being (SWB), psychological well-being (PWB) and workplace well-being (WWB). As made explicit by Page and Vella-Brodrick, the model does not include eudaimonic WWB constructs. To overcome this limitation, we have included work engagement as an eudaimonic WWB construct. The constructs and their categorization are summarized in Table 2.1. Table 2.1. also contains a brief characterization based on the academic literature surrounding the individual constructs.

2.2.2.1. Subjective well-being

SWB encompasses diverse aspects of people's evaluations of how their lives are going (Diener et al., 1999) *Life satisfaction*, the cognitive evaluation of satisfaction with life circumstances, is a trait-like, context-free, positive well-being construct (Diener et al., 1999). Affect, "people's on-line evaluations of the events that occur in their lives" (Diener et al., 1999, p. 277), is constituted by both trait-like and state-like components, which can vary in their valence as well as their degree of arousal (active vs. passive, Barrett & Russell, 1999). Some aspects of a person's affect are relatively stable over time. Accordingly, *dispositional affect* is a trait-like construct and has been defined as "durable dispositions or long-term, stable individual differences that reflect a person's general tendency to experience a particular affective state" (Gray & Watson, 2007, p. 172). Other affect-related constructs within SWB follow a fluctuating course and classify as state-like (Gray & Watson, 2007). For instance, *moods* are emotional states that can last days or even a week, occur relatively frequently, have nonspecific triggers and manifestations

4 We excluded hybrid constructs from our discussion – broad constructs that integrate hedonic and eudaimonic constructs – such as human flourishing (Huta & Waterman, 2014) and thriving (Spreitzer et al., 2005), from our selection of worker well-being constructs. Considering their broad scope, hybrid constructs often lack clear theoretical justification and are characterized by fuzzy construct boundaries (Martela, 2017).

(e.g., positive mood), and are primarily manifested in behavior and subjective experiences of people. *Emotions* can last seconds to, at most, a few minutes, are intense, occur infrequently, have specific triggers and manifestations (e.g., anger, joy), and are manifested in different forms, e.g., behavior, subjective experiences, brain activity, and physiological response (Gray & Watson, 2007).

2.2.2.2. Psychological well-being

Although its various aspects can be studied individually, we treat *PWB* as a single construct concerning the "formulations of human development and existential challenges of life" (Keyes et al., 2002, p. 1007). PWB is often represented by Ryff's (1989b) six-factor model, including self-acceptance, personal growth, purpose in life, positive relations with others, environment mastery, and autonomy. PWB is grounded in the eudaimonic well-being tradition, and is a trait-like, context-free, positive well-being construct (Page & Vella-Brodrick, 2009; Ryan & Deci, 2001).

2.2.2.3. Workplace well-being

Within WWB, we consider the constructs of job satisfaction, dispositional job affect, job emotions, job moods and work engagement. *Job satisfaction* can be defined as "a positive (or negative) evaluative judgment one makes about one's job or job situation" (H. M. Weiss, 2002, p. 175). Job satisfaction is a domain-specific, hedonic and trait-like construct (Bowling et al., 2005, 2010; C. D. Fisher, 2014). As such, job satisfaction is the work-specific counterpart to the context-free life satisfaction construct we described above.[5] *Dispositional job affect, job moods* and *job emotions* are equivalent to context-free conceptions of dispositional affect, moods and emotions, except for their narrower, work-specific focus. For example, we could be narrowly interested in a worker's general affect while working (dispositional job affect) or more broadly interested in the worker's general affect across life domains (dispositional affect, Ilies & Judge, 2004). In contrast to these hedonistic constructs, *work engagement* is an eudaimonic construct (C. D. Fisher, 2014) concerned with how workers experience the exercise of their capacities at work. Work engagement has been defined in various ways, but is generally described as a domain-specific construct characterized by high levels of identification with work, positive affect, enthusiasm and energy (Bakker et al., 2008) and is theoretically distinct from other constructs, such as job satisfaction and organizational commitment (Schaufeli & Bakker, 2010). Work engagement could be defined as "harnessing of organization mem-

5 Although it is most common to consider job satisfaction in terms of a workers' cognitive evaluations of their jobs, it is also worthwhile to examine worker's affective psychological responses or feelings specifically regarding their jobs (E. R. Thompson & Phua, 2012). If the affective component is emphasized, the resulting job satisfaction construct comes close to the *dispositional job affect* construct we discuss next, which also concerns workers' feelings while *at* work, though not necessarily *about* work.

bers' selves to their work roles: in engagement, people employ and express themselves physically, cognitively, emotionally and mentally during role performances" (Kahn, 1990, p. 694) and "a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (Schaufeli et al., 2002, p. 74). Work engagement turns out to be relatively stable over time (Seppälä et al., 2015), hence its classification as trait-like.[6]

Table 2.1 | Worker well-being constructs and their categorization

Construct	Characterization	Philosophical tradition	Temporal stability	Scope	Valence
Life satisfaction	Cognitive evaluation of satisfaction with life situation.	Hedonic	Trait-like	Context-free	Positive
Dispositional affect	General tendency to experience emotional states.	Hedonic	Trait-like	Context-free	Positive and negative
Moods	Emotional states that remain stable for hours or days, occurring relatively frequently with nonspecific triggers.	Hedonic	State-like	Context-free	Positive and negative
Emotions	Emotional states that remain stable for seconds or minutes, occurring infrequently with specific triggers.	Hedonic	State-like	Context-free	Positive and negative
Psychological well-being	Generally healthy psychological condition, involving self-perception, relationships, personal development, and autonomy.	Eudaimonic	Trait-like	Context-free	Positive
Job satisfaction	Cognitive evaluation of satisfaction with the work situation.	Hedonic	Trait-like	Domain-specific	Positive
Dispositional job affect	General tendency to experience emotional states at work.	Hedonic	Trait-like	Domain-specific	Positive and negative
Job moods	Emotional states, experienced at work, that remain stable for hours or days, occurring relatively frequently with nonspecific triggers.	Hedonic	State-like	Domain-specific	Positive and negative
Job emotions	Emotional states, experienced at work, that remain stable for seconds or minutes, occurring infrequently with specific triggers.	Hedonic	State-like	Domain-specific	Positive and negative
Work engagement	A positive, work-related state of mind, characterized by vigor, dedication, and absorption.	Eudaimonic	Trait-like	Domain-specific	Positive

6 Various researchers have contended that *state* job satisfaction and *state* work engagement should be distinguished next to more trait-like conceptions of job satisfaction and work engagement, as the temporal stability of the two constructs may vary from week to week or from day to day (for discussions on state job satisfaction, see Grube et al., 2008; Ilies & Judge, 2004; Niklas & Dormann, 2005; for discussions on state work engagement, see Bakker & Bal, 2010; Xanthopoulou et al., 2008; Sonnentag, 2003). To limit the scope of the article, we focus on the trait-like constructs of job satisfaction and work engagement, which have traditionally been the most common focus of research.

2.3. HOW CAN WORKER WELL-BEING CONSTRUCTS BE MEASURED?

2.3.1. Measure classification

Constructs, like each of those just discussed, are put together to study real phenomena that cannot be observed directly and perfectly (Edwards & Bagozzi, 2000). A measure, "an observed score gathered through self-report, interview, observation or some other means" (Edwards & Bagozzi, 2000, p. 156), can therefore be regarded as the empirical equivalent of a construct. A measure thus does not necessarily perfectly reflect the well-being construct it is intended to measure; rather it provides an instrument-dependent representation of it. In this article, we introduce two classifications that will prove important for selecting the most appropriate measure for a given construct. The first classification concerns the extent to which obtaining a measure interferes with the workers' affairs and experience, and the second considers the different types of data a researcher can obtain.

2.3.1.1. Measure obtrusiveness

Regarding the extent of interference with a workers' affairs and experience, we distinguish between three measurement approaches for worker well-being: unobtrusive measurement, reaction-based obtrusive measurement and observation-based obtrusive measurement. *Unobtrusive measures* are methods that allow researchers to gain insights about subjects without the researcher, the subject, or others intruding into the research context and draw their data from naturally occurring circumstances and events (Hill et al., 2014; Webb et al., 1966). *Obtrusive measures*, methods characterized by active cooperation of subjects (Hill et al., 2014; Webb et al., 1966), come in two forms. *Reaction-based obtrusive measures* are based on the instruments that ask subjects for conscious, subjective input, whereas *observation-based obtrusive measures* are based on instruments that collect data automatically but require subjects to operate them. In other words, observation-based measures rely solely on the practical cooperation of subjects, and reaction-based measures rely both on practical cooperation and subjects' effort to offer responses.

2.3.1.2. Measure types

We distinguish between four types of measures: closed question measures, word measures, behavioral measures and physiological measures (Luciano et al., 2017). We will describe both the general characteristics of these types, as well as their relations to the obtrusiveness classifications just discussed.

Closed survey question measures are obtained from workers' responses to one or more survey questions or statements with a finite number of answer categories, as with multiple-choice questions and discrete number scales. Most often, self-report closed survey question measures are used, which are inherently reaction-based obtrusive. In light of common method biases associated with self-report measures, well-being researchers have used other-report (e.g., spouses, friends, children, colleagues) well-being measures to validate self-report measures (Schneider & Schimmack, 2010). Other-report measures are observation-based obtrusive because, even though subjects do not have to exert cognitive effort, they must cooperate with a researcher to identify and contact relevant others who can fill out a survey.

Two classes of survey measures are distinguished: attitudinal or experience-based measures (Grube et al., 2008). Attitudinal measures are designed to uncover a person's overall, usually retrospective assessment of trait-like attitudes, such as life and job satisfaction. Experience-based measures are designed to measure a person's momentary state, e.g., moods and emotions. Typical experience-based survey instruments prompt questions about whereabouts, events, company, activity and feelings of the respondent for several days, either multiple times during the day (i.e. experience sampling method) or at the end of the day (i.e. day reconstruction method; Kahneman et al., 2004).

Word measures are derived from spoken or written text, and can represent the relevant semantic content of the speech or writing (i.e., meaning), or the pattern of speech (Luciano et al., 2017). Word data can be manually analyzed by independent coders or processed automatically by computer software and can be collected either obtrusively (e.g., administering open-ended survey questions) or unobtrusively (e.g., scraping social media data).

Behavioral measures consist of observations of individual behavior, and come in many forms, e.g., data on movement, position, body posture, facial expression, online behavior, substance abuse, etc. (Luciano et al., 2017). Behavioral measures can be either unobtrusive (e.g., publicly available video data) or observation-based obtrusive (e.g., video data obtained from a lab experiment).

Physiological measures are markers that reveal the state of a person's body or its subsystems (Luciano et al., 2017). Building on the work of Akinola (2010) on the most widely used physiological measures in organizational sciences, we distinguish four prominent subcategories: endocrine activity (e.g., cortisol, testosterone, oxytocin, dopamine and serotonin), electrodermal activity (e.g., skin conductance response, skin conductance level), cardiovascular activity (e.g., blood pressure, heart rate, cardiac efficiency) and neurological activity (e.g., frontal lobe activation). These markers reflect changes in the autonomic nervous system, a part of the peripheral nervous system that serves regulatory functions by helping the human body adapt to internal and external demands (Akinola, 2010).

Because physiological data is not recorded naturally, researchers typically rely on observation-based obtrusive measures. The obtrusiveness of these instruments varies substantially (Eatough et al., 2016; Ilies et al., 2016). Devices such as arm-cuff digital blood pressure monitors, fingertip pulse oximeters and cotton swab saliva sampling require substantial effort for subjects (e.g., attaching a device to the body) and can be uncomfortable in use (e.g., some activities could be inhibited by the device), while devices such as wearable bracelets and smartphone applications are almost completely hassle-free.

2.3.2. Illustrations of measures

Below, we provide illustrations of measures for constructs falling into the framework that we used for illustrating our construct taxonomy. We echo our previous disclaimer that the list of measurement options is non-exhaustive and will not cover all potential conceptual nuances. In addition, we want to note that the different measures vary in their degree to which they are valid for the constructs they are purported to measure. For example, evaluative constructs such as job satisfaction and life satisfaction are likely best measured using subjective measures, while affective constructs such as emotions and moods can validly be gauged with both subjective and objective measures (Brulé & Maggino, 2017). We will discuss the validity of measures in the next section.

2.3.2.1. Life satisfaction

Life satisfaction is most often measured using closed question survey measures (Veenhoven, 2017). These measures can be either single-item (Abdel-Khalek, 2006; Cantril, 1965; Commission of the European Communities, 2017; OECD, 2013) or multiple-item, e.g., Satisfaction With Life Scale (Diener et al., 1985), Happiness-Unhappiness Scale (Andrews & Withey, 1976), Gurin Scale (Gurin et al., 1960), and the Happiness Measure (Fordyce, 1977). In general, convergence exists between self-report and other-report measures of life satisfaction (Heller et al., 2006; Judge & Locke, 1993; Lucas et al., 1996; Nave et al., 2008; Pavot et al., 1991; Sandvik et al., 1993, 1993; Schneider et al., 2010; Schneider & Schimmack, 2010; Zou et al., 2013). For other closed question survey measures of life satisfaction and reflections on their validity, see Veenhoven (2017, 2020).

Beyond closed question survey measures, life satisfaction has been measured by analyzing naturally occurring texts on social media sites such as Facebook and Twitter (Collins et al., 2015; P. Liu et al., 2015; Schwartz et al., 2016; Yang & Srinivasan, 2016) and transcripts from clinical life satisfaction interviews (Frisch, 1988; Nave et al., 2008; Neugarten et al., 1961; Thomas & Chambers, 1989). Facial expression data obtained from pictures have been linked to later life satisfaction (Harker & Keltner, 2001; Seder & Oishi, 2012). Unobtrusive data on online behavior has also been linked to life satisfaction (S. Collins et al., 2015; Kosinski et al., 2013). Some studies have found correlations between self-report life satisfaction scores and peripheral systolic and mean arterial blood pressure (Thege et al., 2014).

2.3.2.2. Dispositional affect

Dispositional affect has been measured mostly with closed question survey measures, e.g., the Affect Balance Scale (ABS, Bradburn, 1969), Differential Emotions Scale (DES, Izard et al., 1974), Positive and Negative Affect Schedule (PANAS; Watson et al., 1988), the Multiple Affect Adjective Check-List-Revised (Zuckerman & Lubin, 1985), State-Trait Anxiety Inventory (Spielberger & Gorsuch, 1983), Scale of Positive and Negative Experience (SPANE, Diener et al., 2010) and Affectometer 2 (Kammann & Flett, 1983). Often, self-report measures of dispositional affect converge substantially with other-report measures (Lucas et al., 1996; Pavot et al., 1991; Watson et al., 2000). For more complete overviews on closed question measures of dispositional affect, see Gray and Watson (2007) and Boyle et al. (2015). There is only limited research on measures of dispositional affect other than closed question surveys. Self-reported dispositional affect has been linked to the content in answers to open-ended questions (Sandvik et al., 1993) and salivary cholesterol (Ryff et al., 2004).

2.3.2.3. Moods

Moods are also typically measured using survey scales. These are either specially designed to measure moods, e.g., Profile of Mood States (POMS, McNair et al., 1981), Shortened POMS (Shacham, 1983), Multidimensional Mood State Inventory (Boyle, 1992), Four Dimension Mood Scale (Huelsman et al., 1998) and Affect Grid (Russel et al., 1989), or adaptations of general affect scales, e.g., PANAS, SPANE and DES. Self-report and other-report measures tend to converge (Bleidorn & Peters, 2011; Pavot et al., 1991). Considering mood's cyclic nature (Gray & Watson, 2007), scholars have often used experience-based survey instruments, e.g., adopting experience sampling method (e.g., Dockray et al., 2010; Ilies & Judge, 2004) and day reconstruction method designs (e.g., Dockray et al., 2010; Kahneman et al., 2004).

Concerning non-survey measures, various researchers have shown that word measures can be used to measure mood, e.g., sentiment in blog posts (Bollen et al., 2011; Keshtkar & Inkpen, 2009; Mishne, 2005), social media updates (Dodds et al., 2011; Golder & Macy, 2011; Greyling et al., 2019; Iacus et al., 2020; Jaidka et al., 2020) and responses to open-ended questions (Amabile et al., 2005). Other studies have shown that behaviors can be used as a proxy for moods, e.g., facial behavior (Kulkarni et al., 2009) and online activity (Drake et al., 2013; LiKamWa et al., 2013).

2.3.2.4. Emotions

Like moods, emotions are typically measured using experience-based closed question survey measures like the DES and PANAS (Verduyn et al., 2009; Zelenski & Larsen, 2000). Non-survey researchers have shown that emotions can be inferred from short instant messaging texts (A. J. Gill et al., 2008; Hancock et al., 2007). Other research has shown that social media (Greyling et al., 2019) and online search behavior can be used to monitor specific emotional states (Brodeur et al., 2021; Ford et al., 2018). Lab research has shown that emotions can be inferred from observation-based obtrusive measures, such speech characteristics (Dasgupta, 2017; B. L. Smith et al., 1975; C. E. Williams & Stevens, 1972), combinations of acoustic variables (Banse & Scherer, 1996) and voice pitch (Mauss & Robinson, 2009). Researchers have found that data on body postures (Mauss & Robinson, 2009; Tracy & Matsumoto, 2007) and facial expressions can be used to infer emotions (Ekman et al., 1990; Mauss et al., 2005). There is, however, controversy about the use of facial expression behavior, as certain facial expressions may be associated with multiple emotions and the meaning of them varies substantially across cultures and situations (Barrett et al., 2019). Physiological measures are regularly used to measure emotions. For instance, emotional valence and arousal have been linked to neuroendocrine activity, e.g., cortisol levels (Denson et al., 2009; Dickerson & Kemeny, 2004), testosterone (Mazur & Booth, 1998; Mehta & Josephs, 2006; Zilioli et al., 2014), oxytocin (Grewen et al., 2005; Kosfeld et al., 2005), dopamine (Depue & Collins, 1999) and serotonin (Katz, 1999), electrodermal activity, e.g., skin conductance response and skin conductance level (Akinola, 2010; Kreibig, 2010; Sequeira et al., 2009; Weinberger et al., 1979), cardiovascular activity, e.g., systolic and diastolic blood pressure, heart rate, heart rate variability, cardiac efficiency and respiration (Akinola, 2010; Kreibig, 2010; Shiota et al., 2011) and neurological activity (Sato et al., 2004; Vytal & Hamann, 2010).

2.3.2.5. Psychological well-being

PWB is most often measured by Ryff's (1989a) attitudinal closed question survey measure: Scales of Psychological Well-being. These scales have been linked to measures of psychological functioning and physical health, e.g., neuroendocrine, cardiovascular, immune (Ryff et al., 2004), cardiorespiratory (Thege et al., 2014), neurological (Urry et al., 2004). Behavioral markers (e.g., expressive face, voice or gestures, social skills, awkward interpersonal style) and clinical ratings after an in-depth interview (e.g., productivity, aspiration level) also correlated to self-report measures of PWB (Nave et al., 2008).

2.3.2.6. Job satisfaction

Job satisfaction is most often measured using attitudinal single-item and multiple-item survey scales (D. G. Gardner et al., 1998; Nagy, 2002; Wanous et al., 1997). It is either measured by aggregating the scores on several job facets or by asking respondents directly about a general evaluation of their job (H. M. Weiss, 2002). Frequently used job facet scales include the Job Satisfaction Survey (Spector, 1985), Facet Satisfaction Scale (Bowling et al., 2018) and Job Diagnostic Survey (Hackman & Oldham, 1974), and overall job satisfaction scales include the Minnesota Satisfaction Questionnaire (D. J. Weiss et al., 1967), Job in General Scale (Ironson et al., 1989), Abridged Job in General scale (Russell et al., 2004), Job Satisfaction Scale (Warr et al., 1979), Job Satisfaction Index (Brayfield & Rothe, 1951), Michigan Organizational Assessment Questionnaire (Cammann et al., 1979), Faces scale (Kunin, 1955) and Brief Index of Affective Job Satisfaction (E. R. Thompson & Phua, 2012).[7] Self-report measures and other-report measures of job satisfaction have been found to converge (Ilies et al., 2006; MacEwen & Barling, 1988; Spector et al., 1988; Trice & Tillapaugh, 1991).

Obtrusive, reaction-based word measures have also been used, for example, open and semi-open-ended questions about job satisfaction (Borg & Zuell, 2012; Gilles et al., 2017; Poncheri et al., 2008; Taber, 1991; Wijngaards et al., 2019; Young & Gavade, 2018). Job satisfaction has also been inferred from unobtrusive textual data sources such as job review websites (Jung & Suh, 2019; Moniz & Jong, 2014) and social media (Hernandez et al., 2015). Other research found that job satisfaction can be inferred from an overall impression of behavior (Glick et al., 1986).

2.3.2.7. Job affect

Because most research on job affect has been based on closed question measures, we group dispositional job affect, job moods and job emotions in one paragraph. In line with their conceptual distinction, dispositional job affect is generally measured using attitudinal measures (Brief et al., 1988; Van Katwyk et al., 2000) and job moods and job emotions are generally measured using experience-based measures (e.g., Beal & Ghandour, 2011; Dimotakis et al., 2011; Miner et al., 2005). For this, dedicated job affect scales are most often used, e.g., Job Emotions Scale (C. D. Fisher, 2000), Warr's (1990) and Van Katwyk et al.'s (2000) Job-related Affective Well-being Scale, Job Affect Scale (Burke et al., 1989) and Affective Well-Being scale (Daniels, 2000). Different versions of such

7 In light of the conceptual difference between affective and cognitive job satisfaction (E. R. Thompson & Phua, 2012; H. M. Weiss, 2002), researchers have to be mindful that some measures of job satisfaction relate more strongly to the cognitive component and others more to the affective component (Kaplan et al., 2009). Researchers thus can view job satisfaction measures on a continuum from primarily tapping into cognitive job satisfaction to primarily tapping into affective job satisfaction (C. D. Fisher, 2000).

measures can be used to accommodate the temporal dimension of the target construct (e.g., changing the reference frame from the "in the last four weeks" to "today").

2.3.2.8. Work engagement

Work engagement has mostly been measured using attitudinal closed question survey measures (Bakker et al., 2008; Schaufeli & Bakker, 2010), e.g., Maslach Burnout Inventory (MBI; Maslach et al., 1986), the Oldenburg Burnout Inventory (OBI; Demerouti et al., 2002), Utrecht Work Engagement Scale (UWES-17; Schaufeli et al., 2002, UWES-9; 2006, UWES-3, 2019), Job Engagement Scale (Rich et al., 2010), and the Gallup Q^{12} (Harter et al., 2002). A handful of studies have considered measures other than self-report surveys. For example, studies have linked work engagement to cardiovascular activity (Seppälä et al., 2012; Van Doornen et al., 2009).

2.4. HOW SHOULD A WORKER WELL-BEING MEASURE BE SELECTED?

With such a wide assortment of measures for worker well-being constructs, the next question is how to choose one in your research. In this section, we will show why demonstrating measurement fit, "the degree of alignment between how a construct is conceptualized and measured" (Luciano et al., 2017, p. 593), is a challenging task. Luciano et al.'s (2017) framework of measurement fit illustrates that researchers have to go through various (iterative) steps to make well-reasoned measurement decisions: researchers must explicate the construct thoroughly (e.g., map a construct's content, dimensionality, stability and hypothesized manifestation), determine measurement features (e.g., identify a measure's content, source and aggregation strategy), consider the research context (e.g., state-of-the-science and research purpose), ethics of a proposed research plan (e.g., privacy, discrimination, paternalism) and feasibility, accuracy and completeness of a measure. Considering space concerns, we cannot follow Luciano et al.'s full model for each worker well-being construct. Instead, we sketch a high-level picture of the various relevant considerations for choosing a measure and refer the reader to dedicated works for more elaborate discussion. We summarize this overview in the form of a checklist in Table 2.2.

2.4.1. Conceptualization

One must decide on the construct or constructs of study before a measure can be selected. This decision is driven by many factors, e.g., the objective of the research, the employment situation of the workers you study, the research context and the research question(s). For example, when researchers are interested in evaluating the well-being

Table 2.2 | Checklist for selecting a worker well-being measure

Theme	Questions
Conceptualization	In the selection of a worker well-being construct, did you ...
	… begin by clarifying the objective for the research within the organization?
	… clearly articulate your research question?
	… consider the distinctive characteristics of the population of research subjects, including any distinctive subpopulations?
	… consider whether the scope and stability of the construct make it a good match for the decisions and policies that the research will inform?
	… examine whether hedonic or eudaimonic constructs better align with your research objective?
	… consider a sufficiently diverse range of constructs to reflect all of the potentially relevant considerations and tradeoffs?
	… read some of the existing literature on the construct you selected?
Measurement	In the selection of a measure, did you …
	… look at the different measures available for the chosen construct?
	… scrutinize the explanation of the theoretical validity of the measure?
	… check the evidence on the empirical validity of the measure?
	… make sure it is possible to mitigate the particular sorts of measurement error that the measure introduces?
Practicality	In devising and developing your research and measurement strategy, did you ...
	… identify cost and time constraints imposed by the organization in which the research will be situated?
	… consult organizational decision-makers regarding their willingness to use the results of the research?
	… consult with any stakeholders whose cooperation is necessary for performing the research?
	… consider how any obtrusive measures selected may interfere with the lives or experience of the workers?
	… ensure that any unobtrusive measures are used in ways that allows research subjects to understand their role in the research?
	… obtain informed consent of the workers?
	… identify the institutional and legal requirements regarding measurement procedures and the data collected?
	… have the finalized research plan reviewed by an independent ethics committee?
	… consider whether the research plan remains realistic for those who will actually conduct the research?
	… after checking all the other requirements, review your original research objective to make sure it has not been accidentally distorted or unduly compromised?

enhancing potential of a new coffee machine, they are well-advised to select a very narrow, domain-specific construct, such as *satisfaction with facility management*, rather than a broader construct, such as job satisfaction. For another example, when researchers are tasked to evaluate the well-being enhancing potential of receiving a compliment, they may want to consider a more dynamic, state-like well-being construct, such as job emotions, rather than a stable, trait-like well-being construct, such as job satisfaction, because the effects of compliments will likely be only temporary.

For the selection of appropriate worker well-being construct, we recommend researchers measure as many well-being constructs as possible and maximize diversity. As the measures on different constructs are not easily aggregated, we urge researchers to report well-being measures individually, in the spirit of a dashboard (Forgeard et al., 2011). Such broad measurement of worker well-being is relevant for several reasons.

First, since most researchers' goals for studying worker well-being will be largely motivated by moral considerations and general goodwill, it is important to ensure sufficient breadth of measurement. The reason for this is that constructs vary in their intrinsic value.[8] Most context-free well-being constructs reflect theoretically and philosophically grounded conceptions of human value, e.g., PWB (Aristotle, 340 C.E.; Zagzebski, 1996), life satisfaction (Sumner, 1996) and dispositional affect (Bentham, 1789; De Lazari-Radek & Singer, 2014; F. Feldman, 2004). For domain-specific constructs such as job satisfaction and work engagement, the moral case favoring attention to these constructs is slightly harder to make, as they do not *necessarily* and *inherently* contribute to worker well-being. Work engagement, for instance, could have a dark side (Bakker et al., 2011; Dolan et al., 2012), as illustrated by research showing that it, in some cases, may instigate work-family conflict (Halbesleben, 2011; Halbesleben et al., 2009). None of this is to deny that varieties of domain-specific well-being may frequently, or even usually, drive general well-being, and thus are valuable. It is just that the value of domain-specific well-being constructs depends on the contingencies of their causal interplay with context-free well-being constructs, which better reflect a worker's overall well-being.

Researchers can mind such well-being trade-offs by measuring a diverse set of constructs. To illustrate, it may be necessary to study constructs with negative valence, such as burnout or work addiction, to uncover downsides of policies driven by the goal of increasing positive affect at work. An organization's increasing focus on social responsibility may increase engagement, but with the unintended effect of enticing some workers to be too engaged in their work, giving rise to work addiction (Brieger et al., 2019). A dashboard covering a variety of domain-specific and context-free constructs allows researchers to keep all possible tradeoffs in view. However, if the selection of

8 In ethical theory, it is common to distinguish between what is intrinsically valuable and what is instrumentally valuable. Objects are *intrinsically valuable* when they are good in themselves and worth pursuing independent of any other goals. In contrast, objects are *merely instrumentally valuable* when their value depends on their capacity to help realize other things that are valuable. Of course, a single object can have both intrinsic and instrumental value (for discussion and finer distinctions, see Korsgaard, 1983).

constructs must be constrained, researchers may prioritize constructs that are most likely to uncover those tradeoffs.

Second, for researchers who are motivated to study worker well-being in the service of other objectives, keeping an open mind to the measurement of multiple worker well-being constructs will likely pay off. This holds for researchers with various research objectives, e.g., academics interested in testing theory or practitioners aiming at advancing organizational performance through the enhancement of worker well-being. The reason is that worker well-being constructs can be related to other constructs and factors in unexpected ways. To illustrate, concerning antecedents of worker well-being, a meta-analysis of Steffens et al. (2017) showed that social identification processes relate more strongly to positive well-being constructs than to negative well-being constructs. Regarding outcomes, a meta-analysis by Erdogan et al. (2012) demonstrated that life satisfaction correlates significantly stronger to organizational commitment and turnover intention than to job performance. In conclusion, having a sufficiently broad measurement scope will enable researchers to uncover the most interesting and important relationships among variables.

For researchers interested in making an academic contribution, there is an additional impetus for measuring multiple constructs. Like many research fields in social sciences, the field of worker well-being is burdened with the problem of construct proliferation: "research streams are built around ostensibly new constructs that are theoretically or empirically indistinguishable from existing constructs" (Shaffer et al., 2016, p. 81). For example, research suggested that employee engagement is not distinct from constructs like job burnout (Cole et al., 2012) and job satisfaction (Christian et al., 2011). Measuring multiple, ostensibly distinct constructs will help researchers to demonstrate or refute the theoretical and empirical distinctiveness of well-being constructs and thereby advance the science of worker well-being.

Once one or more constructs have been chosen, researchers are well-advised to turn to established literature to carefully define the construct and understand the conceptual nuances to it. Articles covering best practices for construct definition (Podsakoff et al., 2016) and conceptual works on the conceptualization and categorization of worker well-being (e.g., our current work, S. Johnson et al., 2018; Page & Vella-Brodrick, 2009; Zheng et al., 2015) could be helpful. When constructs have been selected and adequately conceptualized, researchers can move into the constructs' ideal measurement strategy.

2.4.2. Measurement

One of the most important considerations in choosing a suitable measure is a measure's validity. Validity can be described as "the degree to which scores on an appropriately administered instrument support inferences about variation in the characteristic that the instrument was developed to measure" (Cizek, 2012, p. 35). A measure must be the causal outcome of a construct (Borsboom et al., 2004), which means that it has to satisfy the following four conditions for causality: (i) definition of a construct must be chosen and articulated independently and prior to the measure, so that the relationship between the two is not merely tautological, (ii) substantial association (or covariation) between the construct and the measure, (iii) realization of the construct temporally prior to the measurement, and (iv) elimination of rival explanations that could explain the relationship between a construct and a measure, such as history and instrumentation (Edwards & Bagozzi, 2000). In summary, for a measure to be valid for a hypothesized construct, it must be the hypothesized construct – and only the hypothesized construct – that causes the measure.

Proving that a measure is a valid requires a process of theoretical and empirical validation (Borsboom et al., 2004), "the ongoing process of gathering, summarizing, and evaluating relevant evidence concerning the degree to which that evidence supports the intended meaning of scores yielded by an instrument and inferences about standing on the characteristic it was designed to measure" (Cizek, 2012, p. 35). Researchers interested in using a previously developed measure are therefore advised to understand how that measure has been validated and assess the adequacy of the validation process. Researchers aiming to innovate in the development of a new measure must accept the responsibility of performing, or otherwise ensuring, a proper process of measure validation. Either way, understanding the validation process is essential to avoid relying on misleading indicators of the relevant constructs and drawing specious conclusions.

Theoretical validation starts with a logical analysis of measure-construct fit, often performed by academic and/or practitioner subject matter experts (Bornstein, 2011; Luciano et al., 2017). This is where the preparatory work from the conceptualization phase comes into play: a high-quality conceptual definition and deep understanding of conceptual nuances are useful for making methodological decisions. For instance, as the definition of life satisfaction suggests that a valid measure of this construct should be based on a cognitive evaluation and will typically remain stable over time (Diener, 1994; Shin & Johnson, 1978), one can safely forego dynamic, unobtrusive or observation-based obtrusive word, behavioral or physiological measures, and narrow the methodological scope to reaction-based obtrusive, subjective measures, such as surveys and interviews. In sharp contrast, one is well advised to consider more objective behavioral and physiological measures when the measurement of affective states or other state-like constructs is of interest, as their conceptual definition permits it (Mauss & Robinson, 2009). In case the research contexts necessitates survey measurement of affect, one would need to accommodate the state-like nature of affect by focusing on experience-based measures instead of attitudinal measures (C. D. Fisher, 2000).

After theoretical validation, a measure must be empirically validated. This is traditionally done by demonstrating adequate reliability of a measure and demonstrating appropriate statistical associations between a new measure and measures of related or unrelated constructs (Bornstein, 2011; for early examples, see Campbell & Fiske, 1959; Cronbach & Meehl, 1955). More specifically, one can examine a new measure's convergent validity, discriminant validity, predictive validity and incremental validity, in relation to other validated measures, or design experiments to uncover biases in measures and to unravel the underlying mechanisms causing the measurements observed (Bornstein, 2011; Edwards, 2003). Often, one can draw on existing validation research to substantiate the empirical validity of a measure and pick appropriate validation tests (e.g., confirmatory factor analysis, internal consistency analysis, Edwards, 2003). For example, in the development of new closed question job satisfaction measures, Ironson et al. (1989), Thompson and Phua (2012) and Bowling et al. (2018) all followed common practice (e.g., Clark & Watson, 1995; Edwards, 2003; Hinkin, 1998) by examining the new measures' convergent validity (i.e., alignment with) with existing job satisfaction scales and their discriminant validity (i.e., departure from) with measures of related, but distinct constructs.

During empirical validation, one should pay serious attention to the various kinds of measurement error that measures are susceptible to. For instance, closed question survey measures, word measures based on social media and physiological measures obtained from wearable sensors are all vulnerable to selection bias: subjects self-select themselves into participating to a survey, using social media and utilizing a wearable sensor (Ganster et al., 2017; Kern et al., 2016; Landers & Behrend, 2015). Closed question survey measures and word based social media measures are both susceptible to social desirability biases (Marwick & Boyd, 2011; Podsakoff et al., 2003; N. Wang et al., 2014), while physiological data is not. Other sources of measurement error are relevant for specific measurement instruments. Surveys are vulnerable to careless responding, the tendency to respond to questions without regard to the content of items (Meade & Craig, 2012; e.g., an intense experience sampling study, Beal, 2015; lengthy batteries of job satisfaction questions, Kam & Meyer, 2015). Word measures obtained through computer-aided textual analyses will be vulnerable to algorithm error, the pattern of error observed when multiple computer-aided textual analysis techniques produce different measures using the same methods and texts (McKenny et al., 2018; Short et al., 2010). Instruments collecting physiological data will inescapably introduce noisy data (Chaffin et al., 2017; Ganster et al., 2017). Researchers should ensure that they have the appropriate expertise to catch and mitigate the relevant sorts of errors.

We conclude with a note on the varying complexity of theoretically and empirically validating measures. As previously indicated, obtrusive measures such as closed questions, open-ended questions and interviews are relatively straightforward to validate. For theoretical validation, this mainly is due to the deliberate alignment of the measure with the construct definition (e.g., during item pool generation and item purification, Brod et al., 2009; Hinkin, 1998). By maximizing the semantic equivalence of the questions and the construct definition, researchers are able to eliminate alternative explanations prior to the collection of data. The theoretical validation of an unobtrusive measure is much less straightforward because one has little to no influence over the way data is collected. With an unobtrusive measure we have much less guarantee that the cause of the measurements is limited to factors relevant to the construct to be measured. Because of inherent differences between the instrument and the intended construct, one is forced to rely heavily on theory to make a case for why the content of a measure best resembles the construct of interest rather than related, but distinct constructs (Hill et al., 2014). The same pattern of difficulty holds for empirical validation. Empirical validation of obtrusive measures is relatively convenient, as a multitude of validation guidelines and validated measures have accumulated over time. Empirically validating an unobtrusive measure is much more challenging, as it is often impossible to find a well-validated unobtrusive measure for comparison and introducing a validated obtrusive (e.g., survey) measure in an obtrusive measurement design takes away the valuable unobtrusive nature of the data (Hill et al., 2014).

2.4.3. Practicality

After conceptualization and measurement, researchers must consider the practicality of a measurement strategy in a given research context. In some way, all researchers must accommodate the preferences and demands of stakeholders, e.g., organizations, employees and institutions. At the same time, they must safeguard their scientific and ethical integrity. Finally, they must always remain mindful of their own resource limitations.

2.4.3.1. Organizations

Organizations may use their position as facilitator of worker well-being research to put pressure on researchers to do research as cheaply and efficiently as possible (Lapierre et al., 2018). For example, organizations may be hesitant to facilitate physiological measurement, as purchasing and distributing wearable devices are still much more costly than administering questionnaires (Akinola, 2010; Ganster et al., 2017). Relatedly, organizations may prefer single-item measures over their psychometrically superior multiple-item counterparts, as the opportunity costs associated with filling out multiple-item measures are expected to be too high (G. G. Fisher et al., 2016; D. G. Gardner et al., 1998).

Beyond the need to deal with unequal power relations, it is important for researchers to be wary of the values and leadership in an organization. In particular, for well-being research to have an effect on the well-being of workers, an organization's leadership has to value *both* research and well-being (Nielsen et al., 2006; Nielsen & Noblet, 2018). Without commitment from senior management, worker well-being research, regardless of its rigor, will be of limited value, as any resulting policy recommendations will not be implemented. Hence, it is advisable to start well-being research only if the topic is a strategic topic in the organization and there is a culture of receptivity to research and evidence-based practices. On the other hand, organizational change must always begin somewhere, and we should not lose hope that well-presented, well-timed research on a topic of moral importance may occasionally prove pivotal.

2.4.3.2. Workers

Researcher on worker well-being is, of course, typically motivated by a moral interest in the lives and experiences of workers. However, when striving to obtain valid measurements of worker well-being, researchers must not lose sight of the impact of measurement on those very workers whose well-being is to be measured. For choosing a well-being measurement strategy, the rights and interests of the research subjects matter for both practical and ethical reasons. Practically, without satisfactory buy-in from them, measures will be subject to substantial non-response or validity issues (Rogelberg et al., 2000). It is therefore advisable to accommodate workers' tendency to dislike lengthy batteries of questions or long interviews, as participation can be unpleasant and distracting. Further ethical considerations emerge in light of the inherent moral significance of well well-being research and the increasing convenience of collecting (big) data (see Israel & Hay, 2006 for an extensive overview of research ethics for social science; Metcalf & Crawford, 2016). Here we briefly touch upon important ethical considerations and direct readers to referenced works for more information.

First of all, there is an obligation that will be obvious to academic researchers but perhaps less familiar to professionals in organizations: In order to ensure that research does not harm the workers who are the research subjects, researchers must adhere to the principles of research ethics (e.g., American Psychological Association, 2017). In most instances, a review by an independent ethics committee is highly advisable (Wassenaar & Mamotte, 2012), as any research conducted by an organization on employees of that same organization presents special problems, due to pressure employees may feel to "volunteer" for the research (P. T. Kim, 1996). In cooperation with the ethics committee, researchers must be prepared to justify any measurement choices for which a less obtrusive, invasive or burdensome alternative might have been available.

Second, although it is sometimes neglected with novel forms of social research (Flick, 2016), the informed consent of research subjects is of paramount importance. This requires that researchers adequately inform workers about the study, thereby taking into account their expectations and social norms (Brody et al., 2000; Manson & O'Neill, 2007), and ensuring that their participation is voluntary, not coerced (Faden & Beauchamp, 1986). The imperative of informed consent has implications for measurement strategies. When practical, it is advisable to use measures that have a clear and intuitive connection to the constructs to be measured (high face validity), as is the case with most survey measures. This makes it more straightforward to fully inform workers about the connection between the research and their well-being, and hence reduces barriers to consent and willing participation. Where experimental design precludes full transparency in advance, a thorough debriefing session after the experiment becomes critically important (Brody et al., 2000; S. S. Smith & Richardson, 1983; Sommers & Miller, 2013). Novel or esoteric measurement techniques require extra care with regard to informing and debriefing, simply because these techniques may run contrary to workers' expectations of the research process.

Third, it is essential to mind ethical considerations regarding autonomy and privacy, as respectively associated with obtrusive and unobtrusive measurement. Since obtrusive measures, by their nature, interfere with workers' work and other experience, use of such measures implicates the autonomy of workers. Significant interference with their lives should be limited as much as possible and explained clearly. This ensures that workers' abilities to make sure their own choices are not unduly diminished, and not affected beyond the participation to which they have consented (Faden & Beauchamp, 1986). On the flip side, unobtrusive measures raise special concerns about the privacy of workers because, by the very design of the measurement methods, the subjects may not be aware of the information collected about them (Motro et al., 2020). Hence, it is incumbent upon researchers to ensure that workers are not monitored beyond what is relevant to the study, or beyond that to which they have consented. In general, pitfalls of both obtrusive and unobtrusive measures can be largely mitigated by diligent procedures for informed consent.

2.4.3.3. Institutions

Researchers must also navigate institutional pressure and legal requirements. The relevant regulations are very much dependent on the type of study and the location where the study is conducted. For instance, the General Data Privacy Regulation (GDPR, European Parliament and Council, 2016) has outlined strict rules on the analysis, collection, sharing and storage of individual-level data and, in particular, health data (e.g., biometric data, survey data on mental health, Guzzo et al., 2015). If the analysis of health data is of interest, researchers within an organization may want to consider a collaboration with external researchers who specialize in managing such data securely and responsibly. Finally, if the workers are unionized, proactive communication with union representatives is advisable. Although unions support initiatives to advance worker well-being, they may well be wary of measurement procedures that appear to diminish worker autonomy or privacy.

2.4.3.4. Researchers

In light of the many, often divergent preferences and demands of various stakeholders, researchers are forced to be pragmatic and accommodating. Making concessions, however, does not mean that the researchers' own objectives should be discounted. The responsibility falls to researchers themselves to ensure that well-being is measured in a valid way and that, therefore, research questions are answered adequately. In addition, as researchers' time, skills, and resources are finite, certain well-being measures will be infeasible in certain contexts. For instance, if an organization wants to evaluate a company-wide vitality promotion program using wearable devices and dynamic surveying, researchers must be certain to have enough time and resources available to prepare data collection (e.g., selecting vendors, customizing instruments, training subjects) and to analyze the data (e.g., collaborating with researchers in other fields, learning new analytical techniques Chaffin et al., 2017; Eatough et al., 2016). Being pragmatic and minding resource limitations does not have to undermine the validity of measures. Researchers can draw from extant literature to select validated alternatives to the more time-consuming and costly measures. If one wants to measure job affect using the experience sampling method, and an organization suggests a cross-sectional survey to do this, researchers can suggest day reconstruction method as a valid alternative (Dockray et al., 2010; Kahneman et al., 2004). If one wants to use well-established multiple-item scales to measure well-being constructs, and an organization rejects this idea, researchers might want to suggest validated single-item measures (e.g., G. G. Fisher et al., 2016; Wanous et al., 1997) or shortened scales (e.g., Russell et al., 2004; Schaufeli et al., 2006, 2019). This may allow investigation of several constructs with satisfactory precision instead of a single construct with higher precision, which should be a desirable trade-off in many contexts, for the reasons noted above.

In the process of managing stakeholders, good communication is key. Organizations, in particular, are not easily convinced by the presentation of statistical or theoretical evidence (Hodgkinson, 2012). For this reason, it is key to communicate about topics such as instrument validity, research design and construct choice in an understandable and persuasive manner (Lapierre et al., 2018). We refer the reader to research on the communication of evidence-based practice (Baughman et al., 2011; Highhouse et al., 2017; Hodgkinson, 2012; Lapierre et al., 2018; D. C. Zhang, 2018) and bridging the academia-practice gap (Banks et al., 2016; Rynes, 2012) for best practices.

2.5. DISCUSSION

Our work aimed at answering three questions that are relevant for the study of worker well-being. We addressed the first question, *What is worker well-being?,* by proposing a construct taxonomy based on four dimensions: philosophical foundation, scope, stability and valence. We illustrated the taxonomy by classifying the ten worker well-being constructs. By synthesizing the many conceptual models of worker well-being, the taxonomy helps researchers to make sense of the burgeoning but messy field of worker well-being.

To answer the question, *How can worker well-being constructs be measured?,* we offered a multi-disciplinary overview of traditional (e.g., surveys and interviews) and novel data sources (e.g., wearable sensors) that can be leveraged to measure worker well-being. Therein, we distinguished four broad types of data sources: closed question survey, word, behavioral and physiological measures, and further classified them as either unobtrusive, reaction-based obtrusive or observation-based obtrusive.

Taken together, our construct taxonomy and our overview of existing measurement approaches uncovered some notable gaps in the current science of worker well-being. In particular, we showed that several of the most important work-specific well-being constructs have been measured primarily using closed question surveys. In light of the fact that the context-free counterparts of these constructs have undergone innovation in measurement methodology, we encourage researchers to draw from other research strands to develop new measures of these important work-specific constructs. More generally, we hope that our overview inspires researchers to think outside their current methodological toolboxes and to foster collaborations outside the social sciences to leverage new measurement and data collection techniques.

To address the final question, *How should a worker well-being construct measure be selected?,* we described the importance of good conceptualization, rigorous operationalization and pragmatic stakeholder management. Because of its broad scope, this discussion was not intended to be exhaustive. Instead, we hope that the discussion provides a useful map of the most important considerations and guidance to detailed references on particular topics (e.g., construct definition, validation, ethics, and communication).

In conclusion, with our work, we intended to bridge the gap between the popular buzz about worker well-being and the extant scientific research about it. Our work has provided guidelines to go beyond the ad-hoc study of worker well-being and conduct rigorous, responsible research. It is our hope that researchers, whether working in organizations, in academia or both, will feel more competent to take the well-being of workers into account, eventually permitting them to better understand what drives worker well-being and design policies to promote it accordingly.

3

Steering towards happiness

Based on paper: Wijngaards, I., Hendriks, M., & Burger, M.J. (2019). Steering towards happiness: An experience sampling study on the determinants of happiness of truck drivers. *Transportation research part A: policy and practice, 128*, 131-148.

3.1. INTRODUCTION

Truck drivers continue to play an integral part within the world economy. However, due to high job demands, truck drivers are at high risk for anxiety (Apostolopoulos et al., 2016; De Croon et al., 2004), depression (Da Silva-Júnior et al., 2009), and fatigue (Boyce, 2016). More generally, data on subjective well-being (SWB) show that employees working in the transportation sector score well below average on life satisfaction and job satisfaction (De Neve & Ward, 2017). The struggles of truck drivers are powerfully illustrated by an interview subject of Apostolopoulos et al. (2016): "It's rough and rugged … It's hard and it's stressful. You know, maybe that's why I turn to drugs, I don't know. It's not the type of life I really want to live but, you know, it gives me what I need to maintain my family and to maintain me and my lifestyle" (p. 55).

Low levels of well-being among truck drivers can have various adverse effects, including lower work productivity (Stewart et al., 2003), poor health outcomes (Apostolopoulos et al., 2013) and reduced personal and public safety (Apostolopoulos et al., 2016). In addition, due to the prospect of low truck driver happiness, logistics companies have difficulties attracting new talent. These adverse effects are particularly pertinent because many Western countries currently face a shortage of transportation workers caused by a combination of high voluntary turnover (Prockl et al., 2017; Staats et al., 2017), a rapidly aging workforce (American Trucking Association, 2018), and difficulties finding young, capable drivers (Rauwald & Schmidt, 2012; Schulz et al., 2014). For instance, the United States currently faces a shortage of 50,000 drivers, a figure that could increase to 174,000 drivers by 2026 (American Trucking Association, 2017). Similarly, it is expected that in Germany, 40% of truck drivers on the road today will retire in the next ten years, leading to a large shortage of drivers (R. Weiss, 2013). As noted by Suzuki et al. (2009) and Fournier et al. (2012), these low retention rates and labor shortages turn out to be a very costly issue for transportation companies.

To adequately address these issues faced by the transportation industry, it is crucial to better understand the subjective experience of its employees (Schulz et al., 2014). Various studies have addressed truck drivers' job satisfaction and its antecedents (e.g., De Croon et al., 2002; J. C. Johnson et al., 2011; McElroy et al., 1993; Prockl et al., 2017), but, to the best of the authors' knowledge, no studies have investigated truck drivers' momentary happiness and its antecedents. This gap in the literature is deemed significant because the sole focus on job satisfaction is unwarranted. First, although overall job satisfaction provides some useful information about truck drivers' overall happiness at work, studies focusing exclusively on statically measured job satisfaction ignore much of the variation in happiness that takes place over the course of a day (C. D. Fisher, 2000; Ilies & Judge, 2002), and they fail to examine the effects of specific (work) events (Miner et al., 2005).

Second, past studies' close attention to job satisfaction may be disproportionate, since it only constitutes one dimension of subjective well-being (Diener, 1984; Diener et al., 1999) and affective states (e.g., moods and emotions) are better predictors of certain work outcomes than evaluative states (e.g., job satisfaction, Bakker & Oerlemans, 2011; Van Katwyk et al., 2000).

In light of this, the current study contributes to the existing literature in several ways. First, this study intends to build on current studies on the well-being of truck drivers by focusing on the momentary happiness (i.e., affective and transient feelings) of truck drivers. Specifically, this study examines the differences in momentary happiness during various job and off-job activities and assesses the impact of occupation-relevant job characteristics on the momentary happiness of truck drivers. The consideration of off-job activities is important because happiness during off-job activities can spill over to the work context and vice versa (Ten Brummelhuis & Bakker, 2012), and plays an important role in a person's general happiness set-point (Diener et al., 2006). The findings of this study can offer logistics companies insights about what makes truck drivers happy and unhappy, and this information can be used to improve the well-being of truck drivers and address commonplace problems in the transportation sector, such as difficulties to attract new staff and employee turnover.

Second, this study tests whether the core proposition of the job demands-resources (JD-R) model (Demerouti et al., 2001) that job demands (e.g., long working hours and job insecurity) and job resources (e.g., social support and job variety) are negative and positive determinants of well-being in every occupation, respectively, by examining how momentary happiness relates to several core job demands and resources of truck drivers. Additionally, to the best of the author's knowledge, this study is the first to not only investigate how truck drivers' happiness relates to relatively stable *trait* job demands and resources (e.g., job insecurity and pay), but also the role of various highly fluctuating *state* job demands and resources (e.g., road congestion and road quality during a specific trip or work day). These state-like variables are important, as they can play a significant mediating role in the relationship between trait job demands and resources and trait well-being (Schaufeli & Van Rhenen, 2006) and may have particularly strong and unique effects on transient feelings of happiness.

Third, this study offers a methodological contribution to the transportation literature by capturing momentary happiness and state-like job characteristics using an experience sampling method measure (ESM, Csikszentmihalyi & Hunter, 2003), a method that asks respondents to report on their moods and time spending several times per day, thereby explicitly incorporating the dynamic aspect of day-to-day happiness and activities (Scollon et al., 2009). This type of multiple moment assessments method reduces memory bias, relies less on global heuristics, increases ecological validity, controls for the top-down effect in the assessment of SWB, and allows for a better view on the situational circumstances that influence an experience (Kahneman et al., 2004; Scollon et al., 2009).

In summary, this study intends to answer the following three research questions:
(1) How do the momentary happiness levels of truck drivers differ across job and off-job activities?
(2) How do trait-like job demands and job resources moderate the relationship between truck-drivers work-related job activities and momentary happiness?
(3) How do state-like job demands and job resources moderate the relationship between truck driving and momentary happiness?

The remainder of this paper is structured as follows. First, a conceptualization of SWB is provided, and multiple sets of hypotheses are presented. Next, the study's sample and research procedure, survey instruments, and approach to statistical analyses are discussed, followed by a presentation of the research findings. Finally, a discussion of the research findings and conclusions are offered.

3.2. THEORY

3.2.1. Subjective well-being

The concept of SWB concerns the appreciation of one's personal condition and comprises affective experiences (i.e., moods, emotions, affectivity) and cognitive comparisons (Diener, 1984; e.g., life satisfaction, Diener et al., 1999; Veenhoven, 2000).[9] SWB comprises context-free states (e.g., life satisfaction or general mood) as well as context-specific states (e.g., job satisfaction and job affect, Taris & Schaufeli, 2015). This study focuses on context-free states by considering truck drivers' moods: "diffuse affect states, characterized by a relative enduring predominance of certain types of subjective feelings that affect the experience and behavior of a person" (Scherer, 2005, p. 705). These affective states are also often characterized as momentary happiness (e.g., Bryson & MacKerron, 2017; Csikszentmihalyi & Hunter, 2003; Howell et al., 2011). Momentary happiness encapsulates various positive (e.g., joyful, engaged) and negative states (e.g., stressed, angry, Bakker & Oerlemans, 2011). Although SWB constructs generally show significant intercorrelations (Bowling et al., 2010; Krueger & Schkade, 2008), the correlations between affective SWB and cognitive SWB and between context-free and context-specific states are only modest. For example, affectivity's relationships with job

9 SWB should therefore be considered a general concept or field of study rather than a metric in and of itself that can be operationalized by aggregating construct scores (Diener et al., 1999).

satisfaction (Bowling et al., 2010), job facet satisfaction (Bowling et al., 2008) and life satisfaction (Kahneman & Deaton, 2010) are typically below 0.4.

3.2.2. Activities and momentary happiness

The truck driving occupation is characterized by high job demands (De Croon et al., 2004), including frequently working overtime and low task variety amongst other demands, and a lack of recovery opportunities (C. Chen & Xie, 2014; Morrow & Crum, 2004; for evidence from the Netherlands, see Van Zenderen et al., 2017). Both can be expected to negatively affect happiness, possibly leading to momentary happiness levels below a driver's happiness set-point (Kuykendall, Tay, & Ng, 2015). Their combined negative effect may go beyond their individual negative effects because recovery in the form of leisure activities plays an important role in mitigating the effects of job demands on job stress (Sonnentag & Fritz, 2015) and happiness more generally (Kuykendall et al., 2015), and vice versa for a lack of recovery. Many theories have been proposed that underlie this notion (for an extensive reviews, see Newman et al., 2014; Sonnentag & Fritz, 2015). A prominent example in this regard is the conservation of resources (COR) theory (Hobfoll, 1989), which proposes that individuals build resources (e.g., energy, concentration, motivation) during leisure activities that, in turn, can be used at work. Another example is activity theory (Havighurst, 1963), which argues that happiness is increased by the engagement in meaningful and social leisure activities outside work, such as meeting others and doing volunteering work. Accordingly, in most occupations, people generally feel happier during leisure activities than during work activities (Bryson & MacKerron, 2017) and we believe truck drivers are no exception given the relatively high job demands and lack of recovery opportunities in this occupation. For these reasons, the following hypothesis is posed:

> **Hypothesis 1a:** *Off-job activities are associated with higher momentary happiness than job activities among truck drivers.*

While truck drivers mostly engage in work-related job activities during work time (e.g., driving, deliveries, and pick-ups), they also engage in some non-work-related job activities (typically eating and resting breaks). COR theory as well as the effort-recovery model (Meijman & Mulder, 1998) predict that the buffering effect of engaging in recovery activities such as breaks also holds for recovery activities during the work day (Hunter & Wu, 2016). Empirical studies confirm that lunch breaks (Hunter & Wu, 2016; Trougakos et al., 2014) and micro-breaks (S. Kim et al., 2017) can help people to recover from daily stressors (e.g., by satisfying the basic need to interact with other people). Some studies suggest that these theories could also apply to the truck driving occupation, as breaks reduce fatigue and crash risks (C. Chen & Xie, 2014) and improve overall occupational health (Apostolopoulos et al., 2012). As such, it is expected that non-work-related job activities (i.e. breaks) trigger higher momentary happiness than work-related job activities. Therefore, the following hypothesis is posed:

> **Hypothesis 1b:** *Non-work-related job activities are associated with higher momentary happiness than work-related job activities among truck drivers.*

3.2.3. Job characteristics and momentary happiness

This study draws on the JD-R model (Bakker et al., 2004; Bakker & Demerouti, 2017; Demerouti et al., 2001) to further expand upon hypothesis 1a. The negative relationship between work-related job activities and momentary happiness is likely to be dependent on the favorability of truck drivers' job characteristics.

The JD-R model posits that every job characteristic can be classified in two general categories: job demands and job resources (Schaufeli & Taris, 2014). Job demands refer to "those physical, social, or organizational aspects of the job that require sustained physical or mental effort and are therefore associated with certain physiological and psychological costs (e.g., exhaustion)" (Demerouti et al., 2001, p. 501). Job resources can be defined as "those physical, psychological, social or organizational aspects of the job that may do any of the following: be functional in achieving work goals, reduce job demands at the associated physiological and psychological costs or stimulate personal growth and development" (Demerouti et al., 2001, p. 501). This theoretical model posits that both job demands and job resources work as proximal determinants of various aspects of employee well-being. Although the traditional focus is on motivational states (e.g., work engagement) and health states (e.g., stress, burnout), the model can also be applied to affective feelings of (un)happiness (Bakker & Oerlemans, 2011). Typically, job demands negatively affect employee well-being, and job resources positively affect employee well-being. In turn, employee well-being determines organizational outcome variables, such as productivity, absenteeism and turnover (Bakker & Demerouti, 2007; for empirical evidence, see Crawford et al., 2010). Because this study is interested in the relationship between activities and momentary happiness, it does not follow the tradition of examining the direct impact of job demands and resources on well-being, but instead looks into their alleviating or aggravating potential in the hypothesized negative relationship between work-related job activities and momentary happiness.

The JD-R model is a flexible model, as at its core lies the proposition that while there may be occupation-specific job demands and resources, their general relationships with well-being are relevant across all sectors and occupations (Korunka et al., 2009; Van Droogenbroeck & Spruyt, 2016). It is however vital to select job demands and resources that are relevant or specific to the occupation, since their exact manifestation can be highly dependent on the occupational setting (e.g., De Croon et al., 2002).

Furthermore, JD-R theory distinguishes between *state-like* and *trait-like* job demands, job resources, and well-being variables (Bakker, 2015). States mirror a person's feelings about the environment (e.g., job demands and resources) and the self (e.g., well-being) at particular moments in time and are considered to be highly fluctuant (Kühnel et al., 2012; Xanthopoulou et al., 2008). In contrast, traits are regarded as individual dispositions or global experiences that remain relatively stable over time (Bakker, 2015). This distinction is important because stable long-term effects and transient short-term effects can have divergent determinants and consequences due to differences in their phenomenological nature. For instance, trip duration can both be state-like (e.g., making a longer trip than usual) and trait-like (e.g., making long trips on a daily basis) and these may have unique effects on momentary happiness.

The current study focuses on a selection of state-like and trait-like job demands and job resources that are relevant for the truck driving occupation. This selection was made by reviewing the truck driving literature and in consultation with the Dutch Sector Institute of Transportation and Logistics (in Dutch: *Sectorinstituut Transport en Logistiek*), thereby focusing on the issues that truck drivers commonly mention in their interactions with the Sector Institute. However, given the large number of potentially relevant job demands and resources, this selection is inevitably incomplete.

3.2.3.1. Trait job demands

This study focuses on three trait job demands: the frequency of working overtime, job insecurity, and average trip duration.

The high frequency of working overtime, often associated with long driving hours and extreme workloads, is a straining job demand for truck drivers (Morrow & Crum, 2004; for evidence from the Netherlands, see Boeijinga et al., 2017). Working overtime can interfere with truck drivers' ability to balance their work and private lives (P. Berg et al., 2003), hamper people's ability to recover from work (Beckers et al., 2008), and disturb their sleeping rhythms (Kanazawa et al., 2006), which can in turn reduce their well-being (Beckers et al., 2008) and result in chronic fatigue (Hege et al., 2015).

Job insecurity functions as another job demand for truck drivers, as in recent years more and more Dutch truck drivers started working under temporary employment contracts (Wagenaar, 2018). While truck drivers are generally in high demand (J. C. Johnson et al., 2011), job insecurity can fosters feelings of powerlessness and uncontrollability (De Witte, 1999), which in turn can lead to increased work stress (De Witte, 1999), lower job satisfaction (De Cuyper & De Witte, 2006), and lower life satisfaction (Silla et al., 2009).

Truck drivers' average duration of a trip is a likely occupation-specific job demand. Even though many just-in-time deliveries in a working day can be stressful (Kemp et al., 2013), it is expected that, compared to short-haul truck drivers, truck drivers that have longer average trip durations tend to experience resource depletion by increased feelings of social isolation and monotonous work as well as work overload and work-family conflicts (Apostolopoulos et al., 2013; Crizzle et al., 2017). In line with the above argumentations, the following hypotheses are posited:

> **Hypothesis 2a:** *Having to work overtime frequently aggravates the negative relationship between work-related job activities and truck drivers' momentary happiness.*
>
> **Hypothesis 2b:** *Job insecurity aggravates the negative relationship between work-related job activities and momentary happiness.*
>
> **Hypothesis 2c:** *Having long average trip duration aggravates the negative relationship between work-related job activities and momentary happiness.*

3.2.3.2. Trait job resources

This study examines the role of four resources that are relevant for the truck driving occupation: pay, colleague support, flexibility of work hours, and task variety. Pay, or income more generally, tends to have a positive relationship with emotional well-being for people with relatively low or modest incomes, such as truck drivers (Kahneman and Deaton, 2010). This is illustrated by the fact that truck drivers have indicated that better salary is the most important factor for changing jobs (Van Zenderen et al., 2017) The positive effect of receiving a relatively high pay may be reinforced by the controversy surrounding the pay of Dutch truck drivers. Dutch employers have used the trend that more and more truckers from low-income European Union countries (Hilal, 2008; Pijpers, 2010) have started participating in the international transportation market as an excuse to underpay Dutch truck drivers (Cremers, 2014). The effort-reward imbalance model (Siegrist & Peter, 1996; Van Vegchel et al., 2005) predicts that employee perceptions of being insufficiently rewarded based on his or her efforts reduces employee well-being. The salience of pay unfairness in the truck driving setting might make pay a particularly important determinant of truck drivers' well-being.

The individualistic nature of the truck driving occupation could cause truck drivers to feel socially isolated, and experience limited social support (Crizzle et al., 2017; Orris et al., 1997), resulting in mental health complaints (Kemp, Kopp, & Kemp Jr., 2013; Shattell, Apostolopoulos, Sönmez, & Griffin, 2010). Social support works as resource for truck drivers (Van Zenderen et al., 2017), as it satisfies individuals' desire for relatedness (e.g., social interactions with colleagues are pleasant), facilitates coping (e.g., blowing off steam after a stressful situation) and can be used to decrease workload (e.g., a colleague takes over a ride, Bakker & Demerouti, 2007).

Further, truck drivers regularly deal with tight and sometimes unrealistic schedules (Apostolopoulos et al., 2016; Hege et al., 2015) and extended periods away from home (Shattell et al., 2010). This lack of flexibility in work schedules is likely to diminish truck drivers' sense of autonomy (C. A. Thompson & Prottas, 2006) and well-being (Bakker & Demerouti, 2007). In accordance, it is expected that flexible work hours help alleviate truck driver stress, as they facilitate the reduction of role conflicts and work-life conflict (Rau & Hyland, 2002).

Task variety of truck drivers is generally considered low, as truck drivers often engage in driving for long periods of time (Shattell et al., 2010). This monotonous driving could diminish the meaningfulness of the job (Hackman & Oldham, 1974) and increase feelings of boredom (Parker et al., 2008). Hence, following the assumption that job resources have a positive effect on happiness, the following hypotheses are posed:

> **Hypothesis 3a:** *High pay alleviates the negative relationship between work-related job activities and momentary happiness.*
>
> **Hypothesis 3b:** *Social support of colleagues alleviates the negative relationship between work-related job activities and momentary happiness.*
>
> **Hypothesis 3c:** *Having flexible work hours alleviates the negative relationship between work-related job activities and momentary happiness.*
>
> **Hypothesis 3d:** *Task variety alleviates the negative relationship between work-related job activities and momentary happiness.*

3.2.3.3. State job demands

So far, this study hypothesized the moderating effect of job demands and resources in the relationship between work-related job activities and momentary happiness. Yet, it is pivotal to also examine job demands and resources that are specifically relevant during individual job activities, in particular those related to the main task of truck drivers: driving a truck. One prominent source of job demands relevant to this activity are environmental conditions (Crizzle et al., 2017; Shattell et al., 2010), and we will focus here on two such environmental conditions: road congestion and poor road conditions.

Road congestion functions as job demand (Rowden et al., 2011; Shattell et al., 2010), as it often result negative emotions (Eckenrode, 1984; Hennessy & Wiesenthal, 1999; Rowden et al., 2011), such as frustration and aggression (Shinar & Compton, 2004). Besides, busy roads force truck drivers to deplete energy resources to concentrate on the road (Shattell et al., 2010).

Poor road conditions may also act as job demand (Shattell et al., 2010), although the road quality in the Netherlands is generally good (Bruntlett & Bruntlett, 2018). For example, driving on roads with many potholes results in increased levels of whole body vibration, in turn causing discomfort and, if sufficiently continuous, pain (Bovenzi, 2009). Driving on poorly lit roads make truck drivers drowsy and pressure them to pay extra attention. Following this argumentation, two hypotheses are put forward:

> **Hypothesis 4a:** *Road congestion aggravates the negative relationship between truck driving and momentary happiness.*

> **Hypothesis 4b:** *Poor road conditions aggravate the negative relationship between truck driving momentary happiness.*

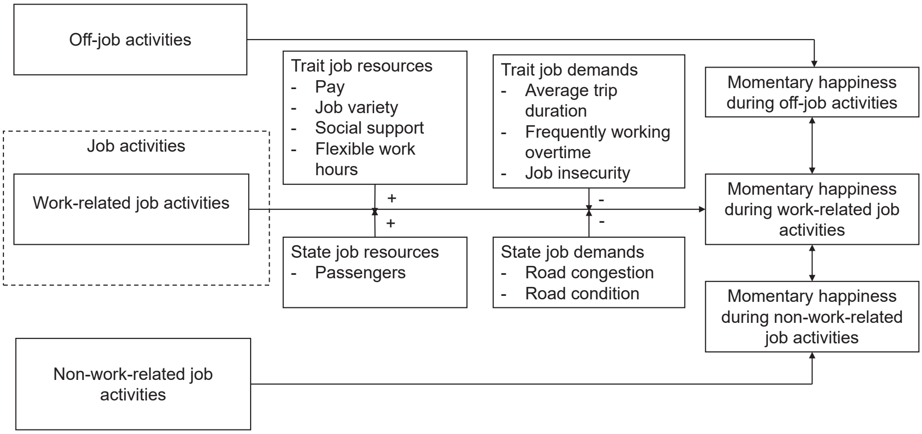
3.2.3.4. State job resources

Social support can also be viewed as a state job resource. Truck drivers typically spend most of their working hours on the road without any physical company and lack the opportunity to virtually connect. The situations when drivers have passengers in the truck provide a valuable opportunity for social support and distraction. For instance, when a driver has passengers with whom he or she can interact, he or she will be "more occupied with something" (R. P. Smith, 1981) and distracted from the "boring road" (Ettema et al., 2012). Some evidence from commuting studies suggests that the negative emotions resulting from job stressors can be attenuated by the presence of passengers (Ettema et al., 2012; Lancée et al., 2017). In a study among truck drivers, Hatami et al. (2019) have shown that having a co-driver decreases feelings of stress and loneliness, and thereby increases SWB. As such, the following hypothesis is posited:

> **Hypothesis 5:** *Having passengers alleviates the negative relationship between truck driving and momentary happiness.*

In Figure 3.1, a conceptual model is presented that summarizes all hypotheses. Hypothesis 1a represents the top arrow, and hypothesis 1b represents bottom arrow, respectively. Hypothesis 2 to 5 concern the arrow in the middle. Hypotheses 2 and 3 involve the moderating effect of trait job demands and trait job resources on the relationship between work-related job activities and momentary happiness. Hypotheses 4 and 5 summarize the argumentation about the moderating effect of state job demands and resources in the relationship between work-related job activities and momentary happiness.

Figure 3.1 | Conceptual model



3.3. METHODS

3.3.1. Procedure and sample

The data collection was conducted by a Dutch academic research institute in collaboration with the Dutch Sector Institute of Transportation and Logistics from February to December 2016. Transportation workers were recruited via the sector institute's newspaper, digital newsletter and website. To incentivize participation, it was announced on these platforms that three randomly selected survey respondents would win a power bank, which is a portable battery that can charge USB-changed devices, such as smartphones and tablets. This convenience sampling procedure resulted in 339 national and international truck drivers participating in a one-time survey asking about trait-like work characteristics and their demographic characteristics.

After this one-time survey, 82 truck drivers voluntarily participated in a follow-up ESM study.[10] The goal of the ESM study was to capture state-like variables and momentary happiness. After stating their agreement to participate in this follow-up study, participants were informed on how to download the ESM application onto their mobile phones. When they had downloaded the application, participants were provided a tutorial with instructions on how to use the application in order to maximize the quality and quantity of responses. Next, in line with common practice in ESM research (C. D. Fisher & To, 2012; Larson & Csikszentmihalyi, 2014), respondents received four notifications each day asking them to indicate (i) how they were feeling, (ii) what they were doing, and (iii) who was with them in the past hour. The notifications were distributed throughout the daytime,

10 A threshold of five ESM observations was adopted, as some participants participated just once or twice.

covering the entire waking day. Two consecutive signals were always more than an hour apart. Out of safety considerations, the truck drivers were instructed to answer this question when they were off the road (e.g., on a break or at a drop-off or pick-up location).[11] The total number of observations in the utilized ESM dataset was 4175, and the median number of responses was 30. The data were fully anonymized and treated confidentially.

Table 3.1 summarizes the demographic composition and well-being of the sample of ESM respondents and compares these to the Dutch truck driver population and the attrition sample (i.e., those who participated in the initial study but not in the follow-up ESM study). The sample of ESM participants was generally representative in terms of demographic composition and well-being of the attrition sample and general population, with some exceptions. For reasons of anonymity, respondents were not asked to indicate for which company they worked. However, as the sector institute is a cooperation of the main employers' associations and employees' organizations in the Dutch transportation and logistics sector, the survey respondents likely worked for a great variety of companies in the transportation and logistics sector.

3.3.2. Measures

Trait-like variables were measured using survey instruments in a cross-sectional survey because they were expected to be rather stable over time. Because of their transient nature, state-like variables were measured through survey instruments in the ESM procedure. The items were presented in Dutch. A list of all the current study's variables and the number of observations per category is provided in Table 3.2.

Except for momentary happiness, all scales were collapsed into fewer categories based on the logical ordering of answer categories (e.g., merging "Strongly agree" and "Agree" into "Agree"). Most variables were measured on ordinal Likert-scales. Likert scales are commonly treated as interval variables in statistical analyses and should generally not be collapsed into fewer categories, as it can result in, for instance, information, power and effect size loss (MacCallum et al., 2002). Yet, because Shapiro-Wilk's test of normality showed that all variables followed a non-normal distribution ($p < 0.05$), variables had to be treated as ordinal. Further, since the skewness of the variables was extreme and certain categories were infrequently or almost completely unused, collapsing the scales into fewer categories was deemed necessary (Agresti, 2018). Without collapsing the scales, statistical tests would have been conducted with limited statistical power, and the results could have mistakenly pointed towards statistically insignificant effects, while effects were in fact economically (or practically) significant.

11 For this reason, we were unable to collect data on *true* momentary activities, feelings or company (e.g., "What are you doing *right now*?") and had to prompt a question that allowed more flexibility.

Table 3.1 | Comparison of reduced sample ($N = 82$), attrition sample ($N = 257$) and representative sample ($N = 76{,}537$)

Variable	Category	ESM sample	Attrition Sample	Representative sample[b]
Demographics				
Gender	Male	96.3	98.1	91.0[c]
	Female	3.7	1.9	9.0[c]
Age	Mean	45.67	52.9[a]	44.0[c]
	SD	12.37	9.3	-
Contract status	Temporary	15.8	20.6	8.0
	Permanent	81.7	75.5	83.0
	Self-employed	1.2	0.8	4.0
	Employment agency	1.2	3.1	5.0
Relationship status	No partner	23.2	13.4[a]	-
	Partner	76.8	66.9	-
Children	No children	40.2	33.1	-
	Children	59.8	66.9	-
Education level	Primary or secondary school	52.2	58.4	59.0[c]
	Professional or higher education	48.8	41.6	41.0[c]
Driver type	National driver	61.0	71.2	-
	International driver	39.0	28.8	-
Personal income (net/monthly)	≤ €1800	20.7	26.8	-
	≥ €1801	79.3	73.2	-
Subjective well-being				
Life satisfaction	Mean	7.35	7.44	7.57
	SD	1.12	1.33	
Trait happiness	Mean	5.30	5.22	-
	SD	1.19	1.18	
Stressful feelings at work	Mean	3.54	3.74	-
	SD	1.97	1.82	

Notes. - = No data available; [a] = The ESM and attrition samples were compared using χ^2-tests (for categorical variables) and independent *t*-tests (for continuous variables). Significant differences at the 5% significance level were found for age and relationship status; [b] = Data of a representative sample of the truck driver population in the Netherlands are based on research by the Dutch Sector Institute of Transportation and Logistics (Van Zenderen & Sombekke, 2016); [c] = While standard deviations were not available and statistical comparisons of means were not possible, it seems that the ESM's distributions of education, gender and contract status diverged from the representative sample. Average age and mean life satisfaction in the two samples seemed to correspond; *SD* = Standard deviation.

For several categorical variables from the cross-sectional survey, some categories were seldom selected by respondents. Without collapsing these scales, statistical tests would have been conducted with limited statistical power. Consequently, the results could have mistakenly pointed towards statistically insignificant effects, while effects are in fact economically (or practically) significant (i.e. type 1 error).

Table 3.2 | Variable overview

Variable category	Variable	Categories	*N*/Mean (*SD*)
State-like variables	Momentary happiness[a]	0 ("Very unhappy") to 10 ("Very happy")	7.45 (1.42)
	Activity	*	-
	Passengers[b]	Passengers	45
		No passengers	916
	Road congestion[b]	Road congestion	257
		No road congestion	435
	Road quality[b]	Good road quality	891
		Poor road quality	72
	Road familiarity[b]	High road familiarity	928
		Low road familiarity	34
Trait-like variables	Working overtime[c]	Once or multiple times a week	47
		Less than once or multiple times a week	35
	Job insecurity[c]	Few worries	60
		Some worries	10
		Many worries	12
	Average trip duration[c]	3 hours or less	48
		More than 3 hours	34
	Pay[c]	≤ €1800	17
		≥ €1801	65
	Colleague support[c]	Disagree	15
		Neutral	9
		Agree	59
	Flexible work hours[c]	Disagree	36
		Neutral	14
		Agree	32
	Task variety[c]	Disagree	9
		Neutral	17
		Agree	56

Notes. [a] $N = 4175$, [b] $N = 962$, [c] $N = 82$, * The observations per category can be found in Figure 3.2.

3.3.2.1. State-like variables

The considered state-like variables can be classified into four groups: state-like employee well-being, activity, state job demands, and state job resources.

State-like happiness

Momentary happiness captures respondents' momentary well-being state and was assessed with a single-item question: "How happy did you feel in the last hour?" Responses were rated on an 11-point Likert scale ranging from 0 ("Very unhappy") to 10 ("Very happy").

Activity
Respondents were asked to report what they had been primarily doing in the last hour. They first had to select whether they were engaged in a job or an off-job activity. For job activities, they could subsequently select one of the following activities: driving, eating, delivery and pick-up, rest/relaxation, administrative task, logistics task, or other. The categories eating and rest/relaxation were combined into a category of non-work-related job activities. For off-job activities, subjects could choose one of the following activities: sleeping, taking care of oneself, taking care of another person, travelling, studying, doing household tasks, eating, communicating with another person, relaxing, watching TV or using a computer, working out, engaging in outdoor activity, or other.

State job demands
When respondents answered driving as an activity, they were asked how busy the road was (1 = "Very unbusy", 2 = "Reasonably unbusy", 3 = "Reasonably busy", 4 = "Very busy") and what the quality of the road was (1 = "Very bad", 2 = "Reasonably bad", 3 = "Reasonably good", 4 = "Very good"). The 4-point Likert scales were dichotomized (e.g., 0 = "No road congestion", 1 = "Road congestion") by combining the lowest two scores and the and highest two scores.

State job resources
As a follow-up to the activity question, respondents were asked if they were alone or with colleagues, customers or friends. This variable was dichotomized to having passengers or not while driving (0 = "No", 1 = "Yes").[12]

3.3.2.2. Trait-like variables
The considered trait-like variables can be classified into two groups: trait job demands and trait job resources.

Trait job demands
Working overtime was measured with the item "How often do you have to work overtime for your job?" This categorical variable was dichotomized to working overtime one or multiple times per week or not (0 = "No", 1 = "Yes") in order to have two categories of approximately the same sample size. Following the same rationale, average trip duration assessed using the question "In general, how long does an average trip from your pick-up location to your drop-off location take you?" was dichotomized (0 = "3 hours or less", 1 = "More than 3 hours"). Job insecurity was measured with the item "To what

12 The most frequent passengers were colleagues (26 observations), followed by customers (9 observations), friends/acquaintances (5 observations) and others (5 observations).

extent do you worry about the possibility of losing your job?" with answer categories on a 7-point Likert scale (1 = "No worrying at all" to 7 = "Worrying a lot"). The variable was re-coded into three categories (1 = "Few worries", 2 = "Some worries", 3 = "Many worries") by combining the lowest three scores and the highest three scores.

Trait job resources

Pay was assessed with the item "To what category does your net monthly income belong?" For the analysis, this categorical variable was dichotomized to create two approximately equally large groups (0 = "€1800 or less", 1 = "€1801 or more"). Colleague support was assessed with the item "Do you have the feeling that you can count on the support and help of your colleagues?" Flexibility in work hours was assessed with "To what extent do you have the feeling that you have flexibility in determining your work hours?" Task variety was measured by the question "Do you have enough variation in your work?" These three questions had answer categories on a 7-point Likert scale (1 = "Totally disagree" to 7 = "Totally agree"). The variables were re-coded into three categories (1 = "Disagree", 2 = "Neutral", 3 = "Agree") by combining the lowest three scores and the highest three scores.

3.3.3. Statistical analyses

Within-subject fixed-effects regressions were performed to test the hypotheses. The results were organized in three parts. First, the authors provided an overview of momentary happiness during various activities using descriptive statistics and three fixed-effects models. A major advantage of fixed-effects models is the exclusion of top-down effects of a person's general well-being on momentary happiness (Bryson & MacKerron, 2017; Lancée et al., 2017; Morris & Guerra, 2015). In other words, individual fixed effects control for individual-specific characteristics that remain constant over time, including people's baseline or reference happiness level. This distortion is caused by the reciprocal relationship between state-like and trait-like SWB constructs. As an explanation, momentary happiness adds to overall satisfaction with life (bottom-up effect), while general life satisfaction also affects momentary happiness during different activities (top-down effect; Headey et al., 1991; for evidence from transportation research, see De Vos, 2018).[13] Since the authors are most interested in the types of activities that affect the momentary happiness of truck drivers, it is important to account for this top-down effect.

13 Examining the relationships in the SWB model, the Pearson correlation coefficients between momentary happiness, job satisfaction, life satisfaction, self-reported health and stress at work were computed. Because this was a between-subject analysis, experience-sampled momentary happiness was aggregated into average scores. The results can be found in Table A3.1. The analyses substantiated the relationships hypothesized by the SWB model.

All fixed-effects models were estimated using individual-clustered robust standard errors. The first model concerned the difference between momentary happiness at work and off work. The second model distinguished between momentary happiness during work-related job activities, non-work-related job activities, other job activities and off-job activities. The last model was identical to the second model, but it instead estimated the impact of specific work-related job activities (i.e., driving, pick-up/drop-off, logistical tasks and administrative tasks).

Subsequently, several fixed-effects models were estimated to explore what trait-like job characteristics moderate the relationship between work-related job activities and momentary happiness. In particular, these models were used to investigate whether specific trait job demands and job resources increase or decrease the difference in momentary happiness between work-related job activities and off-job activities. These models controlled for specific job and off-job activities (driving, relaxing, etc.) to capture variation in momentary happiness caused by these specific activities. Off-job activities were included as a reference category to eliminate the possible confounding effect of between-person differences in affective disposition, which became relevant when trait job characteristics were introduced to the model.

Notably, job demands and resources could theoretically also influence happiness levels during off-job activities and could thus bias the fixed-effect model estimates. To test this, a between-subject linear regression that assessed the influence of different job characteristics on an individual's average happiness during off-job activities was conducted. As shown in Table A3.2, the results of this linear regression model indicate that job characteristics play basically no significant role in predicting momentary happiness during off-job activities. Therefore, the presented differences between job and off-job activities can be interpreted as the influence of job characteristics on momentary happiness during work-related job activities.

Additionally, four fixed-effects models were estimated to assess the extent to which state job demands and resources experienced while driving have the potential to decrease or increase the difference in momentary happiness between driving and off-job activities.

For all models, this study controlled for time of day (i.e., morning, afternoon, evening, night) and day of the week to capture common daily and weekly happiness patterns that are unrelated to specific activities or job characteristics.

3.4. RESULTS

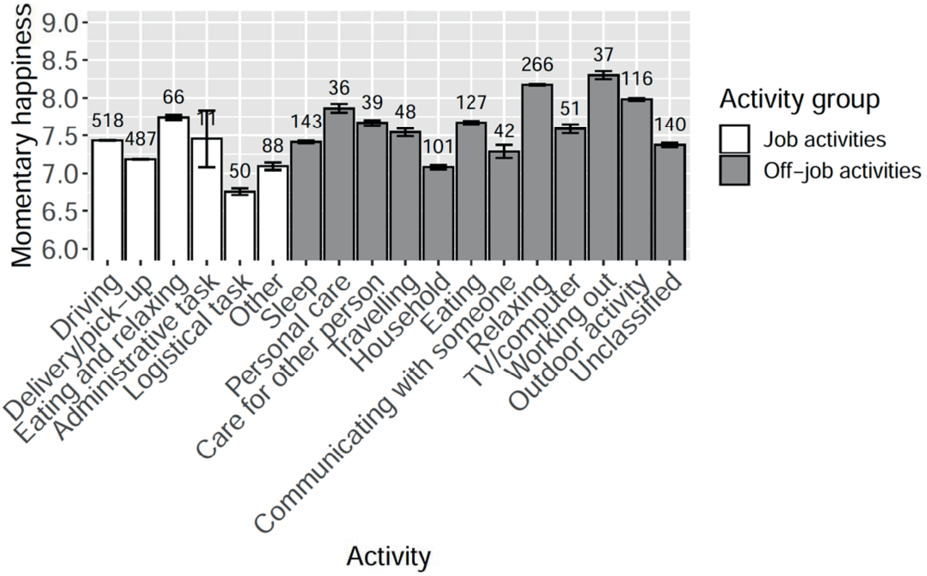
This section begins with an overview of some descriptive statistics about momentary happiness at work and momentary happiness off work. Then, the results of the fixed-effects models are presented and the antecedents of momentary happiness at work are discussed.

3.4.1. Descriptive statistics

The average momentary happiness score of truck drivers was 7.45 (*SD* = 1.42). The average momentary happiness score for off-job activities (*M* = 7.69, *SD* = 1.36) was greater than the average momentary happiness score for job activities (*M* = 7.24, *SD* = 1.43). A between-subject *t*-test showed that the difference in average momentary happiness during off-job activities and job activities was statistically significant, $t(4172) = 10.46$, $p < 0.001$.

Zooming in on the more specific activities, as visualized in Figure 3.2, some activities were associated with higher levels of happiness than others. In terms of job activities, truck drivers reported higher momentary happiness while driving than during other work-related job tasks, though they did not perceive it to be as pleasant as having a break or eating. With respect to leisure activities, truck drivers appeared to be happiest while relaxing or during active leisure activities, particularly working out and outdoor activities.

Figure 3.2 | Bar chart depicting average momentary happiness per activity (including 95% confidence intervals and total observations)



Notes. Unadjusted means reported with 95% confidence intervals, depicted on the top of the bars. Number of observations depicted above the bars. Activity categories with less than 20 observations were omitted from this plot.

3.4.2. Activities and momentary happiness

As shown in Table 3.3, the results from the within-subject analyses show that truck drivers were happier off work than they were at work, providing support for hypothesis 1a. Furthermore, the lower happiness during job activities was driven by work-related job activities as opposed to non-work-related job activities, supporting hypothesis 1b. Model 3 showed that truck drivers were particularly unhappy during logistical tasks and delivery/pick-up tasks, and Wald tests confirmed that truck drivers were significantly happier while driving than during delivery/pick-up tasks (χ^2 = 12.63, $p < 0.001$) and logistical tasks (χ^2 = 6.57, $p < 0.05$).

Table 3.3 | Within-subject fixed effects model linking activity classes and specific activities to momentary happiness levels

Variable	Model 1	Model 2	Model 3
Off-job activities	Reference	Reference	Reference
Job activities	-0.409*** (0.064)		
Work-related job activities		-0.393*** (0.060)	
Driving			-0.281*** (0.059)
Delivery/Pickup			-0.517*** (0.075)
Administrative task			-0.280 (0.186)
Logistical task			-0.621*** (0.145)
Non-work-related job activities		-0.071 (0.083)	-0.072 (0.082)
Other job activities		-0.968*** (0.234)	-0.968*** (0.234)
Controls for time of day and day of week	Yes	Yes	Yes
R^2	0.061	0.072	0.078
ICC	0.515	0.517	0.519
N	82	82	82
Observations	4175	4175	4175

Notes. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; t = time, R^2 = Explained variance; ICC = Interclass correlation; N = Sample size.

3.4.3. Job activities, trait job demands and trait job resources

As exhibited in Table 3.4, the within-subject analyses showed that none of the considered trait-like job demands (i.e., working overtime, job insecurity, and average trip duration) aggravated the relationship between work-related job activities and momentary happiness. As such, hypothesis 2 was not supported. With respect to trait-like job resources, colleague support and flexible working hours alleviated this relationship, while pay and job variety did not. Although the results suggested a moderate interaction effect of job variety, there is too much uncertainty about the true value of the parameter estimate. As a consequence, hypotheses 3b and 3c were supported, while hypothesis 3a and 3d were not supported.

Table 3.4 | Within-subject fixed effects model linking trait job demands and resources during work activities to momentary happiness at work

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Off-job activities	Reference	Reference	Reference	Reference	Reference	Reference	Reference
Work-related job activities[a]	-0.392*** (0.092)	-0.354*** (0.073)	-0.386*** (0.066)	-0.430*** (0.096)	-0.700*** (0.144)	-0.513*** (0.096)	-0.782*** (0.222)
Work-related job activities * Working overtime: one or multiple times a week[b]	-0.003 (0.123)						
Work-related job activities * Job insecurity: some worries[c]		0.130 (0.240)					
Work-related job activities * Job insecurity: many worries[c]		-0.281 (0.189)					
Work-related job activities * Average trip duration: more than 3 hours			-0.019 (0.130)				
Work-related job activities * Monthly net income €1801 or more[e]				0.047 (0.120)			
Work-related job activities * Support of colleagues: neutral[f]					-0.168 (0.262)		
Work-related job activities * Support of colleagues: agree[f]					0.445** (0.152)		
Work-related job activities * Flexible work hours: neutral[f]						0.052 (0.122)	
Work-related job activities * Flexible work hours: agree[f]						0.260** (0.124)	
Work-related job activities * Task variety: neutral[f]							0.456 (0.280)
Work-related job activities * Task variety: agree[f]							$0.415^{\dagger}$ (0.231)
Controls for time of day and day of week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for all specific activities[g]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.072	0.075	0.072	0.072	0.082	0.075	0.075
ICC	0.517	0.515	0.516	0.517	0.519	0.513	0.513
N	82	82	82	82	82	82	82
Observations	4175	4175	4175	4175	4175	4175	4175

Notes. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; R^2 = Explained variance; ICC = Interclass correlation; N = Sample size. [a] = Work-related job activities include driving, pick-up/drop-off, administrative task and logistic task. [b] = Reference category is working overtime a few times a month or less. [c] = Reference category is few worries; [d] = Reference category is average trip duration of 3 hours or less; [e] Reference category is monthly net income €1800 or less. [f] = Reference category is disagree; [g] = Dummies for all specific off-job and job activities were included.

3.4.4. Driving, state job demands and state job resources

The results of the last within-subject fixed-effect models are displayed in Table 3.5. The data showed that only road congestion functioned as job demand in the prediction of truck drivers' momentary happiness. Quality of the road did not have a significant moderating effect on the relationship between truck driving and momentary happiness. In accordance, hypothesis 4a was supported, while hypothesis 4b was not supported. Hypothesis 5 was not supported, as having passengers did not alleviate the negative relationship between work-related job activities and momentary happiness.

Table 3.5 | Within-subject fixed effects model linking state job demands and resources during driving to momentary happiness at work

Variable	Model 1	Model 2	Model 3
Off-job activities	Reference	Reference	Reference
Driving	-0.235** (0.073)	-0.511*** (0.179)	-0.289*** (0.059)
Driving * Road congestion[a]	-0.169* (0.082)		
Driving * Poor road quality[b]		-0.246 (0.162)	
Driving * Passengers[c]			0.157 (0.132)
Controls for time of day and day of week[d]	No	Yes	Yes
Control for other job activities[e]	Yes	Yes	Yes
R^2	0.079	0.079	0.078
ICC	0.519	0.518	0.518
N	82	82	82
Observations	4175	4175	4175

Notes. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; R^2 = Explained variance; ICC = Interclass correlation; *N* = Sample size. [a] = Reference category is no road congestion; [b] = Reference category is good road condition; [c] = Reference category is being alone; [d] Since road congestion is heavily dependent on time of the day and day of the week, these were not included as controls. [e] These activities include pick-up/drop-off, administrative task, logistic task, non-work-related job activities (i.e. eating, relaxing) and other job activities.

3.5. DISCUSSION

In Table 3.6, the outcomes of the hypothesis testing are presented. The present study's findings indicate that truck drivers are happier during off-work activities than during job activities. Moreover, truck drivers reported more momentary happiness during non-work-related job activities (e.g., breaks) than during work-related job activities (e.g., driving, administrative tasks). One job demand, road congestion, was found to aggravate the relationship between work-related job activities (i.e., truck driving) and momentary happiness. The other considered job demands — frequently working overtime, job insecurity, average trip duration and poor road quality — did not function as significant moderators, although also here all coefficients besides that of working overtime were in the expected direction. Two job resources — social support of colleagues and flexible work hours — were found to alleviate the negative relationship between work-related job activities and momentary happiness. The other considered job resources — pay, task variety and having company while driving — did not significantly moderate this relationship, although the coefficients were in the expected direction. Given the limited sample size, the present study's results should be interpreted as showing which job characteristics and activities affect momentary happiness most strongly, but insignificant relationships do not necessarily imply that those job characteristics are irrelevant to momentary happiness. An additional thing that should be taken into consideration is the variation within these job demands and job resources. For instance, while all passenger types were categorized into one category for reasons of sample size, there may be variation in how different passengers influence the happiness of truck drivers. For instance, it is theoretically plausible that the presence of a colleague would evoke more enjoyable conversation and social support than the presence of a customer or supervisor.

Table 3.6 | An overview of the present study's research findings

Hypothesis	Status
H1a. Off-job activities are associated with more momentary happiness states than job activities.	Supported
H2b: Non-work-related job activities are associated with more momentary happiness than non-work-related job activities.	Supported
H2a. Having to work overtime frequently aggravates the negative relationship between work-related job activities and momentary happiness.	Not supported
H2b. High job insecurity aggravates the negative relationship between work-related job activities and momentary happiness.	Not supported
H2c. Having a long average trip duration aggravates the negative relationship between work-related job activities and momentary happiness.	Not supported
H3a. High pay alleviates the negative relationship between work-related job activities and momentary happiness.	Not supported
H3b. Social support of colleagues alleviates the negative relationship between work-related job activities and momentary happiness.	Supported
H3c. Having flexible work hours alleviates the negative relationship between work-related job activities and momentary happiness.	Supported
H3d. Task variety alleviates the negative relationship between work-related job activities and momentary happiness.	Not supported
H4a. Road congestion alleviates the negative relationship between truck driving and momentary happiness.	Supported
H4b. Poor road condition alleviates the negative relationship between truck driving and momentary happiness.	Not supported
H5. Having passengers alleviates the negative relationship between truck driving and truck drivers' momentary happiness.	Not supported

The present study found mixed evidence for the robustness of the JD-R model in a truck driving occupation. More specifically, half of the hypotheses about trait job resources were supported by the data. On the contrary, while road congestion turned out to be an important moderator in the relationship between truck driving and momentary happiness, no other significant interaction effects of job demands were found. This finding demonstrates the importance of selecting job aspects that are relevant for the target population (Bakker & Demerouti, 2007; De Croon et al., 2004). To illustrate, the insignificant interaction of having to work working overtime frequently may have been explained by the fact that the truck driving profession is typically characterized by long and overtime working hours (Beckers et al., 2008), as corroborated in the present study's data, i.e. only 17% of truck drivers never work overtime. Because apparently truck drivers are used to working overtime, they most likely have accepted this job stressor and have adjusted to the situation, which in turn could have reduced the stressor's negative impact on their happiness (Diener et al., 2006; Ritter et al., 2016).

3.5.1. Limitations and future research directions

The present study's limitations regarding the (i) selection of variables, (ii) validity of the measures, and (iii) generalizability of the sample can be addressed in future research.

First, this study only considered a limited selection of job demands and resources that are potentially relevant to the truck driving occupation. Other job demands and resources could also play an important role in predicting truck driver well-being during work activities, and job demands and resources may interact with each other in influencing well-being (Bakker & Demerouti, 2007). For instance, the negative effect of road congestion on well-being may be aggravated when truck drivers deal with very tight schedules or buffered when they have the autonomy to plan their own routes. Valuable future research directions would be the consideration of a complementary or larger set of job demands and resources, an explicit test of interactions between specific job demands and job resources, as well as testing considering other well-being variables such as state work engagement, momentary fatigue and stress.

Second, all survey measures in this study were single-item measures. Single-item momentary happiness measures are considered valid (Tadić et al., 2013), and the use of too many items in an ESM study is even undesirable (Scollon et al., 2009); however, the measurement of the trait-like variables in particular could have been better if multiple-item survey measures had been used. For instance, the Work Design Questionnaire (Morgeson & Humphrey, 2006) could function as means to more reliably and validly measure task variety, social support and working overtime. In addition, most measures used in this study were subjective in nature. As objective data and subjective evaluations of a phenomenon (e.g., heavy traffic) are often complementary (Jahedi & Méndez, 2014), future researchers are encouraged to triangulate subjective and objective measures. For instance, administrative records (e.g., when and where truck drivers often work) combined with open-source traffic data can be used as objective indicators of road familiarity, road congestion, and road quality. Even more ambitiously, behavioral and physiological data generated by sensors (e.g., a smart watch, cameras in trucks) could help researchers measure the interactions between employee well-being and driving behavior (for an example, see B. G. Lee et al., 2015). One specific issue regarding the reporting of activities was that respondents were asked about their primary activity in the past hour. However, drivers may engage in several activities within an hour and the duration of the activity may not always have the strongest effect on their happiness.

Third, the study's sample is subject to limitations. Although the sample was reasonably representative of the Dutch truck driving population in terms of demographic characteristics and well-being, the generalizability of the results to truck drivers in other countries remains an open-ended question and merits attention in future research. In addition, as discussed, the limited sample size sets the bar high for finding supporting evidence for the hypotheses.

3.5.2. Practical recommendations

Within the aforementioned limitations, this study offers practitioners several interesting guidelines for policy making. As expected, truck drivers reported higher momentary happiness during work breaks than during work-related job activities. In line with research that evidenced the importance of high-quality work breaks (Hunter & Wu, 2016; Trougakos et al., 2014), transportation companies are urged to free up enough time and resources to facilitate relaxing breaks for truck drivers. Truck drivers indicated that busy roads take a great toll and negatively affect their momentary happiness at work. Although it may be inevitable that truck drivers must occasionally deal with road congestion, practitioners can prioritize investments in clever scheduling of deliveries to avoid extremely busy roads, such as during rush hour (Kok et al., 2012). As indicated by Johnson et al. (2011), adequate on-the-road training could also make a difference in making truck drivers feel more confident and capable on busier roads. Furthermore, the results show that practitioners can positively influence truck driver happiness by facilitating colleague support and making sure that truck drivers have some flexibility in their scheduling. For example, truck driving companies can create a platform for colleague support by organizing team events and creating social media groups (Kemp et al., 2013; Z. Williams et al., 2011). On a more general level, truck driving companies are advised to pay more attention to the well-being of truck drivers (Boyce, 2016), in turn reducing their turnover intentions (Kemp et al., 2013). This can be done by starting a dialogue and asking truck drivers for feedback about their jobs, their experiences and, more generally, their lives as a whole (Kemp et al., 2013).

3.5.3. Conclusion

Transportation companies are at a turning point. With a growing shortage of truck drivers and considerable turnover rates, there is a strong incentive to start making the well-being of truck drivers a priority. Although measuring work stress, fatigue and other health-related constructs functions as a good starting point, it is pivotal to adopt a more comprehensive approach to truck driver well-being. Particularly by tracking the momentary happiness of truck drivers over time, transportation companies can better understand when, with whom and why truck drivers are happy. In this regard, this study shows that social support from colleagues and a flexible work schedule are pivotal job resources for feeling happy at work, while road congestion is a particularly important factor that impairs truck drivers' happiness at work.

Table A3.1 | Between-subject bivariate Pearson correlations between well-being variables ($N = 82$)

	1.	2.	3.	4.	5.
1. Momentary happiness	-				
2. Job satisfaction	0.46***	-			
3. Life satisfaction	0.66***	0.38***	-		
4. Self-reported health	0.30***	0.21	0.21	-	
5. Feelings of stress at work	-0.39***	-0.13	-0.44***	-0.19	-

Notes. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; N = Sample size. As commonly done in studies assessing happiness (Cheung & Lucas, 2014; Wanous et al., 1997) and health states (Macias et al., 2015), all measures were single-item. The questions had answer categories ranging on a 7-point Likert scale (e.g., 1 = "Never" to 7 = "Very often", and 1 = "Very dissatisfied" to 7 = "Very satisfied"). Job satisfaction was assessed with the question "How satisfied are you with your current job?" Life satisfaction was assessed with the question "Taking all into consideration, how satisfied are you with your life?" Self-reported health was assessed with the question "In general, how is your health". Feelings of stress at work were assessed with the question "In the last 4 weeks, how often did you experience feelings of stress during work?"

Table A3.2 | Between-subject linear regression model on the relationship between average momentary happiness during off-job activities and job characteristics

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	7.423*** (0.537)	7.259*** (0.518)	7.337*** (0.517)	7.392*** (0.566)	7.384*** (0.602)	7.237*** (0.544)	6.591*** (0.659)
Education level	-0.028 (0.255)	0.061 (0.262)	-0.018 (0.255)	-0.027 (0.256)	-0.020 (0.256)	0.017 (0.261)	-0.120 (0.254)
Age	-0.007 (0.010)	0.007 (0.010)	0.007 (0.010)	0.007 (0.010)	0.007 (0.010)	0.007 (0.010)	0.012 (0.010)
Working overtime: one or multiple times a week[a]	-0.133 (0.255)						
Job insecurity: some worries[b]		0.495 (0.397)					
Job insecurity: many worries[b]		-0.115 (0.369)					
Average duration trip: more than 3 hours[c]			0.057 (0.261)				
Monthly net income €1801 or more[c]				-0.064 (0.313)			
Support of colleagues: neutral[e]					-0.310 (0.503)		
Support of colleagues: agree[e]					0.008 (0.333)		
Flexible work hours: neutral[e]						0.260 (0.369)	
Flexible work hours: agree[e]						0.072 (0.281)	
Task variety: neutral[e]							1.072* (0.471)
Task variety: agree[e]							0.522 (0.401)
R^2	0.011	0.030	0.008	0.008	0.015	0.013	0.075
N	81	81	81	81	81	81	81

Notes. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; t = time; R^2 = Explained variance; N = Sample size. [a] = Reference category is working overtime a few times a month or less. [b] = Reference category is few worries; [c] = Reference category is average trip duration of 3 hours or less; [d] Reference category is monthly net income €1800 or less. [e] = Reference category is disagree. To ensure that the nature of the different off-job activities did not bias the results of this analysis, the dependent variable, average momentary happiness during off-job activities, was corrected for the more specific off-job activities (based on a fixed effects regression in which momentary happiness scores were regressed on dummies for all specific off-job activities). One person was excluded from the analysis (N = 81 instead of N = 82), as this person did not provide any ESM-responses during off-job activities.

4

Cognitive crafting and work engagement in the healthcare industry during the COVID-19 pandemic

Based on paper: Wijngaards, I. Pronk, F.R., Bakker, A.B., & Burger, M.J. 2021. Cognitive Crafting and Work Engagement: A Study among Remote and Frontline Healthcare Workers during the COVID-19 Pandemic. *Health Care Management Review*.

4.1. INTRODUCTION

The outbreak of the coronavirus disease 2019 (COVID-19) continues to have a profound impact on industries across the globe (Kniffin et al., 2020). One of the most affected industries is the healthcare sector (Black et al., 2020). Most notably, nurses, doctors and others vital for high-quality healthcare (e.g., cleaners, receptionists) have been coined 'essential workers' (Kniffin et al., 2020) and work excessive long hours with limited breaks (International Labour Organization, 2020). Despite the strain on their well-being (Giusti et al., 2020; Pappa et al., 2020), frontline healthcare workers are aware of the essential role they play in safeguarding public health, as illustrated by the return of retired healthcare workers to the frontline (ABC, 2020a) and evidence highlighting that healthcare workers feel it is their duty to battle COVID-19 (Q. Liu et al., 2020). Meanwhile, they receive more tokens of appreciation from society than usual (Bennett et al., 2020; Hennekam et al., 2020; Q. Liu et al., 2020), for instance, public applause and singing (ABC, 2020b), television commercials (Today, 2020) and calls for better compensation (Brookings, 2020).

A group of healthcare workers rarely put in the spotlight are those not labeled 'essential' in battling the pandemic: workers in support functions such as planning, administration, management, human resources (HR), finance, information technology (IT), and legal. A large share of support workers was instructed to (partially) work from home to minimize infection risks (Kniffin et al., 2020). Although research suggests that these workers experience less emotional exhaustion and sleep problems than workers who directly work with COVID-19 patients (Van Roekel et al., 2021), working from home (WFH) during the pandemic does not come without costs. The American Center for Disease Control and Prevention has included "feelings that you are not contributing enough to work or guilt about not being on the frontline" as a common work-related stressor during this pandemic (CDC, 2020). Indeed, a recent cross-national study confirmed that the perceived loss of job meaningfulness is one of the greatest disadvantages of being required to WFH (Ipsen et al., 2020). This problem of meaningfulness seems especially pertinent for remote workers in healthcare, as frontline healthcare workers – their reference group for evaluating their jobs' value – play an important role in patient care *and* are publicly appraised (Hennekam et al., 2020; cf. Festinger, 1954; Gerber et al., 2018). As the perceived significance and meaning of work are favorably linked to individuals' engagement at work (Goštautaitė & Bučiūnienė, 2015; Hirschi, 2012; May et al., 2004; Van Wingerden, Bakker, et al., 2017a; Van Wingerden et al., 2018) - "a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (Schaufeli et al., 2002, p. 74), being required to WFH could pose a significant problem to the engagement of healthcare workers.

The possibility that remote healthcare workers perceive that their jobs are less visible or meaningful than those of frontline healthcare workers does not mean that their jobs are unimportant (Bapuji et al., 2020; Cowden et al., 2010). For example, workers in support functions play an essential role in the development and implementation of practices that promote frontline healthcare workers' mental and physical health (Kilroy et al., 2017; Walton et al., 2020). In light of this, we hypothesize that cognitive crafting may be a relevant strategy for remote workers to stay engaged at work. Cognitive crafting refers to the altering of the perceptions one has about their tasks and relationships with the aim to enhance the meaningfulness of work (e.g., directing attention to the most meaningful aspects of the job, Slemp & Vella-Brodrick, 2013; F. Zhang & Parker, 2019). Even though the literature on cognitive crafting is still in its infancy (F. Zhang & Parker, 2019), evidence suggests that it is a good predictor of work engagement (e.g., Devotto et al., 2020; Q. Hu et al., 2020; Iida et al., 2021; S. H. Lee et al., 2017) and an especially relevant cognitive strategy for workers whose work meaningfulness is at risk (Bindl et al., 2019; Buonocore et al., 2020; Geldenhuys et al., 2020). In accordance, we further hypothesize that cognitive crafting is less strongly related to work engagement for frontline healthcare workers because frontline healthcare workers have probably experienced an increase in perceived professional prestige and socially compare 'better'.

By testing these assumptions on data collected in a Dutch healthcare setting during the COVID-19 pandemic, this study makes several contributions. First of all, our study contributes to an emerging literature on individualized mental health interventions in times of COVID-19 (Holmes et al., 2020). Specifically, we empirically test the claim that job crafting is a fruitful approach to help workers maintain adequate levels of well-being at work in these times of crisis (Dutton & Wrzesniewski, 2020; Kniffin et al., 2020). Second, in light of the increased attention for behavioral forms of job crafting, i.e., task and relational crafting (Rudolph et al., 2017; F. Zhang & Parker, 2019) and crafting job demands and resources (Tims et al., 2012), our study addresses the dearth of studies on cognitive crafting. Third, the results from this study could be helpful for organizations that struggle with declined engagement levels in their remote workforces since the outbreak of COVID-19, as cognitive crafting can be taught and cognitive crafting interventions have shown to increase work engagement (Sakuraya et al., 2016, 2020). The practical implications are not limited to healthcare organizations: More industries may be dealing with a sudden division between remote workers and workers that are required to work on the frontline (e.g., public transport, supermarkets).

4.2. THEORY

4.2.1. Top-down work design and bottom-up job crafting

Over the past decades, scholars have developed a vast array of theories and constructs on the topic of work design or "the content and organization of one's work tasks, activities, relationships, and responsibilities" (Parker, 2014, p. 662). Most research has adopted a top-down approach of job design, investigating how organizations can modify jobs or specific tasks in ways that advance the goals of organizations and workers (Bakker & Demerouti, 2017; J. M. Berg et al., 2013; Parker et al., 2017). For example, an organization's HR department may improve scheduling procedures to avoid work overload of certain groups of workers; an IT director may invest in new software to reduce administrative hassles of the entire workforce; or a line manager may organize regular team building activities to facilitate social support among colleagues.

However, with the increasing diversity in the workforce and increasing levels of uncertainty and complexity in modern workplaces, it has become increasingly difficult to centrally design task descriptions that fit all employees for an extended period of time (J. M. Berg et al., 2010; Grant & Parker, 2009). These developments gave rise to the bottom-up approach of job crafting or "the physical and cognitive changes individuals make in the task or relational boundaries of their work" (Wrzesniewski & Dutton, 2001, p. 179). In the literature, job crafting behaviors are often categorized into three groups: task crafting, relational crafting, and cognitive crafting (J. M. Berg et al., 2013; Slemp & Vella-Brodrick, 2013; Wrzesniewski & Dutton, 2001; F. Zhang & Parker, 2019). Task crafting encompasses altering aspects of the boundaries of tasks by changing the number, scope or kind of job tasks performed at work, e.g., taking on other tasks to make the job more challenging. Relational crafting concerns changing aspects of the job that involve social relationships employees have at work, e.g., intensifying the contact with patients to satisfy the need for human connection. As mentioned before, cognitive crafting refers to the altering of the perceptions one has about their tasks and relationships with the aim to enhance the meaningfulness of work, e.g., directing attention to the most meaningful aspects of the job.

4.2.2. Cognitive crafting and its role in the job crafting process

In contrast to relational and task crafting, cognitive crafting is a mental strategy and not a behavioral form of job crafting. Cognitive crafting does not change any objective characteristic of the job and thus solely takes place inside the mind of people. As all job crafting initiatives start with a cognitive evaluation of the characteristics of the job and person job-fit, cognitive crafting can be considered the first step in the job crafting process (J. M. Berg et al., 2010; Melo et al., 2021; Sturges, 2012). The idea that cognitive crafting is a prerequisite for behavioral crafting does not mean that all cognitive crafting activities have behavioral consequences. In certain situations, workers may be unable to resort to behavioral crafting or find it easier to handle their jobs by solely framing it in a different way (Melo et al., 2021; F. Zhang & Parker, 2019).

The literature has distinguished three kinds of cognitive crafting strategies (J. M. Berg et al., 2013). First, workers can cultivate meaningfulness by reminding themselves of the holistic purpose of their jobs, rather than thinking of their jobs as a set of distinct tasks and relationships (*expanding perceptions*). This approach helps workers to see the eventual impact of their work and its beneficiaries. For example, a hospital janitor could frame his job as supporting the recovery of ill people rather than just cleaning the hospital building. Second, workers could actively focus on the aspects of work that are most meaningful or significant to them (*focusing perceptions*). For example, a hospital receptionist who perceives face-to-face patient contact as the most enjoyable work task and who actively dislikes administrative work, may reframe the unpleasant paperwork as an indispensable means to deliver high-quality healthcare. Third, workers can increase the meaningfulness of their work tasks by making mental linkages between specific tasks and relationships, on the one hand, and interests, outcomes or parts of their identities that are meaningful to them, on the other hand (*linking perceptions*). For example, an administrative assistant with a passion for stand-up comedy could make a mental link between the experience of performing comedy and the moments during the working day spent cracking jokes to connect with patients and colleagues.

In this study, we focus on the expanding perceptions strategy. We do this for two reasons. First, the expanding perceptions strategy seems most relevant when healthcare workers who work remotely engage in social comparisons with their frontline colleagues. After all, realizing the overarching meaning of the job is more difficult for remote healthcare workers, as, compared to their colleagues on the frontline, their contribution to the functioning of the organization is less apparent. Second, the expanding perceptions strategy classifies as an approach crafting strategy (Lazazzara et al., 2020). Research has shown that approach crafting strategies relate more favorably to work outcomes, such as work engagement, job strain and performance, than avoidance crafting strategies (Lichtenthaler & Fischbach, 2019; Rudolph et al., 2017).

4.2.2. Antecedents and consequences of cognitive job crafting

Research has found that for (cognitive) job crafting to occur, workers need to have the ability, motivation and opportunity to do so (Niessen et al., 2016; Rudolph et al., 2017). Regarding ability, robust traits such as agreeableness, conscientiousness, extraversion, openness to experience, general self-efficacy and proactivity have been positively linked to job crafting, while neuroticism has a robust negative association with job crafting (Rudolph et al., 2017). Concerning motivation, Niessen et al. (2016) and Bindl et al. (2019) revealed that unfulfilled work-related needs for autonomy, competence and relatedness are positively related to workers' inclination to engage in cognitive crafting. Buonocore et al. (2020) demonstrated that the lack of perceived professional prestige and job insecurity play a key role in shaping intentions to engage in cognitive crafting. In a meta-analysis, Rudolph et al. (2017) showed that workload is a significant predictor of overall job crafting behavior. Regarding opportunity, Kim et al. (2018) reported a significant positive effect of job autonomy and perceived organizational support on cognitive crafting. Similarly, Niessen et al. (2016) documented a positive relationship between job autonomy and cognitive crafting.

Research has shown that cognitive job crafting constitutes a powerful strategy to make work more meaningful, maintain high levels of work engagement and achieve high job performance. For example, cognitive crafting could facilitate a positive self-image and work identity, foster a sense of work autonomy, and motivate workers to keep working vigorously (J. M. Berg et al., 2013; Slemp & Vella-Brodrick, 2013). In support of this, recent empirical studies have reported positive correlations ranging from 0.29 to 0.69 between cognitive crafting and work engagement or one of its constituents (Devotto et al., 2020; Q. Hu et al., 2020; Iida et al., 2021; S. H. Lee et al., 2017; Letona-Ibañez et al., 2019; Schachler et al., 2019; Slemp & Vella-Brodrick, 2013). Cognitive crafting has also been linked to in-role and extra-role performance (Geldenhuys et al., 2020), innovation performance (Bindl et al., 2019), reduced turnover intentions (Hommelhoff et al., 2021), and organizational citizenship behavior (Niessen et al., 2016).

Linking these findings to our study context, we predict that cognitive crafting is more beneficial for remote healthcare workers than for their colleagues who work in the frontline. Compared to frontline healthcare workers, remote healthcare workers have less access to significant others with whom they work, including colleagues, patients, and suppliers. This means that they are more often working in solitude and may need their fantasy and imagination to craft their job such that work becomes more meaningful (Wrzesniewski & Dutton, 2001). In addition, remote workers may perceive themselves less competent than frontline healthcare workers, as their contribution to patient health is more indirect and they are appreciated much less frequently. Put differently, we expect that remote healthcare workers have a more profound need for connection and competence than frontline healthcare workers and may therefore benefit more from cognitive job crafting. We thus hypothesize:

> **Hypothesis 1:** *WFH moderates the positive relationship between cognitive crafting and work engagement, such that the positive relationship will be stronger for remote healthcare workers than for frontline healthcare workers.*

4.3. METHODS

4.3.1. Data collection and participants

Data collection took place in a hospital in the Netherlands employing about 2309 people in a region characterized by many COVID-19-related hospital admissions during the time of the research. Data collection lasted from May 7 – June 2, 2020, a period when the Netherlands was gradually relaxing the COVID-19 protective measures (Hale et al., 2020; Hoekman et al., 2020). The advice to work from home if possible remained in effect. The hospital's HR department sent an invitation for an online survey to all employees. Participation was voluntary and anonymous.

4.3.2. Measures

4.3.2.1. Cognitive crafting

Cognitive crafting was measured using the five-item cognitive crafting subscale in the Job Crafting Questionnaire (JCQ, Slemp & Vella-Brodrick, 2013, sample item: "Think about how your job gives your life purpose", α = .82). The three-factor factor structure from original (English) JCQ has been found in translations in German (Schachler et al., 2019), Spanish (Letona-Ibañez et al., 2019), Dutch (IJbema & Brenninkmeijer, 2018) [14] and Chinese (Slemp et al., 2020). Answer categories ranged on a 7-point scale from 1 = "never" to 7 = "strongly agree".

4.3.2.2. Working from home

WFH was measured using the question "Do you work from home because of the outbreak of COVID-19?" Answer categories ranged from 1 = "yes, completely", 2 = "yes, in part" and 3 = "no".

4.3.2.3. Work engagement

Work engagement was measured using the Dutch three-item Utrecht Work Engagement Scale (Schaufeli et al., 2019; Schaufeli & Bakker, 2010), i.e., "I am enthusiastic about my job", "At work, I feel bursting with energy" and "I am immersed in my job" (α = 0.85). Answer categories ranged on a 7-point scale from 1 = "never" to 7 = "strongly agree".

14 Together with three other researchers specialized in organizational psychology, the second author evaluated whether the Dutch translation from IJbema and Brenninkmeijer (2018) adequately captured the original English items. This evaluation resulted in slight modifications to the original Dutch translation.

4.3.2.4. Control variables

As demographic characteristics can influence job crafting behaviors (Rudolph et al., 2017), we considered age group (1 = "45 years old or below", 2 = "46 years old or above") and household composition (i.e., children: 1 = "no", and = "yes"; cohabiting: 1 = "no", and = "yes") as control variables. We also controlled for mood, as it can infer with scores on more cognitive well-being constructs (Hicks et al., 2010). We used a single-item measure for this (i.e., "How happy do you feel today?") with answer categories ranging from 1 = "very unhappy" to 10 = "very happy". For similar reasons, we controlled for perceived stress at work, which was captured using a single-item measure ("My work is stressful"), with answer categories ranging from 1 = "never" to 5 = "always".

Finally, we included position-by-department dummies as control variables in our regression. Utilizing such a within-occupation design, we look at variation of work engagement within (broad) occupations which we define by position-by-cluster (e.g., direct care workers working in surgery). In terms of position, we distinguish between 5 categories: direct care workers (e.g., doctors and nurses), paramedical workers (e.g., physiotherapists and lab technicians), facility management (e.g., catering and cleaning staff), managerial workers, and supportive workers (e.g., HR and controllers). In terms of clusters, we are able to distinguish between 15 clusters in the hospital, ranging from the pharmacy to the elderly care facilities. Hence, in the multivariate analyses, we are comparing people working from home and people working onsite that have the same function and work within the same department. This within-occupation analysis is particularly helpful in avoiding distortion by differences in job characteristics across employees, which may confound the relationship between cognitive crafting, WFH and work engagement.

4.3.3. Data analysis

We summarized the sample demographics, cognitive crafting and work engagement per WFH category and used χ^2 and analysis of variance tests to discover significant between-group differences. We presented bivariate Pearson correlations between the study's focal variables. We used multiple linear regression models to test our hypothesis. All statistical analyses were conducted using Stata version 16 (StataCorp, USA). *P*-values < 0.05 were accepted as statistically significant. We reported heteroscedasticity-consistent (or robust) standard errors.

4.4. RESULTS

4.4.1 Response rate and sample characteristics

We received a total of 382 responses. The response rate of 17% is not unconventional for unsolicited online surveys for healthcare professionals (Dykema et al., 2013; T. Taylor & Scott, 2019). The low response rate may also be explained by the great workload healthcare professionals were facing at the time of data collection. From all respondents, 64 did not answer any questions, 33 respondents did not provide informed consent and 7 respondents did not fill out all relevant questions. Our dataset therefore consisted of 278 respondents.

The sample characteristics are summarized in Table 4.1. Respondents predominantly worked as direct care worker (43%), support staff (29%) and paramedical worker (14%). Only 7% of our respondents had a managerial position. To examine the representativeness of the sample, we examined the response per department and department-level headcount obtained from the hospital's HR administration. This comparison suggested that workers in supportive departments were overrepresented in our sample. We do not consider this a problem, as we are primarily interested in differences between staff working from home and working at the hospital and, for the different function categories, we have people represented from all departments. Most respondents were between 36 and 55 years old (59%), which is typical for the Dutch healthcare sector (Van Roekel et al., 2021). The majority of respondents had children (64%) and was cohabiting (84%). In total, 64% of respondents did not work from home at all, 17% worked partly from home and 19% worked from home completely. WFH occurs much less frequently in direct care and facility management, while WFH is almost the standard for administrative support staff.

4.4.2 Survey properties and bivariate correlations

The mean scores on cognitive crafting and work engagement were 3.56 (*SD* = 1.11) and 4.95 (*SD* = 1.02), respectively. For the individual cognitive crafting items, averages ranged from 3.06 to 3.87 on a 7-point scale. For the individual work engagement items, averages ranged from 4.76 to 5.12 on a 7-point scale. As shown in Table 4.1 and Table 4.2, WFH was not significantly associated with the level of cognitive crafting, while it was significantly associated with work engagement. More specifically, remote and (partial) frontline healthcare workers engage in cognitive crafting to similar extents and remote healthcare workers are less engaged than their counterparts working (partially) on the frontline. In addition, as shown in Table 4.2, cognitive crafting was unrelated to work engagement, which suggests that healthcare workers that often cognitively craft their job are not necessarily more engaged.

Table 4.1 | Demographic characteristics of healthcare workers in the sample

Characteristics	Total sample (N = 278)		WFH_{no} (N = 178)		$WFH_{in\ part}$ (N = 48)		$WFH_{completely}$ (N = 52)		p-value[a]
Categorical variables	N	%	N	%	N	%	N	%	
Position									0.00
Direct care workers	120	43%	111	62%	8	17%	1	2%	
Paramedical workers	39	14%	28	11%	10	21%	1	2%	
Facility management	19	7%	19	5%	0	0%	0	0%	
Managerial workers	20	7%	9	6%	6	13%	5	9%	
Supportive workers	80	29%	11	16%	24	50%	45	87%	
Age									0.17
18-24	9	3%	7	4%	2	4%	0	0%	
25-35	48	17%	37	21%	5	10%	6	12%	
36-45	72	26%	47	26%	8	17%	17	33%	
46-55	91	33%	54	30%	21	44%	16	31%	
56 or older	58	21%	33	19%	12	25%	13	25%	
Children									0.07
Yes	177	64%	120	65%	32	65%	26	50%	
No	101	36%	58	35%	17	35%	26	50%	
Cohabiting									0.42
Yes	241	84%	154	87%	38	79%	43	83%	
No	45	16%	24	13%	10	21%	9	17%	
Continuous variables	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	
Cognitive crafting	3.56	1.11	3.60	1.10	3.51	1.27	3.45	1.03	0.75
Work engagement	4.95	1.01	4.99	0.97	5.20	0.96	4.58	1.14	0.00

Notes. WFH = Working from home, N = sample size; *SD* = standard deviation. [a] = The χ^2 test of significance between people working from home completely, partially and not at all for categorical variables, and F-test (using ANOVA) for all continuous variables. [b] = Direct care workers include nurses, polyclinical assistants and medical specialists; paramedical workers include physiotherapists and pharmacy assistants; facility management workers include catering, cleaning, technical workers; managerial workers include heads of departments and managers; supportive staff concerns office workers.

Table 4.2 | Bivariate Pearson correlations (N = 278)

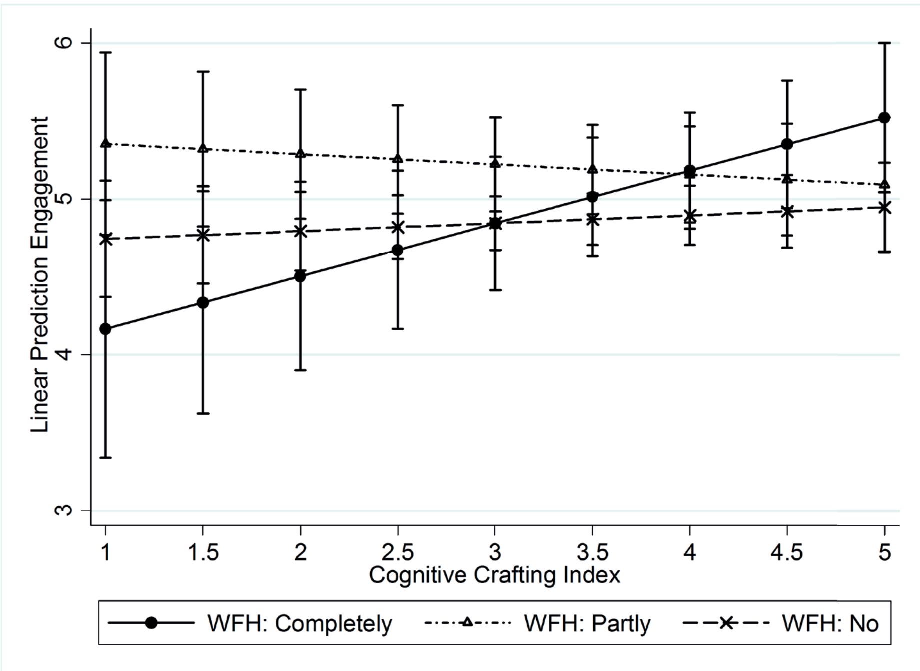
	1.	2.	3.	4.	5.
1. Cognitive crafting	-				
2. Working from $home_{completely}$	-0.04	-			
3. Working from $home_{in\ part}$	-0.02	-0.22***	-		
4. Working from $home_{no}$	0.05	-0.60***	-0.61***	-	
5. Work engagement	0.07	-0.17***	0.11	0.05	-

Notes. *** $p < 0.01$. The correlation matrix containing all control variables can be obtained by contacting the first author of the study.

4.4.3 Hypothesis testing

As demonstrated in Table 4.3, the regression analysis results from Model 1 show that cognitive crafting is positively related to work engagement and WFH is negatively related to work engagement. In line with our hypothesis, the results from Model 2 suggest that the interaction between cognitive crafting is statistically significant. This means that the relationship between cognitive crafting and work engagement is only significant in the sample of remote healthcare workers. Cognitive crafting does not seem to contribute to the work engagement of healthcare workers who partially work from home or healthcare workers who do not work from home at all. An inspection of the explained variance in Model 1 (cognitive crafting and WFH, R^2 = 4%) and Model 2 (cognitive crafting, WFH, and cognitive crafting*WFH, R^2 = 6%) suggests that the explanatory value of cognitive crafting is limited in our sample. Despite the low variance explained, as demonstrated in Models 3 and 4, the interaction term remains significant if we control for a range of demographic and job-specific variables and position-by-cluster dummies. The interaction effect (based on Model 4) is visualized in Figure 4.1.

Figure 4.1 | Visualization of Interaction Effect



Notes. WFH = Working from home.

Table 4.3 | Regression analysis result

	Model 1	Model 2	Model 3	Model 4
Cognitive crafting (mean-centered)	0.06 (0.06)	0.35 (0.15)**	0.39 (0.14)***	0.34 (0.13)**
$WFH_{completely}$	Reference category	Reference category	Reference category	Reference category
$WFH_{in\ part}$	0.61 (0.21)***	0.58 (0.20)***	0.30 (0.18)*	0.15 (0.20)
WFH_{no}	0.40 (0.17)**	0.37 (0.16)**	0.33 (0.15)**	-0.16 (0.25)
Cognitive crafting*$WFH_{in\ part}$		-0.37 (0.19)**	-0.43 (0.16)***	-0.40 (0.17)**
Cognitive crafting*WFH_{no}		-0.34 (0.18)**	-0.36 (0.15)**	-0.29 (0.15)*
Mood			0.38 (0.05)***	0.36 (0.06)***
Stress at work			0.02 (0.06)	-0.01 (0.07)
Age				
18-25			0.13 (0.28)	0.16 (0.34)
26-35			0.08 (0.15)	0.15 (0.16)
36-45			Reference category	Reference category
46-55			0.18 (0.16)	0.15 (0.17)
56 or older			0.33 (0.16)**	0.30 (0.18)*
Cohabiting (0 = "no", 1 = "yes")			-0.27 (0.17)	-0.33 (0.18)*
Children (0 = "no", 1 = "yes")			0.14 (0.12)	0.10 (0.13)
Position-by-cluster dummies[a]	NO	NO	NO	YES
N	278	278	278	278
R^2	0.04	0.06	0.29	0.41

Notes. WFH = Working from home. Robust standard error between parentheses. [a] = This includes 41 dummies; *$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

4.5. DISCUSSION

The outbreak of COVID-19 has led to a drastic change in the organization of work in the healthcare sector. In this study, we argued that healthcare workers who have been ordered to work from home are likely to perceive their jobs as less valued than before, as frontline healthcare workers are essential in battling the pandemic and are publicly appreciated, and that therefore their work engagement is at risk. We drew upon cognitive crafting theory to hypothesize that cognitive crafting can help remote healthcare workers strengthen the meaningfulness of their jobs and optimize their work engagement. We additionally hypothesized that frontline healthcare workers would not benefit from cognitive crafting, due to their comparably larger perceived professional prestige. Our results supported both predictions, as demonstrated by a significant interaction effect of cognitive crafting and WFH on work engagement. However, in disagreement with our hypothesis, we found no significant effect of cognitive crafting on work engagement for healthcare workers only partially working from home. A possible explanation might be that such workers feel important when they are onsite and believe that the public appreciation for frontline healthcare workers is also directed at them, making cognitive crafting an ineffective coping strategy. Alternatively, it may be that healthcare workers that partially work from home have more cognitive space to engage in cognitive crafting.

4.5.1. Practice implications

This study has several practical implications. Primarily, cognitive crafting seems a fruitful strategy for remote healthcare workers to maintain adequate levels of work engagement: reminding oneself of the meaning of the job seems to help remote workers neutralize the experience of being away. Hence, we recommend organizations to promote cognitive crafting among remote healthcare workers. These initiatives should aim at improving remote workers' ability, motivation and opportunity to cognitively craft their jobs. We propose two courses of action.

First, we recommend healthcare organizations to offer cognitive job crafting interventions. Previous research suggests that an effective job crafting intervention consists of multiple training days over several weeks and combines an introduction of job crafting theory and practical exercises (Knight et al., 2019; Sakuraya et al., 2016, 2020; Van den Heuvel et al., 2015; Van Wingerden, Bakker, et al., 2017a, 2017b; Van Wingerden, Derks, et al., 2017). Practical exercises can be delivered to individual workers, e.g., completing the Michigan Job Crafting Exercise (J. M. Berg et al., 2010) and developing a personal job crafting plan, as well as to the group, e.g., sharing personal crafting stories and brainstorming about effective job crafting strategies. As face-to-face training may be infeasible during the COVID-19 pandemic, we recommend online cognitive job crafting interventions. To make sure these online interventions are effective, organizations are well-advised to maximize virtual connection with the trainer and colleagues and engage participants by sending reminders and giving homework (Imamura et al., 2015; Ouweneel et al., 2013). As attrition is higher in internet interventions due to an unfulfilled desire for human connection (Mitchell et al., 2009), we urge organizations to make extensive use of videoconferencing software during training.

Second, we encourage organizations to expose remote healthcare workers to testimonies of people who are positively affected by their work. These testimonies can help workers to think of relevant cognitive crafting strategies and serve as input during cognitive crafting training. For example, records indicating that clinical professionals have access to enough protective medical equipment and feel safer at work may lead to an increased sense of meaningfulness among those remote workers in charge of purchasing and distributing this equipment. Indeed, previous research suggests that connecting workers to the beneficiaries of their work may lead to an increased sense of work meaningfulness (Michaelson et al., 2014). We advise organizations to focus on testimonies of healthcare workers instead of testimonies of patients, as the impact of the work of remote healthcare workers often remains invisible to patients. Testimonials can be obtained by including open-ended questions in an online survey (Dykema et al., 2013; Lagu et al., 2013; McColl et al., 2001).

Notably, as cognitive crafting explains limited variance in work engagement and seems less important for frontline healthcare workers, we want to emphasize that promoting cognitive crafting alone is not enough to safeguard work engagement in healthcare organizations. What is needed is a sustainable, comprehensive work design policy approach. Specifically, we recommend organizations to engage in effective top-down work design and foster a climate for cognitive as well as behavioral job crafting strategies (Kniffin et al., 2020). For example, healthcare executives and line managers may want to use top-down strategies to reorganize work tasks to maximize perceived job autonomy (Antoinette Bargagliotti, 2012), make sure that work schedules are realistic and efficient (Maenhout & Vanhoucke, 2013), ensure that the strategic position of all jobs in healthcare organizations are acknowledged (Hennekam et al., 2020) and create ample opportunity for workers to proactively optimize their job demands and seek job resources in order to thrive at work (Gordon et al., 2018; Tims et al., 2012).

4.5.2. Limitations and future research

Although our study shows several new insights on the relation between cognitive crafting and work engagement, our study has several limitations. As our data are cross-sectional, our results should be interpreted as a conditional association rather than a causal relationship. For instance, recent organizational psychological research suggests that the relationship between job crafting and work engagement is reciprocal (Bakker & Demerouti, 2017). To study the causal relationship between cognitive crafting and work engagement, we therefore recommend researchers to measure the current study's variables at multiple time points and examine changes over time. This longitudinal data would help test the temporal robustness of our interaction term. It may be that, as the pandemic continues or ends, a decline in public appreciation and professional prestige occurs (Hennekam et al., 2020), possibly rendering cognitive crafting a relevant coping strategy for frontline healthcare workers. In support of this, pre-pandemic research shows that cognitive crafting is positively related to the work engagement of frontline healthcare workers (Q. Hu et al., 2020). Also, our study does not shed light on the psychological mechanisms that underpins the moderation model. Therefore, to unravel this mechanism, we encourage researchers to consider meaningful work (Steger et al., 2012) as a mediating variable.

Furthermore, as we only relied on quantitative measures to test our hypothesis, we recommend mixed methods research to increase understanding of how, when and why individual healthcare workers cognitively craft (Niessen et al., 2016). In-depth interviews could indicate in what way perceived meaningfulness and decrease professional prestige ignite cognitive crafting practices and in which circumstances workers especially mentally craft their work experiences.

Finally, in light of the unusual timing of study (i.e., the first wave of the COVID-19 pandemic), specific healthcare context (i.e., a Dutch hospital) and a relatively low response rate (i.e., 17%), the generalizability of our findings to other healthcare organizations, industries or countries may be limited. In addition, because of the unavailability of pre-pandemic data and detailed data on work tasks, we cannot be certain that cognitive crafting is effective for all kinds of remote healthcare workers and ineffective for all kinds of frontline healthcare workers. It may be that experienced remote workers in managerial positions with high perceived prestige struggle less with work meaningfulness and hence do not benefit from cognitive crafting as much as their subordinates. It might equally be that hospital workers treating non-COVID-19 patients feel that their contribution is (wrongly) underappreciated and thus benefit from cognitive crafting. In light of these limitations, future studies are advised to collect specific data on work tasks, experience with remote working before the pandemic and perceived professional prestige and use this data to differentiate within the healthcare sector for a more nuanced understanding. Furthermore, it would be interesting to test the current hypotheses in other countries and in other essential sectors during the pandemic, including supermarkets, public transportation, and law enforcement.

4.5.3 Conclusion

In this article, we extended the job crafting literature and explored the cognitive dimension of job crafting for remote healthcare workers' jobs in the context of the COVID-19 pandemic. We found that cognitive crafting may especially aid remote healthcare workers in staying engaged at work during difficult times. We hope that this study will incite further research into the workings of cognitive crafting and will increase the awareness of supporting remote healthcare workers during the COVID-19 outbreak, similarly.

5

For whom and under what circumstances does email batching work?

Based on paper: Wijngaards, I. Pronk, F.R., & Burger, M.J. *For whom and under what circumstances does email batching work?* Submitted.

5.1. INTRODUCTION

> "The trick is to turn it off and only check occasionally and people do not expect immediate answers. If it is urgent, they can phone me"
>
> – Pignata et al. (2015).

Email continues to be the most ubiquitous medium for organizational communication (Barley et al., 2011; Ragan, 2020; Rosen et al., 2019; H. Taylor et al., 2008). A recent survey among US workers in administrative or management roles suggested that, on average, workers spend over 3 hours per day on the exchange of work-related email (Adobe, 2019). Another study revealed that 75% of US workers working in small to medium-sized businesses reply to email within 1 hour, and 53% expect colleagues to do the same (Kelleher, 2013).

The use of email in the workplace has promises and pitfalls (Wajcman & Rose, 2011). Email is functional for organizational communication, building good interpersonal relationships, and promoting adequate job performance (Lowry et al., 2009; Mano & Mesch, 2010; Sheer & Rice, 2017; Ten Brummelhuis et al., 2012; Wajcman & Rose, 2011). For example, Wajcman and Rose (2011) demonstrated that for many workers high connectivity is pivotal for staying informed on task statuses and new developments, and getting work done. At the same time, for many, receiving, processing and answering online messages serve as most prominent sources of interruption that can significantly thwart their well-being (Fonner & Roloff, 2012; Puranik et al., 2020; H. Taylor et al., 2008). Several studies have shown that frequent email interruptions and high connectivity can instigate work overload, time pressure, job dissatisfaction, work disengagement, stress and feelings like anger and sadness (Barley et al., 2011; Derks et al., 2021; Jerejian et al., 2013; Mano & Mesch, 2010; Sonnentag et al., 2018; Ten Brummelhuis et al., 2012). Hence, it is not email per se that poses a problem to worker well-being and performance, but rather the continuous influx of work interruptions it brings when workers do not restrict the frequency of email interaction.

To address the interruption caused by emails at work, scholars have investigated the effectiveness of email batching – processing emails only at certain times of the day (e.g., Kushlev & Dunn, 2015; Robbins, 2004; Mark et al., 2012; Dabbish & Kraut, 2006; Mark et al., 2016). They consider email batching a useful email management strategy because it could reduce the total number of daily email interruptions and consequent occurrences of task switching, which in turn alleviates workers' overall cognitive strain (Kushlev & Dunn, 2015). This upkeep of cognitive effort and the continuance of the workflow allows workers to make adequate goal progress and keep exhaustion and negative emotions at bay (Puranik et al., 2020).

At the same time, empirical studies on the effectiveness of email batching have yielded mixed results (Mark et al., 2016 see the discussion in the next subsection). The potential reasons for this inconclusive evidence are manifold. It could be that the positive interruption-reducing effects of email batching are cancelled out by the distress that not attending an overflowing inbox brings (Dabbish & Kraut, 2006) and the discomfort associated with the disruption of habits (B. Gardner, 2015; Wood et al., 2005). Alternatively, it may be that the relevance of email batching depends on individual differences (Akbar et al., 2019), the importance of emailing to get work done (Mark et al., 2016), or the organizational expectations regarding responsiveness (Barley et al., 2011; Reinke & Chamorro-Premuzic, 2014). Therefore, we used data collected during a quasi-experimental top-down HR intervention within a Dutch financial services organization to investigate *for whom* and *under what circumstances* email batching is effective for reducing email interruptions and supporting well-being. In the subsection below, we first elaborate on theoretical underpinnings of email batching and give an overview of relevant empirical evidence.

5.1.1. Theoretical underpinnings and empirical evidence

There are several psychological theories that can explain why interruption-induced task switching is associated with higher cognitive load and depleting available cognitive resources (Kushlev & Dunn, 2015; Puranik et al., 2020). Research building upon the *memory for goals theory* (Altmann & Trafton, 2002; Trafton et al., 2003) holds that the goals of the suspended interrupted task decay from memory during an interruption and cause resumption and completion times of the interrupted task to be higher and performance to be lower (Altmann et al., 2014; Altmann & Trafton, 2007). According to the *control theory of self-regulation* (Carver & Scheier, 1990) and *action regulation theory* (Hacker, 2003), workers will as a result exhaust their reservoirs of self-regulatory resources – cognitive resources that govern self-regulation, "the modification of habitual, natural, or dominant response" (Hamilton et al., 2011, p. 14) – to reorganize their work sequences and set things straight. The *time-based resource sharing model of attention* (Barrouillet et al., 2004) explains that even the very act of switching between tasks requires cognitive effort (Liefooghe et al., 2008). Finally, the *load theory of attention* (Lavie, 2010) argues that a high cognitive load and depleted reservoirs of cognitive resources could make people even more prone to distractive stimuli and motivate them to task switching, resulting in a spiral of cognitive resource loss (Lavie et al., 2004; Lavie & De Fockert, 2005; Leroy, 2009).

Email interruptions not only drain (cognitive) energy, they can also negatively affect well-being. As most workers perceive the continuous engagement in a certain work task as a pleasurable, behavioral momentum (e.g., flow, work absorption, Bakker et al., 2004; Csikszentmihalyi & Csikszentmihalyi, 1988), an interruption will be regarded as unwelcome event and trigger a negative emotional response. Furthermore, following *affective events theory* (H. M. Weiss & Cropanzano, 1996), email interruptions are likely perceived as events that are incompatible with goal progress and goal attainment and, for this reason, thwart affective well-being (Puranik et al., 2020). In a daily diary study, Sonnentag et al. (2018) showed that interruptions due to emailing at work lead to more time pressure, which in turn elicits negative affective responses. Similarly, Baethge and Rigotti (2013) showed that hindered goal progress due to work interruptions can result in increased time pressure and feelings of irritation. Notably, negative affective responses may further fuel cognitive resource loss. The *conversation of resources theory* (Hobfoll, 1989, 2001) and *ego-depletion theory* (Baumeister et al., 1998; Baumeister & Vohs, 2007) predict that workers are forced to use self-regulatory resources to suppress the negative affective responses caused by interruptions in the workplace (Lin et al., 2013).

In sum, it can be argued that email interruptions lead to the depletion of cognitive resources and trigger negative affective responses. Email batching has the potential to reduce these interruptions, herewith being more beneficial for well-being than checking online messages continuously. As mentioned earlier, the support for this hypothesis is mixed. In a within-subjects field experiment, Bradley et al. (2013) showed that checking email once a day induces less stress than checking email continuously as usual. Using a similar research design, Kushev and Dunn (2015) found that participants experience less stress on days that they checked email three times a day than when they had no limits. However, the effect on other well-being outcomes was limited. Blank et al. (2020) lab experimentally showed that participants that were exposed to continual email interruptions experienced more negative emotions during task completion than participants that received emails in a single batch. In contrast, in a correlational study, Dabbish and Kraut (2006) showed that restricting the moments of checking email, rather than checking email when a message came in, was associated with email overload. Drawing upon computer logs, biosensors and daily surveys of 40 knowledge workers, Mark et al. (2016) documented a non-significant correlation between email batching behaviors and stress. Using similar kinds of data, Bradley et al (2011) showed that only 12% of respondents handled email by means of batches, and hypothesized that the unpopularity is likely due to workers' perception that email batching has limited promise for stress prevention. In a lab study, Akbar et al. (2019) showed that email batching alleviates stress for emotionally stable participants and aggravates stress for those scoring higher on the neuroticism spectrum.

5.1.2. Present research

In this study, we make use of data collected in a between-subjects quasi-experiment within a Dutch financial services organization to test the hypothesis that checking email during three batches a day (i.e., intervention condition) leads to less email interruptions and better well-being than checking email continuously as usual (i.e., control condition).

Well-being was captured using two variables, emotional exhaustion and work engagement. We adopted this multi-dimensional approach because email batching (Kushlev & Dunn, 2015; Mano & Mesch, 2010; Jerejian et al., 2013) and organizational interventions more generally may not affect different aspects of well-being to a similar degree (Briner & Walshe, 2015; Nielsen, Randall, et al., 2010; Wijngaards et al., 2021). We selected emotional exhaustion, "a state of depleted work-related emotional and motivational resources" (Halbesleben et al., 2013, p. 493) and the main constituent of burnout (Seidler et al., 2014), as research drawing upon resource-based theories have often treated it as an indicator of low energy and negative sentiment as a result of depleted self-regulatory resources (Hobfoll et al., 2018; e.g., Lam et al., 2017; Lin et al., 2013; Wheeler et al., 2013). We chose work engagement, "a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (Schaufeli et al., 2002, p. 74), the antipode of burnout, as email interruptions likely take a heavy toll on workers' energy resources, may be demotivating due to their negative association with goal progress and could hamper prolonged absorption in the job (Parke et al., 2018).

We extend experimental research on the topic of email batching in two main ways. First and foremost, in contrast to participants in previous experimental research, participants in our study did not self-select into the email batching intervention. Instead, the treatment was delivered in the form of a top-down HR intervention by the organization itself – planned, behavioral, theory-based actions aimed at improving worker health and well-being by transforming the design, organization and management of work (Nielsen, Taris, et al., 2010). This research design allows us to empirically verify the recent theoretical proposition that the effectiveness of online message batching depends on individual and contextual factors (Fitz et al., 2019; Kushlev & Dunn, 2015) and examine whether email batching is also effective in a real-world setting. We considered the role of preference for multi-tasking, the intensity of email batching intervention, email volume and organizational expectations for email response times as relevant factors. In addition, next to effect tests, we evaluated the intervention process, e.g., the satisfaction about the intervention, intent to use email batching in the future and suggestions for improvements (Nielsen, Randall, et al., 2010; Randall et al., 2009). Second, we investigated whether the intervention effects were sustainable over time by estimating well-being effects based on well-being data collected right after the intervention ended and data from a follow-up survey two weeks later.

5.2. METHODS

5.2.1. Procedure

The email batching intervention that is studied is part of a HR program of a regional branch of a Dutch financial services organization that aims at improving worker well-being. The authors were asked to (1) develop an intervention that could help workers to deal with the struggles associated with remote working, (2) recommend questions for the survey evaluation of the intervention, and (3) analyze the data. The intervention was developed by the second and third author and was based on Kushlev and Dunn's (2015) experiment. With support of the second author, the HR department further tailored the intervention to the organization context and needs, and implemented it. The data collection was administered through HR and a third party that conducted all worker well-being surveys within the organization. The HR department presented the intervention to the participants as an 'email challenge' instead of a (quasi)-experiment or intervention because workers in the organization are exposed to 'challenges' regularly (e.g., a step challenge).

Prior to the start of the intervention, the HR department assigned teams to 'intervention' and 'control' conditions based on geographic location, since a randomized experimental setup was impossible due to a risk of contamination. Consequently, as shown in the participant flowchart in Figure 5.1, from the 112 selected workers, 39 nested in three teams were assigned to the control condition and 73 nested in four teams were assigned to the intervention condition. Within the intervention group, 39 participants were invited for an additional challenge. This challenge asked participants to also batch their instant messages (IM) to three times per day. In the design of the experiment, we hypothesized that participants that only received an email batching intervention may compensate for their unfulfilled need to check email behaviors by continuously checking their IM platforms. The more intensive intervention allowed us to control for this potential confounder in the analyses. The intervention period was one month.

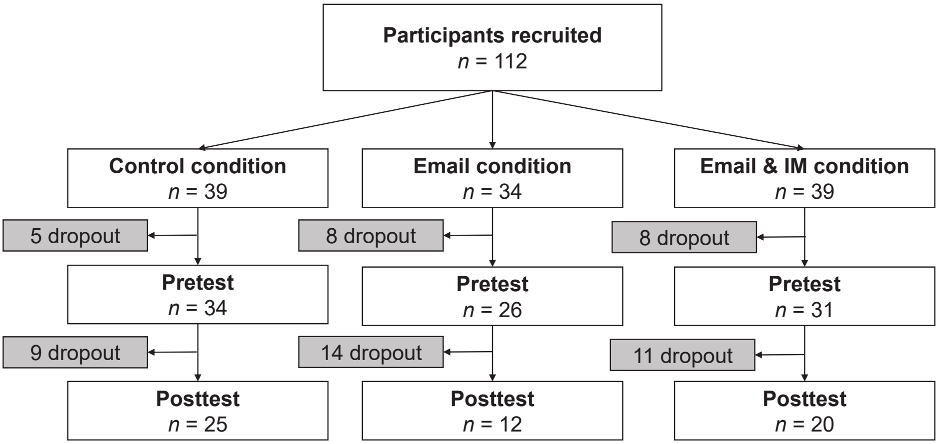
The intervention group was introduced to the idea of email batching in an interactive, 1-hour (virtual) kick-off session, hosted by an HR officer from the organization. The managers of the participating teams, the regional director and second author were also present. In the briefing, the HR officer and, in particular, the second author explained the reason behind this intervention and challenged how participants could alternatively manage their email notifications. Specifically, participants were explained how to change continuous email notifications to email notifications in batches on computer and phone and were encouraged to schedule (max 3) blocks in their online agenda during which email could be answered and set up several reminders for the surveys. The case for the intervention was made by reporting on an earlier survey in the host company: A study among 446 workers in June 2020 showed that workers struggled with concentrating in their remote offices during the coronavirus pandemic and scored very high on the question "My work requires a lot of attention and concentration" (M = 4.08, SD = 0.71) that was answered on a five-point Likert scale (Bakker, 2014), with answer categories ranging from 1 (*completely disagree*) to 5 (*completely agree*). The sessions were recorded so that participants who were not able to attend were able to watch the session at their own convenience. Of the respondents who filled out both the pre-test and follow-up survey, 84% of participants attended the kick-off session in person, 9% did not but watched the recording, and 7% did neither. It should be noted that participation in the email batching intervention was completely voluntary, but encouraged by the organization (e.g., participants had to alter their own settings for notifications and were free to check their email if they felt like it).

After the kick-off meeting, participants in the intervention group received three emails from the HR department: an email with the recording of the kick-off meeting and a summary of the most important insights, an email with the invitation to participate in the pre-test survey, and a reminder for the pre-test survey. Participants were instructed to start with the intervention after they completed the pre-test survey. During the intervention, participants could contact HR and their respective managers for support. In the three weeks after the pre-test survey (thus during the intervention), participants received email invitations for intermediate weekly surveys. In the week after the intervention ended, participants received an invitation to the post-test survey. Two weeks after the post-test survey, participants were invited for a follow-up survey and received an email in case they did not complete the survey. Participants in the control group received an introductory email from HR that described that their organization wants to know more about the role of email and IM in the working lives of workers and that they were asked to provide this input. Like the participants in the intervention groups, participants in the control group received a pre-test survey, three intermediate surveys, a post-test survey and a follow-up survey. Once the intervention ended, it was up to the participant to decide whether they would continue to batch their email. In all surveys, respondents were asked for informed consent. Once all data was collected and analyzed, all participants and their managers received a debriefing on the study design and research findings.

5.2.2. Sample

From the total sample of 112 selected workers, 79 completed the pre-test survey (response rate = 71%). Of the participants that completed the pre-test survey, 53 completed the post-test survey and 57 completed the follow-up survey. A more detailed account by condition is provided in the participant flowchart in Figure 5.1. We described the emailing behavior of the participants in the sample based on the pre-test survey data. The attrition analyses were also based on the pre-test data. The demographics of the sample were described based on the follow-up survey, as it was in this survey that the demographic profile of participants was captured.

Figure 5.1 | Participant flowchart



Notes. *n* = sample size.

Of the 79 participants, 94% indicated that email is an important part of their job and 60% indicated that they found the exchanging of email a pleasant work task. In total, 30% received 25+ emails per day and 21% indicated that the daily number of emails results in stress. Seventy-one percent of participants indicated that the organization expects them to respond to emails quickly. The majority of the participants were male (68%) and aged 45 or older (70%). Participants worked in a variety of departments, including insurance and private banking. Most participants worked between 31 and 40 hours per week (73%); only 5% had a managerial position. Because of the government rules to mitigate the spread of the coronavirus, all participants worked mostly from home.

As a substantial number of participants dropped from the post-test survey and follow-up survey, we followed Goodman and Blum's (1996) approach to test for systematic response differences by conducting two multiple logistic regression analyses: one with participation to the post-test survey as dependent variable and one with participation to the follow-up survey as dependent variable. We considered nine predictors in both regressions: assigned group, email volume, importance of email, the pleasantness of emailing at work, the stressfulness of high email volume, organizational expectations regarding email response times, preference for multi-tasking, work engagement and emotional exhaustion. Attrition analyses indicated that organizational expectations regarding email response times ($B = 0.09$, $p = 0.048$) and high email volume ($B = 0.24$, $p = 0.046$) were positively related to drop-out in the post-test survey and the stressfulness of high email volume was negatively associated to dropout ($B = -0.13$, $p = 0.011$). Dropout in the follow-up survey was only significantly related to the stressfulness of high email volume ($B = -0.11$, $p = 0.025$). It thus seems that there is a degree of self-selection in the current quasi-experiment: participants experiencing a high email volume and participants who feel that the organization does not support delayed email response times are underrepresented in this study. These findings are not surprising, as workers with a high workload are more prone to non-response than workers with a low workload (Rogelberg et al., 2003). In the current context, email volume and perceived norms for fast response times may be an indicator of high (perceived) workload. Participants who experience stress from their email volume are overrepresented. This finding can be explained by the fact that participants that are not in need of a well-being intervention will drop out of an intervention quicker and neglect survey invitations about the intervention (Lyubomirsky et al., 2011; Nielsen & Noblet, 2018). On a more general note, it is plausible that a proportion of the participants dropped out because of the turbulence that the coronavirus pandemic caused in their professional and private lives (e.g., sickness absence, poor internet connection).

5.2.3. Measures

All measures used in this study were based on self-reports. All items were in Dutch. Because of demands from the organization, shortened scales and single-item measures were included in the survey. The measures were summarized in Table 5.1 (category, construct, schedule, participants, source, number of items, items and response categories). The internal consistency of the multiple-item scales was considered satisfactory, as Cronbach's α values exceeded 0.8.

The manipulation check was based on several single-item measures of the successfulness of the manipulation. In specific, the actual change and estimated change in email checking behavior were measured. Three outcome measures were included. Daily email interruptions were measured using adapted 3-item scales (Sonnentag et al., 2018; Ten Brummelhuis et al., 2012). Work engagement was measured using the Dutch 3-item Utrecht Work Engagement Scale (Schaufeli et al., 2006, 2019). Emotional exhaustion was captured using the Dutch 4-item Utrecht Burnout Scale (Schaufeli & Van Dierendonck, 2001; cf. Maslach et al., 1986). The pre-test survey and follow-up survey included single-item measures of preference for multi-tasking, email volume and organizational norms about email response times. We used administrative data to assign participants to the high-intensity and low-intensity intervention groups. As a general rule, the data from the pre-test survey was used. When participants did not fill out the pre-test measure, the data from the follow-up survey was used. The follow-up survey contained single-item measures on satisfaction with particular aspects of the intervention, reasons for not following intervention guidelines, motivation to batch email in the future, aspects of email batching to be sustained in the future and suggestions for email batching interventions.

5.2.4. Analytical strategy

We did a manipulation check by asking participants for their perceived following of the manipulation guidelines and reporting the descriptive statistics. The omnibus tests regarding the main effect of email batching on email interruptions, emotional exhaustion and work engagement were based on analysis of variance (ANOVA) tests. In the multivariate analyses, four dependent variables were considered. For both emotional exhaustion and work engagement, we considered two difference-measures: one based on the difference between the pre-test survey and the post-test survey and the other based on the pre-test survey and the follow-up survey. We build models in steps. We started with estimating the main effect of email batching. Then, we estimated four models, each containing the main effect of email batching and one of the four moderators. Finally, we estimated a full model that included all variables. We considered age, gender, hours and department as control variables in the regression, but decided to refrain from presenting these results because no control variables were statistically significant and including nonsignificant control variables unnecessarily reduces degrees of freedom (Bernerth et al., 2018). After the moderation analyses, we used data from the follow-up survey to contextualize the omnibus analyses and multivariate analyses. A *p*-value of 0.05 was considered statistically significant in the analyses.

5.3. RESULTS

5.3.1. Manipulation checks

The mean scores on the item asking participants about the extent they were able to follow the intervention guidelines prompted in the intermediate surveys, scored on a 1-7 Likert scale, was 3.23 (SD = 1.61). Upon examination of the mean scores per survey wave, we found a downward trend: 3.38 (SD = 1.91) in the first intermediate survey, 3.26 (SD = 1.65) in the second, 3.12 (SD = 1.39) in the third and 3.06 (SD = 1.39) in the post-test survey. The follow-up survey question about the success in limiting the frequency of checking email behaviors three times a day over the entire course of the email challenge painted a somewhat more positive picture, with an average score of 4.53 (SD = 0.75). In summary, it can be concluded that, even though participants did not feel that they were not able to fully comply with the intervention guidelines on a weekly basis, the guidelines were generally followed over the course of intervention.

Table 5.1 | Measures and descriptive statistics for study outcomes

Category	Construct	Schedule	Participants	Source	Item details	Response scale	α
Manipulation check	Estimated change in email checking behavior	Intermediate surveys, Post-test survey	Intervention	-	"Did you succeed in checking your work-related email maximally three times a day last week?"	1 – Never 7 - Always	-
		Follow-up survey	Intervention	-	"Did you succeed in limiting the frequency of checking work-related email to maximally three times a day during the entirety of the email challenge?"	1 – Never 7 - Always	-
Interruptions	Daily email interruptions	Intermediate surveys	Intervention and control	Ten Brummelhuis et al. (2012) and Sonnentag et al. (2018)	"Today, incoming work-related emails kept me from doing my job." "Today, work-related emails have reached me at inconvenient moments." "Today, work-related emails disturbed me in doing my work."	1 – Never 7 - Always	0.87-0.90
Well-being	Emotional exhaustion	Pre-test survey, Post-test survey, Follow-up survey	Intervention and control	Maslach et al. (1986) and Schaufeli & Van Dierendonck (2001)	"I feel emotionally drained from my work." "I feel used up at the end of the workday" "I feel fatigued when I get up in the morning and have to face another day on the job." "A full day of work feels like a heavy burden for me."	1 – Never 7 - Always	0.89-0.94
	Work engagement	Pre-test survey, Post-test survey, Follow-up survey	Intervention and control	Schaufeli et al. (2006, 2019)	"At my job, I feel bursting with energy." "I am enthusiastic about my job." "I am immersed in my job".	1 – Never 7 - Always	0.83-0.86
Moderating variables	Preference for multitasking	Pre-test survey, post-test survey	Intervention and control	Poposki and Oswald (2010)	"If I had to choose between focusing on one task or multi-tasking, I would rather focus on just one task".	1 – Never 7 - Always	-
	Email volume	Pre-test survey, post-test survey	Intervention and control	-	"How many work-related emails do you receive daily, on average?"	0-24 emails 25 or more emails	-
	Organizational expectations for email response times	Pre-test survey, post-test survey	Intervention and control	Day et al. (2012)	"In my organization, it is expected that I quickly respond to emails."	1 – Never 7 - Always	

Table 5.1 | Measures and descriptive statistics for study outcomes (continued)

Category	Construct	Schedule	Participants	Source	Item details	Response scale	α
Variables for additional analyses	Satisfaction with intervention	Follow-up survey	Intervention	-	"How satisfied are you about the email challenge regarding the following aspects? - the challenge guidelines; - the challenge's effect for yourself; - the degree to which the challenge can be implemented in the daily work practice; - the usefulness of the challenge for your own work; - the communication surrounding the challenge"	1 – Very dissatisfied 7 - Very satisfied	-
	Reasons for not following intervention guidelines	Follow-up survey	Intervention	-	"What was the main reason for not being able to batch email to three times a day? Multiple options are possible."	Own temptation to check; Client-related matters; Notifications; Colleagues; Others, namely …	-
	Motivation to batch email in the future	Follow-up survey	Intervention	-	"Do you feel motivated to regulate your emailing behavior in the future? Give a score between 1 and 10, where 1 stands for 'not at all' and 10 for 'very much.'"	1 – Not at all 7 – Very much	-
	Support in the future	Follow-up survey	Intervention	-	"Do you need support from [the organization] with regard to email management strategies?"	Yes; No	-
	Suggestions for email batching interventions	Follow-up survey	Intervention	-	"According to you, what does it take to make this challenge a success? This will help us with the design of interventions on happiness at work in the future."	Open-text box	-

Notes. IM = Instant messaging, α = Range of Cronbach's α values across survey waves.

5.3.2. Omnibus effects

We found a marginal effect of batching on email interruptions. The mean score on the interruption index in the control group was 3.38 (SD = 0.75) and the mean in the intervention group was 2.90 (SD = 1.19), $t_{36.20}$ = -1.82, p = 0.077. Concerning our well-being outcomes, we found a significant negative omnibus effect of email batching on emotional exhaustion measured in the post-test survey ($F_{1,130}$ = 9.04, p = 0.003) and follow-up survey ($F_{1,134}$ = 7.55, p = 0.007). We found no support for the relationship between the intervention and work engagement, as indicated by nonsignificant omnibus in the post-test ($F_{1,\,130}$ = 0.14, p = 0.709) and follow-up survey ($F_{1,\,134}$ = 0.33, p = 0.569).

5.3.3. Multivariate analyses

In line with the results from the ANOVA tests and as exhibited in Table 5.2, email batching had a significant effect on the difference between emotional exhaustion measured in the pre-test survey and the post-test survey (Model 1). Moderation analyses showed that intervention intensity and preference for multi-tasking did not affect this relationship (Model 2 and 3). The analyses provided evidence for the moderating role of email volume and organizational expectations regarding email response times (Model 4 and 5, respectively). Specifically, for participants with a high email volume (receiving 25+ emails per day), email batching was more effective in lowering emotional exhaustion than it was for participants receiving little emails every day. For participants believing that their organization expects them to reply to emails quickly, the exhaustion-diminishing effects of email batching were less profound than for participants that believe the opposite. A model that includes all variables suggests that email volume and organizational expectations regarding email response times are robust moderators (Model 6).

The results from regression analyses based on the difference between the pre-test survey and the follow-up survey did not reveal a significant effect of email batching on emotional exhaustion (B = -0.11, p = 0.500). A comparison of this effect size with the effect size of Model 1 based on the post-test survey data (-0.29) suggests that the effects of email batching wear off quickly. Additionally, in these analyses, no interaction terms reached statistical significance. This result diverges with the significant omnibus effect detected in the ANOVA tests. We expect that this discrepancy is caused by the fact that, in contrast to the regression analysis, an ANOVA test does not consider the baseline level of the independent variable. In addition, the regression analyses were performed on a smaller dataset (n = 53 vs. n = 136) and therefore may have lacked statistical power.

Regression analyses confirmed the nonsignificant relationship between email batching and work engagement found in the ANOVA tests, as shown in Table 5.3. The analyses did not reveal any significant moderators. Evidence for this conclusion is found in the analyses based on engagement based on the follow-up survey with a nonsignificant effect of the intervention (B = -0.02, p = 0.315) and all interaction terms.

5.3.4. Additional analyses

5.3.4.1. High satisfaction with the intervention

Overall, participants in the experimental group were satisfied with different aspects of the intervention (all measured on a 1-7 Likert scale). Nonetheless, substantial differences between the satisfaction scores were apparent. Participants were the most satisfied with the guidelines set in the intervention (M = 4.97, SD = 0.64), its usefulness for their jobs (M = 4.53, SD = 0.95) and the communication about the intervention (M = 5.44, SD = 0.80) and the least satisfied about the results of the intervention (M = 4.34, SD = 1.15) and how easy the intervention was to implement in their daily practice (M = 4.09, SD = 1.12).

5

5.3.4.2. Client-related concerns as the main reason for not following intervention guidelines

Client-related concerns as the main reason for not following intervention guidelines. On the question why people failed to completely follow the intervention guidelines, participants most often mentioned client-related concerns (72%). Their own temptation (31%) and colleagues (28%) were also frequently mentioned. Of the ten participants that selected the 'other reasons' (31%), nine mentioned the high dependence on email to do work effectively as the primary reason for why they did not follow the intervention guidelines. For example, "I obtained additional work tasks that come for 100% via email and instant messaging" and "My clients ask their questions via email and expect a prompt reply." The one remaining participant reflected on the relevance of the intervention for his personal situation: "I don't experience pressure from incoming messages and work better if I know what comes in. I am perfectly able to find a balance and I know when to put my email aside."

5.3.4.3. Only a few aspects of the intervention were internalized once the intervention was ended

Of all the participants in the intervention group, 53% indicated that they continued email batching after the intervention was finished and 81% expressed an interest in retaining one or more aspects of the email batching intervention in their work. The most popular aspects were keeping email notifications off (66%) and batching email in blocks (56%). Less popular were reducing overall email time (34%), deciding on email-related norms within the team (22%) and starting the day without email (13%). Interestingly, 94% of participants indicated that no additional support regarding email management was desired in the future.

Table 5.2 | Regressions predicting the difference between emotional exhaustion in post-test survey and pre-test survey ($N = 53$)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Email batching[a]	-0.29† (0.16)	-0.61 (0.45)	-0.23 (0.21)	-0.12 (0.17)	-1.61** (0.58)	-1.24† (0.70)
Preference for multi-tasking		-0.06 (0.07)				-0.02 (0.07)
Email volume[b]				1.04** (0.32)		0.92** (0.34)
Organizational expectations for email response times					-0.19* (0.09)	-0.13 (0.09)
Email batching[a] × Preference for multi-tasking		0.07 (0.10)				0.03 (0.09)
Email batching[a] ×Intervention intensity[c]			-0.09 (0.21)			-0.08 (0.20)
Email batching[a] × Email volume[b]				-1.11** (0.38)		-0.98* (0.40)
Email batching[a] × Organizational expectations for email response times					0.28* (0.12)	0.21† (0.12)
R^2	0.06	0.07	0.07	0.23	0.16	0.29

Notes. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. [a] 0 = "Control", 1 = "Email batching intervention"; [b] 0 = "less than 25 emails per day", 1 = "25+ per day"; [c] 0 = "Email batching intervention", 1 = "Email and instant messaging batching intervention"; R = explained variance.

Table 5.3 | Regressions predicting the difference between work engagement in post-test survey and pre-test survey ($N = 53$)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Email batching[a]	0.04 (0.16)	0.49 (0.45)	0.14 (0.21)	-0.03 (0.18)	-0.37 (0.61)	-0.09 (0.76)
Preference for multi-tasking		0.04 (0.07)				0.04 (0.07)
Email volume[b]				-0.51 (0.35)		-0.59 (0.36)
Organizational expectations for email response times					-0.06 (0.09)	-0.11 (0.10)
Email batching[a] × Preference for multi-tasking		-0.10 (0.09)				-0.11 (0.10)
Email batching[a] ×Intervention intensity[c]			-0.14 (0.21)			-0.16 (0.22)
Email batching[a] × Email volume[b]				0.53 (0.41)		0.58 (0.42)
Email batching[a] × Organizational expectations for email response times					0.09 (0.12)	0.14 (0.13)
R^2	0.00	0.03	0.01	0.04	0.01	0.11

Notes. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. [a] 0 = "Control", 1 = "Email batching intervention"; [b] 0 = "less than 25 emails per day", 1 = "25 or more emails per day"; [c] 0 = "Email batching intervention", 1 = "Email and instant messaging batching intervention"; R = explained variance.

5.3.4.4. Suggestions for improvements

Of the eighteen participants that offered concrete suggestions, eight commented about the impetus of considering job tasks when implementing email batching, e.g., "That you want to try it [email batching] yourself, especially if you are burdened by email (greater necessity)", "[The effectiveness of email batching] is very dependent on your function and how client-oriented it is" and "It [email batching] has to align with the kind of work I do". Six participants emphasized the importance of aligning organizational expectations regarding internal communication to the intervention guidelines, e.g., "Broader policy about approach and necessity of internal communication [is needed]. A multitude of messages does not mean that much information is shared", "Clarity about the universality of the [new] way of working [is needed], so that no misunderstandings emerge about availability" and "Making arrangements within the team, for example, that one doesn't have to answer immediately". Two participants reflected on the vitality of effective delivery of an email batching intervention: "You will get commitment from the participants by keeping it [the email batching intervention] simple. I think that you were successful in that regard." and "I feel that the intervention was implemented well and the weekly email with questions was a reminder of the [email batching] challenge. If I wouldn't have received a reminder, the challenge wouldn't have been adopted as well, I think". In sum, participants indicated that future email batching interventions should be offered to people whose job allows it, should be aligned with organizational norms surrounding internal communication, and should be delivered using multiple reminders.

5.4. DISCUSSION

Building on several psychological theories and findings from earlier experiments of email batching, we evaluated a quasi-experimental field experiment to examine whether workers receiving an email batching intervention, as delivered as top-down HR intervention, experience higher well-being than workers in a control group that were asked to check as usual. More specifically, we investigated for whom and under what circumstances email batching is effective for reducing email interruptions, preventing emotional exhaustion and improving work engagement.

We found that most participants were able to adopt email batching in their daily practice during the experiment and it generally reduced email interruptions. Moreover, we documented a significant, negative association between email batching and emotional exhaustion and a nonsignificant association between email batching and work engagement. This finding is in line with research that suggests that email interruptions and strategies to reduce them have a stronger effect on negative well-being indicators than positive well-being indicators (Jerejian et al., 2013; Kushlev & Dunn, 2015; Mano

& Mesch, 2010; Sonnentag et al., 2018; Ten Brummelhuis et al., 2012). Ten Brummelhuis et al. (2012) argued that virtual interruptions may be positively related to dedication and vigor at work due to increased perceptions of digital connectedness and negatively related to absorption at work due to a break of workflow, rendering the overall effect on work engagement nonsignificant. Sonnentag et al. (2018) showed that perceived interruptions predict positive affect via responsiveness to these messages.

Furthermore, we showed that the effects of the intervention on emotional exhaustion quickly wore off, although the majority of participants internalized one or more email batching behaviors after the intervention ended. This suggests that email batching is unlikely to lead to robust improvements in well-being if it is promoted as a temporary project. It is likely that for sustainable behavioral change and robust well-being improvements to occur, email batching should be integrated into the culture and core practices of an organization. Along with the finding that the overwhelming majority of participants did not have any desire for more support regarding email management once the intervention was ended, this result indicates that email batching, by no means, should not be treated as a magic bullet for ensuring high levels of worker well-being.

Finally, we demonstrated that the effects of email batching on emotional exhaustion varied across workers. First, workers that dealt with low email volumes reaped significantly less the benefits from email batching than workers facing higher volumes. Receiving relatively little email will not only limit the amount of task switching and the pressure on workers' cognitive resources but will also lead to a small difference between checking email when it comes in as usual and checking email three times a day. This is in line with the earlier observation by Sonnentag et al. (2018), who found that work pressure mediates the relationship between email interruptions and negative affect. Second, email batching only seems to be effective if organizational norms are such that not a (very) fast response time is expected (Barber & Santuzzi, 2015; Barley et al., 2011; R. Brown et al., 2014; Day et al., 2012). Accordingly, it is unlikely that the implementation of email batching in an organizational unit will be successful if colleagues in other parts of the organization still expect a fast response time. Related to this point, additional analyses revealed that some jobs might not be suitable for email batching. We found that not only co-worker expectations but also client expectations play an important role in not completing the email batching challenge: when email batching interfered with achieving workers' goal to serve clients well, the email management strategy was perceived as a hindrance rather than a solution.

5.4.1. Limitations

There are several limitations to the present work. First, even though our focus on a single organizational context has allowed us to evaluate the practical feasibility of the email batching in an organization, it inherently limited the external validity of the findings (Landers & Behrend, 2015). For example, with the study taking place during the coronavirus pandemic, all study participants had to work from home and were completely reliant on virtual media to stay connected with colleagues and clients. Indeed, the Microsoft 2021 Work Trend Index revealed that this transition from the office to work has globally led to a spike in email traffic (Microsoft, 2021). It is plausible that once participants are allowed to work from the office again, email volumes and email reliance diminish and email management strategies, such as email batching, become less relevant. Although participants in our sample worked in various departments and therefore seemed representative of a typical regional branch of a financial institution in the Netherlands, the effects may not generalize to other organizations in other industries and countries. For example, email batching may be more effective in organizations where the prompt satisfaction of *virtual* client needs is not central to work performance (e.g., healthcare workers, police officers and supermarket managers). As another example, with cross-cultural research showing that cultural differences exist in preferred email communication styles (Holtbrügge et al., 2013), it may be that the effectiveness of email batching is contingent on national culture. Against this background, we advise researchers to replicate the current study's findings in a diverse set of organizations.

Second, even though we adopted an inclusive approach towards operationalization of well-being and considered various moderators, we need more comprehensive research to help practitioners to make a case for email batching and understand the most important preconditions for effective implementation. For example, the construct of flow at work would have been an especially relevant well-being construct to consider, due to its close theoretical linkage with work interruptions (Baethge & Rigotti, 2013; Moneta, 2017). It would also be interesting to examine how email batching relates to dynamic well-being constructs, such as state work engagement (Breevaart et al., 2012) and state emotional exhaustion (Riedl & Thomas, 2019), and whether it has spillovers to well-being in the non-work domain (Becker et al., 2021; Ilies et al., 2007). In addition, researchers are encouraged to consider performance-related outcomes, e.g., email response time (Gupta et al., 2011) and perceived productivity (Kushlev & Dunn, 2015), triangulate subjective and objective measures of email behaviors to control for recollection biases (Bargh, 2002; Collopy, 1996; Fitz et al., 2019) and include additional moderators, e.g., telepressure (Barber & Santuzzi, 2015), managers perceptions about the intervention (Nielsen, 2013; Randall et al., 2009) and neuroticism (Akbar et al., 2019). Finally, future research may benefit from investigating the effectiveness of the different components of an email batching intervention and alternative email management strategies, such as email filing and filtering (Dabbish & Kraut, 2006; Jerejian et al., 2013). Our additional analyses, for example, suggested that starting the day without email was perceived as infeasible by the majority of participants.

Third, the attrition in our sample was high and, provided that employees are likely to drop out sooner when email batching does not work for them, the eventual impact of email batching may be even lower than reported. The disproportionate drop-out of employees with a high email volume is particularly worrisome in this regard. At the same time, the most plausible reasons for this group to drop out are client-related concerns and existing organizational norms regarding response times. Hence, the high attrition rate merely underlines that email batching is not a *sine qua non* improving worker well-being and that organizational context and culture are of pivotal importance for the feasibility of this intervention.

5.4.2. Implications

This study corroborates findings that email handling strategies are more strongly related to negative, rather than positive indicators of well-being (Jerejian et al., 2013; Kushlev & Dunn, 2015; Mano & Mesch, 2010) and supports the theoretical proposition that the effectiveness of online message batching may depend on individual and contextual factors (Fitz et al., 2019; Kushlev & Dunn, 2015). More broadly, this study strengthens the case for focusing on the question "what works for whom in which circumstances?" rather than the more general question "what works?" (Nielsen & Miraglia, 2017, p. 40; Nielsen, Randall, et al., 2010; Nielsen & Noblet, 2018) and provides reasons for why organizational interventions derail (Karanika-Murray & Biron, 2015).

We suggest that organizations should not regard email batching as a panacea for enhancing worker well-being. In case an organization wants to implement email batching, it is well-advised to foster a work climate where (expectations of) instantaneous email responses are discouraged prior to its introduction and only encourage workers to adopt this practice if it suits their jobs. Without the appropriate circumstances in the organization and without email being a considerable stressor at work, it is unlikely that an email batching intervention will change behaviors or improve worker well-being. Concretely, an organization may consider top-down communication of healthy email expectations, tailor the principles of email batching to the needs of teams and develop an email protocol that helps workers to use email responsibly, e.g., putting email expectations in email signature and changing the default notification settings in email software. On a more general note, this study highlights that the successfulness of organizational interventions does not only depend on the content of the intervention, but also on the context it is implemented in. When an organization wants to make an enduring positive change, it needs to embed the intervention into daily practice.

6

The promise of open survey questions for measuring job satisfaction

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6.1. INTRODUCTION

Organizational scientists have been leveraging written texts in their study of psychological constructs and business phenomena for decades (Duriau et al., 2007; Hayes & Krippendorff, 2007; Short et al., 2018). While manual human coding of texts continues to be the gold standard for annotating text, rapid advances in computer-aided text analysis (CATA) have opened up a venue for analyzing open texts in a drastically more efficient but still reliable manner (Short et al., 2010). CATA is a kind of content analysis that facilitates the measurement of constructs by converting text into quantitative data based on word frequencies (Short et al., 2010). One of the most popular applications of CATA is sentiment analysis, the practice of automatically detecting opinions, sentiments, attitudes and emotions about certain objects in human-generated texts (R. Feldman, 2013; B. Liu, 2015). Social scientists typically perform computer-aided sentiment analysis on bodies of relatively lengthy texts (e.g., Tov et al., 2013; N. Wang et al., 2014), probably because detecting sentiment in short informal texts is more challenging than sentiment detection in lengthier texts (Kiritchenko et al., 2014; Thelwall et al., 2010). It is therefore not surprising that research on performing CATA on brief responses to open survey questions thin on the ground within the organizational sciences (Gilles et al., 2017). This is unfortunate, as surveys still have a prominent place in organizational scientists' methodological toolboxes (Aguinis et al., 2009; Bono & McNamara, 2011), open survey questions can function as valuable supplements to their closed counterparts (Mossholder et al., 1995; Singer & Couper, 2017; Spector & Pindek, 2016), and researchers outside the discipline have proposed a multitude of promising solutions for mining textual survey data (Esuli et al., 2019; Li & Yamanishi, 2001; Patil & Palshikar, 2013; Rosell & Velupillai, 2008; Schonlau & Couper, 2016; Zehner et al., 2016).

Complementing closed questions with open-ended questions may have various benefits. First, open-ended questions can function as a counter to common method biases in questionnaires that primarily contain closed questions (Podsakoff et al., 2003). For instance, closed question survey scales can suffer from careless responding (Meade & Craig, 2012). We believe the inclusion of open-ended questions could be used to get respondents to respond more carefully, as open questions force respondents into a different and possibly more intensive form of cognitive processing (Krosnick, 1999). Second, complementing closed questions with open questions facilitates triangulation of methods (Turner et al., 2017). Next to using open questions to determine the construct validity of closed questions (and vice versa), researchers could leverage the responses to open-ended questions to obtain a more holistic perspective on the construct of study (Jick, 1979; Turner et al., 2017). Researchers could, for example, use the responses to assess when, why and how a construct is manifested (Spector & Pindek, 2016) and unravel the psychological processes that influence the self-report responses to closed survey questions (Edwards, 2008) because open-ended questions naturally prompt more spontaneous and elaborate responses (Reja et al., 2003).

Job satisfaction is a construct that organizational researchers typically study with closed questions (for examples, see Kaplan et al., 2009), and it has gained considerable attention in the literature (Judge et al., 2017). Job satisfaction has rarely been studied using text-based measures based on responses to open-ended questions (Gilles et al., 2017). We argue that this is a missed opportunity, as evidence suggests that the measurement of job satisfaction is complex (H. M. Weiss, 2002) and that closed question job satisfaction measures tend to suffer from careless responding (Kam & Meyer, 2015). Sentiment analysis appears to be a suitable method for the creation of a text-based measure. As suggested by several empirical studies (e.g., Borg & Zuell, 2012; Moniz & Jong, 2014; Poncheri et al., 2008; Taber, 1991; Young & Gavade, 2018), the sentiment found in texts seems to be a natural manifestation of the pleasant and unpleasant emotions, beliefs and cognitions employees have – factors that jointly constitute job satisfaction (e.g., Judge et al., 2012; Locke & Dunnette, 1976; H. M. Weiss, 2002).

We address two issues in this paper to illustrate the promise of open job satisfaction questions: (1) we investigate the reliability of computer-aided sentiment analysis for constructing text-based job satisfaction measures, and (2) carry out an initial test of the measures' construct validity. We focus on two open-ended response formats: a substitution open job satisfaction question (called hereafter: open-ended question) and a substitution semi-open job satisfaction question (called hereafter: semi-open-ended question). The two questions, "How do you think about your job as a whole?", and "What three to five adjectives come to mind when you think of your job?", are similar in the sense that both are designed to measure general job satisfaction, and are intended as equivalents of closed survey questions (cf. O'Cathain & Thomas, 2004). The questions primarily differ in the degree to which they stimulate respondents to generate structured textual responses. Open-ended questions allow respondents to decide on the length of their textual response, while semi-open-ended questions are much more constraining.

While to date semi-open-ended questions have rarely been used to measure attitudes (Glerum et al., 2014), they may have several advantages over open-ended questions. Respondents may prefer semi-open-ended questions because it takes less time and effort to write down several words that readily come to mind than to write down elaborate sentences (for some descriptive statistics about response burden of different question types, see Axhausen & Weis, 2010). In addition, researchers interested in quantitatively measuring constructs may favor semi-open-ended questions over open-ended questions, as responses to semi-open-ended questions are more convenient for computer-aided sentiment analysis methods to analyze. Even though structured responses to semi-open-ended questions are inherently short, these responses are likely to contain a higher proportion of useful and easy-to-process text than the unstructured texts that open-ended questions generate. Structured texts are likely to contain limited syntax and mainly useful, emotion-loaded words, e.g., adjectives generally carry subjective content (Taboada et al., 2011), whereas unstructured informal texts typically contain a high proportion of irrelevant words, e.g., articles, conjunctions, typing mistakes and negations, which are difficult to deal with using computer-aided sentiment analysis methods (Thelwall et al., 2010).

We contribute to the survey methodology literature by addressing the methodological dilemma of choosing between human and computer-aided content analysis. Even though human coding remains the gold standard for content analysis (Short et al., 2010), e.g., sentiment detection in text (Mohammad, 2016), it can be very time-consuming and expensive (Singer & Couper, 2017) and therefore sometimes unfeasible (Borg & Zuell, 2012). CATA methods are considerably more efficient and can save resources, but inevitably produce measures with attenuated reliability (McKenny et al., 2018). To assist organizational researchers that face this trade-off, we systematically assessed the degree of measurement error in text-based measures by following the guidelines set by McKenny et al. (2018). In particular, we studied the three sources of measurement error that are relevant for CATA research: specific factor error, algorithm error and transient error (McKenny et al., 2018). Additionally, we are among the first to use CATA to construct text-based job satisfaction measures from responses to an open-ended question (hereafter called: open text-based measure) and a semi-open-ended question (hereafter called: semi-open text-based measure) and to test their convergent and discriminant validity by means of closed question measures.

This paper is structured as follows. In the remainder of this section, we discuss the three computer-aided sentiment analysis techniques that were used in this study and formulate hypotheses. Next, we describe our sample, procedures and analytical strategy. We then present our comparative analysis and test our hypotheses. Finally, we discuss our findings and provide an agenda for future research.

6.1.1. Sentiment analysis approaches

Manual and computer-aided sentiment analysis can be used to construct a measure from the responses to open-ended questions (Borg & Zuell, 2012; Mossholder et al., 1995). Human coders subjectively rate text in terms of sentiment. To date, ratings by human coders have been treated as the gold standard and benchmark for computer-aided sentiment analysis (Mohammad, 2016; Taboada et al., 2011; Thelwall et al., 2010). However, when large volumes of texts have to be analyzed, complete reliance on human coders to analyze texts manually may become infeasible (McKenny et al., 2018). Moreover, humans may introduce bias in sentiment ratings (Mossholder et al., 1995; Zamith & Lewis, 2015), e.g., through individual differences in evaluation strategies (Mikhaylov et al., 2012) and in annotation experience and education (Snow et al., 2008). To mitigate these biases, researchers often make sure that multiple individuals independently annotate the same texts, calculate an inter-rater reliability score and compute an average rater score (Mikhaylov et al., 2012; Poncheri et al., 2008; Taber, 1991).

Two general streams of methods can be identified in computer-aided sentiment analysis: lexicon-based (or CATA-based) and learning-based techniques (Taboada et al., 2011). Lexicon-based methods involve the detection of sentiment in texts based on a dictionary of words that are labeled to reflect their semantic orientation, i.e., polarity and strength of words. Learning-based methods make use of labeled instances of text to build classifiers. Put differently, these methods use textual data that are already labeled with their semantic orientation to train an algorithm, with the purpose of predicting (i.e. classifying) unlabeled textual instances.

Both methods have certain advantages and disadvantages. Learning-based techniques often perform well in the domain that they have been trained, but lack accuracy when training data are small or the classifier is used in another domain (Cambria, 2016; Taboada et al., 2011). Lexicon-based methods do not suffer from these problems, as they do not rely on training data (Cambria, 2016), and domain-specific words can be added to a general dictionary to make a dictionary perform well in specific contexts (Taboada et al., 2011). However, their accuracy typically drops when textual data contains semantic rules and linguistic nuances like sarcasm (Cambria, 2016).

In this study, we relied on lexicon-based methods, as no appropriate dataset was available to train a learning-based sentiment analysis algorithm. We employed Linguistic Inquiry and Word Count (LIWC) 2015 (Pennebaker, Chung, et al., 2015), SentiStrength (Thelwall et al., 2010) and SentimentR (Rinker, 2019) to construct the text-based measures. We describe the similarities and differences between the software programs below.

6.1.1.1. LIWC 2015

The LIWC software is arguably the most widely used CATA technique in the organizational sciences (Short et al., 2018), and has been systematically validated in a large number of studies (Pennebaker, Boyd, et al., 2015). The LIWC software generates scores on a wide variety of constructs, e.g., social orientation, honesty, affective tone, by looking up words in an English dictionary of 6400 words, word stems, and emoticons. Turning to sentiment analysis, the LIWC 2015 software includes a transparent dictionary for positive emotion (620 words) and negative emotion (744 words, Pennebaker, Boyd, et al., 2015), and contains a commercially licensed, non-transparent emotional tone variable (Cohn et al., 2004) that summarizes the positive and negative emotion variables into one sentiment score (Pennebaker, Boyd, et al., 2015).

6.1.1.2. SentimentR

SentimentR is a sentiment analysis software package that is freely available on CRAN (R Core Team, 2014). Various studies outside the organizational sciences have successfully adopted this software for sentiment classification tasks (e.g., J. Chen et al., 2015; Ikoro et al., 2018), and proved its superior performance to other software programs, such as LIWC (Naldi, 2019; Rinker, 2019; Weissman et al., 2019). By default, SentimentR uses Jockers' (2017) English dictionary which contains 10,739 words (Rinker, 2019). Besides being open-access, non-commercialized and specially designed for sentiment analysis, it differs from LIWC in one major way. SentimentR does not just count individual words; the algorithm considers valence shifters to improve the accuracy of its semantic polarity recognition. Valence shifters can be split into negators, amplifiers, deamplifiers, and adversative clauses. A negator changes the sign of a sentiment-loaded word (e.g., "I do *not* enjoy my work"); an amplifier enhances the impact of a sentiment-loaded word on the overall sentiment score (e.g., "I *truly* enjoy my job"); a deamplifier reduces the impact (e.g., "I *hardly* enjoy my work"); an adversative conjunction overrides a sentiment-loaded clause (e.g., "I enjoy my work, *but* hate my boss"). In SentimentR, the valence shifters are considered by weighting the valence shifters found four words before and two words after the polarized word.

6.1.1.3. SentiStrength

Just like SentimentR, SentiStrength is a software program that is specially designed to detect sentiment in texts and is freely available for non-commercial users (Thelwall et al., 2010). It is optimized for sentiment analysis of short informal texts (e.g., tweets, Abbasi et al., 2014; Thelwall et al., 2010), and has found to be reliable (Araujo et al., 2016; Gonçalves et al., 2013; Islam & Zibran, 2017). The SentiStrength dictionary is constructed from several well-validated, English dictionaries – LIWC 2003 (Pennebaker et al., 2003) and the General Inquirer (Stone et al., 1966) – and contains 2310 words (Thelwall, 2017). The developers of SentiStrength deployed a learning-based sentiment analysis technique to optimize the software's performance. As a consequence, the software considers textual aspects such as punctuation (e.g., exclamation marks), the use of multiple vowels (e.g., "*haaappy*"), frequently used idioms (e.g., "*I am like you*" and "*I like you*") and valence shifters in its sentiment score calculation.

6.1.2. Measurement error in text-based measures

In general, three categories of CATA measurement error exist: specific factor error, algorithm error and transient error (McKenny et al., 2018). Specific factor error relates to the word lists that the CATA method uses, and the extent to which they are fit for the task at hand. Specific factor error can be assessed by computing the parallel forms reliability. In our case, this meant examining the convergence between computer-generated and human-coded sentiment measures. Algorithm error is related to the extent to which the measures produced by different CATA techniques vary. The more the measures diverge, the higher the algorithm error will be. This can be thought of as 'interalgorithm' error and can be assessed with Krippendorff's alpha (α) interrater agreement estimate (Hayes & Krippendorff, 2007; Krippendorff, 1980). Transient error is caused by the temporal factors that can impact the responses by a respondent. For instance, mood states can affect the overall valence in a textual response. Transient error can be measured by calculating test-retest reliability.

6.1.2.1. Specific factor error

Open-ended questions inevitably produce more unstructured texts than semi-open-ended questions because of the absence of answering constraints. These texts are likely to contain a high proportion of non-emotion loaded words, misspellings, semantic rules and valence shifters and linguistic characteristics that are generally difficult for lexicon-based sentiment analysis to process (Thelwall et al., 2010). As humans are typically the most competent to detect sentiment from natural, unstructured texts (Thelwall, 2017) and individual adjectives that the semi-open-ended question produces are relatively straight-forward to look-up in sentiment dictionaries, we hypothesized that:

> **Hypothesis 1a:** *The specific factor error in open text-based measures will be higher than the specific factor error in semi-open text-based measures.*

As the selected software packages vary in their suitability to analyze short informal texts, we predicted that the specific factor error in open text-based measure varies from one software package to the other. We expected that SentiStrength will have the highest accuracy because it was designed for the sentiment analysis of short informal texts, has the most advanced algorithm of the three and has outperformed LIWC 2007 in the analysis of short texts (Gonçalves et al., 2013; Shalunts & Backfried, 2015). Further, we predicted that SentimentR would produce more reliable measures than LIWC 2015, because, contrary to LIWC 2015, SentimentR considers valence shifters in its algorithm. As such, we hypothesized that:

> **Hypothesis 1b:** *The specific factor error will vary across open text-based measures, with LIWC 2015 performing the worst and SentiStrength performing the best.*

Semi-open-ended questions only generate context-free words that CATA methods can conveniently look up in their dictionaries without any substantial pre-processing, e.g., stemming and removing stop words. For this reason, the accuracy of a semi-open text-based measure almost exclusively depends on the quality and completeness of the dictionary. We deemed two competing hypotheses plausible. One the one hand, we could hypothesize that SentiStrength and LIWC 2015 will outperform SentimentR because the LIWC dictionary is more systematically validated than Jockers' dictionary. On the other hand, we could hypothesize the SentimentR measure to be most reliable, since the Jockers' dictionary is at least four times bigger than the dictionaries of the other software programs and its overall word coverage is the highest of the methods discussed here. We expected that these benefits cancel each other out, and therefore predicted that:

> **Hypothesis 1c:** *The specific factor error in semi-open text-based measures will not vary across software packages.*

6.1.2.2. Algorithm error

The LIWC 2015, SentimentR and SentiStrength software all use different dictionaries and algorithms for their sentiment analysis, which inevitably causes their measures to vary. The respective dictionaries varied in size, the sentiment coding schemes differed, and the algorithms diverged in their capability to control for semantic rules and nuances. As such, we expected that the agreement between algorithms would not exceed the lower bound for acceptable agreement for human coders, i.e., 80% (Lacy et al., 2015).

> **Hypothesis 2:** *Substantial algorithm error exists between LIWC 2015, SentimentR and SentiStrength measures, as demonstrated by an average agreement of lower than 80%.*

6.1.2.3. Transient error

We did not expect complete consistency of language over time, as demonstrated in very high test-retest reliabilities because the open-ended questions were designed to measure job satisfaction. Test-retest reliability of job satisfaction measures after one year is typically below 0.6 and above 0.2 (Dormann & Zapf, 2001). For this reason, we moved beyond an assessment of absolute test-retest reliability and examined the relative test-retest reliability of the text-based measures. We did this by comparing the text-based measures' test-retest reliabilities with the test-retest reliabilities of the human-coded measures and closed question job satisfaction measure. We hypothesized that:

> **Hypothesis 3a:** *The test-retest reliability of the text-based measures will deviate less than 0.2 from the test-retest reliability of the human-coded measures.*

> **Hypothesis 3b:***The test-retest reliability of the text-based measures will deviate less than 0.2 from the test-retest reliability of the closed question job satisfaction measure.*

6.1.3. Validity as measure of job satisfaction

The open-ended and semi-open-ended questions from this study were designed to measure general job satisfaction. This is why it is pivotal to assess the construct validity of the measures. We did this by examining their convergent and discriminant validity.

First, we tested the measures' convergent validity, the extent to which the two measures that purport to measure the same construct show strong empirical agreement. The few studies that linked text-based measures to closed job satisfaction measures found moderate correlations (Borg & Zuell, 2012; e.g., Gilles et al., 2017; Poncheri et al., 2008; Taber, 1991). Hence, we predicted that the text-based measures and closed question measures of both general job satisfaction and measures of job facet satisfaction would converge. In addition, we expected that the correlations between the text-based measures and the general job satisfaction measure would be higher than the ones between the text-based measures and the job facet satisfaction measures. We therefore hypothesized:

> **Hypothesis 4a:** *The open and semi-open text-based measures will converge with closed question measures of job satisfaction, as demonstrated in positive, significant correlations.*

> **Hypothesis 4b:** *The open and semi-open text-based measure will converge more strongly with the closed question measure of general job satisfaction than with the measures of individual job facet satisfaction.*

Discriminant validity, the degree to which the measures correspond to measures of related but distinct constructs, was assessed by comparing the correlations between the text-based measures and the closed question measure of general job satisfaction with the correlations between the text-based measures and two antecedents, i.e., person-organization (P-O) fit and virtuous leadership, and three outcomes, i.e., life satisfaction, flourishing and organizational citizenship behavior (OCB).

P-O fit, "the compatibility between people and organisations that occurs when: (a) at least one entity provides what the other needs, or (b) they share similar fundamental characteristics, or (c) both" (Kristof, 1996, p. 5) is likely to contribute to job satisfaction, as feelings of fit spark feelings of need fulfilment. Virtuous leadership is a positive leadership characterized by six cardinal virtues: courage, temperance, justice, prudence, humanity and truthfulness (Hackett & Wang, 2012; G. Wang & Hackett, 2016). It is a likely determinant of job satisfaction, as virtuous leadership behaviors are likely to be ethical (Hackett & Wang, 2012) and ethical leadership positively affects job satisfaction (Neubert et al., 2009). We further predicted that job satisfaction is positively related to context-free well-being constructs, such as life satisfaction "the global assessment of a person's quality of life according to his own criteria" (Shin & Johnson, 1978, p. 478) and flourishing, a multi-dimensional construct that concerns "important aspects of human functioning ranging from positive relationships, to feelings of competence, to having meaning and purpose in life" (Diener et al., 2010), as domain-specific well-being tends to spill over into context-free well-being, and vice versa (Judge & Watanabe, 1994). Finally, we expected that job satisfaction will also be associated with OCB, "helpful, constructive gestures exhibited by organisation members and valued or appreciated by officials, but not related directly to individual productivity nor inherently in the enforceable requirements of the individuals role" (Organ, 1988, p. 548), because employees feel that they have to reciprocate good treatment by the organization (e.g., having a careful leader and doing an interesting job).

> **Hypothesis 5a:** *The open and semi-open text-based measures correlate positively with closed question measures of P-O fit, virtuous leadership, life satisfaction, flourishing and OCB.*

> **Hypothesis 5b:** *The open and semi-open text-based measures will converge more strongly with a closed question measure of general job satisfaction than with closed question measures of P-O fit, virtuous leadership, life satisfaction, flourishing and OCB.*

In light of our hypotheses about the higher reliability of the semi-open text-based measures, and the importance of reliability for a measure's validity (Hinkin, 1998), we also hypothesized that:

> **Hypothesis 6a:** *The semi-open text-based measure will show better convergent validity than the open text-based measure.*

> **Hypothesis 6b:** *The semi-open text-based measure will show better discriminant validity than the open text-based measure.*

6.2. METHODS

6.2.1. Procedure and sample

As we desired to obtain input from a large variety of respondents, we outsourced the data collection to Prolific. Prolific is a virtual crowdsourcing platform where people can complete paid tasks, in a similar manner to that of Amazon's Mechanical Turk. Prolific has been found to collect good quality data (Peer et al., 2017). Qualtrics was used for survey administration.

We used a two-wave time-lagged survey design to test our hypotheses. The demographic characteristics of the respondents that participated in our study are presented in Table 6.1. Using Prolific's filtering system, we selected people who were in full-time or part-time employment and lived in either the United States or the United Kingdom. The first wave of data collection in December 2017 resulted in 997 valid responses. In March 2019, we used Prolific again to collect survey data from 125 respondents that had participated in the 2017 survey. Of the initial sample, the majority of the respondents were female, 74.6%. Most of the respondents were in a relationship, 76.5%. The average age was 35.6, and 76.7% of the respondents had at least some college experience. The demographic characteristics of the respondents from the second wave generally corresponded to the characteristics of the initial sample. At the beginning of the questionnaire, respondents were asked to give informed consent to their data being used for this research. Participation was completely voluntary with anonymity guaranteed.

Table 6.1 | Demographics of the wave 1 (*N* = 997) and wave 2 (*N* = 116)

Characteristic	Wave 1		Wave 2	
	N	%	N	%
Age				
Mean	35.6		39.6	
Standard deviation	9.8		10.5	
Gender				
Female	744	74.6	68	58.6
Male	253	25.4	48	41.4
Education				
Less than high school	8	0.8	1	0.9
High school graduate	139	13.9	13	11.2
Professional degree	87	8.7	4	3.5
Some college	258	25.9	23	19.8
2-year degree	79	7.9	13	11.2
4-year degree	278	27.9	40	34.5
Master's degree	126	12.6	20	17.2
Doctorate	22	2.2	2	1.7
Marital status				
Divorced	45	4.5	9	7.8
In a relationship	317	31.8	29	25.0
Married	446	44.7	55	47.4
Single	185	18.6	23	19.8
Widowed	4	0.4	0	0.0

Notes. N = sample size; % = percentage.

6.2.2. Measures

Here, we describe the open-ended question and closed question measures from this study. Note: we used the 'Force response' option in Qualtrics, so we did not have any non-response in the data. Following recommendations of Dunn et al. (2014), we report Cronbach's α and McDonald's (1999) ω as measures of internal consistency of the multiple-item scales. Internal consistency of all multiple-item scales was good, as values of α and ω consistently exceeded 0.7 (Nunnally & Bernstein, 1994). A summary of all measures was presented in Table 6.2.

6.2.2.1. Job satisfaction

We used closed, open-ended and semi-open-ended questions to measure job satisfaction. Eight closed job satisfaction questions were asked. One measured general job satisfaction and read "How satisfied are you with your job?" Seven questions measured satisfaction with job facets, i.e. work content, work-life balance, supervisor, team, company, work environment and pay, all of which had the same format: "How satisfied are you with the following: [Your salary]?" Answer categories ranged on an 11-point scale from 0 (*very unsatisfied*) to 10 (*very satisfied*).

The open-ended question we used, reads: "How do you think about your job as a whole?" We included an extra encouragement and three sub-questions to stimulate respondents to provide a sufficiently elaborate answer, i.e., "It is of vital importance for our research that you take your time to provide a concise and complete answer to this question. Ask yourself questions like: 'How do I feel when I am working?', 'Am I happy with my job?' and 'Do I like my job?'" As another safeguard, we included a response validation of 20 or more characters. The mean number of words in wave 1 was 48. The mean number of words from respondents that completed both surveys was 54 in wave 1 and 65 in wave 2.

Concerning the semi-open-ended question, we followed the guidelines of the adjective generation technique (Potkay & Allen, 1973) to construct the following question: "Which three to five adjectives come to mind when you think of your job as a whole? Adjective 1: […] – Adjective 5 […]" Respondents were forced to report at least three adjectives. The mean number of words in wave 1 was 4.7. The mean number of words from respondents that participated in both surveys was 4.6 in wave 1 and 4.5 in wave 2. It seems that most respondents were able to adhere to the answering constraints, as 56.5% of all words provided in wave 1 and 60.8% of all words provided in wave 2 were adjectives. To prepare the textual data for computer-automated sentiment analysis, we first performed a manual spelling check in Microsoft Excel 2016. Next, we omitted all non-alphabetic characters, e.g., punctuation, special characters and empty lines, and converted the texts into lowercase.

Table 6.2 | Summary of measures

Measure	Words	Rating/scores		
	M/SD	Mean	*SD*	α
Closed question				
Wave 1				
General job satisfaction		6.42	2.37	
Satisfaction with work environment		6.61	2.25	
Satisfaction with work content		6.56	2.26	
Satisfaction with team		7.45	2.08	
Satisfaction with supervisor		6.77	2.79	
Satisfaction with work-life balance		6.45	2.49	
Satisfaction with company		6.47	2.52	
Satisfaction with pay		5.44	2.47	
P-O fit		5.00	1.30	0.87
Virtuous leadership		4.78	1.38	0.97
Life satisfaction		6.80	1.85	
Flourishing		5.38	0.95	0.91
OCB		3.13	0.78	0.87
Wave 2				
General job satisfaction		5.99	2.91	
Open-ended question				
Wave 1	48.47/39.72			
Independent coders		3.35	1.09	
LIWC 2015		4.21	1.34	
SentimentR		2.81	0.62	
SentiStrength		3.09	0.72	
Wave 2	64.99/42.12			
Independent coders		3.24	1.30	
LIWC 2015		3.77	1.55	
SentimentR		3.09	0.83	
SentiStrength		3.16	0.92	
Semi-open-ended question				
Wave 1	4.65/1.93			
Independent coders		3.16	0.91	0.92
LIWC 2015		3.69	1.73	0.49
SentimentR		3.22	0.76	0.74
SentiStrength		3.41	0.68	0.91
Wave 2	4.45/1.62			
Independent coders		3.00	1.30	0.87
LIWC 2015		3.16	1.87	0.69
SentimentR		3.05	1.07	0.69
SentiStrength		3.26	0.78	0.92

Notes. LIWC = Linguistic Inquiry and Word Count; *M* = Mean; *SD* = Standard deviation; α = Cronbach's α.

We illustrated the responses to the different job satisfaction questions by listing the ten most frequently used words for respondents who were dissatisfied with their job (general job satisfaction ≤ 4), neither dissatisfied nor satisfied (general job satisfaction = 5 or general job satisfaction = 6) and satisfied individuals (general job satisfaction ≥ 7) in Table 6.3. Several insights can be gained from these frequency tables. First, we see that most respondents were at least moderately satisfied with their job. Second, the results suggest that the most frequently used words in the responses to the semi-open-ended questions correspond well with the job satisfaction scores, while the responses to the open-ended question are less straightforward to interpret. For instance, words such as "job", "work", "feel" and "like" can be found in the frequency tables of both the satisfied and dissatisfied respondents. The dissatisfied respondents use these words often together with a valence shifter (e.g., "I do *not* like my work"). Third, we noticed that various seemingly negative adjectives, e.g., challenging, busy, stressful, are not only used by dissatisfied respondents.

Table 6.3 | Most frequently used words in responses to open and semi-open job satisfaction question

Low job satisfaction (*N* = 193)				Moderate job satisfaction (*N* = 242)				High job satisfaction (*N* = 562)			
Open		Semi-open		Open		Semi-open		Open		Semi-open	
N	Word*	N	Word	N	Word*	N	Word*	N	Word*	N	Word*
244	Job	56	Boring	282	Job	39	Rewarding	650	Job	131	Rewarding
207	Work	41	Stressful	253	Work	35	Challenging	546	Work	103	Challenging
111	Feel	29	Repetitive	133	Feel	31	Stressful	326	Feel	97	Interesting
109	Like	25	Tiring	105	Like	30	Busy	248	Happy	79	Busy
53	Enjoy	19	Busy	83	Enjoy	27	Interesting	245	Like	73	Fun
53	Get	19	Frustrating	67	Get	26	Boring	224	Enjoy	50	Important
51	Time	16	Challenging	65	Happy	25	Hard	141	Working	44	Stressful
50	People	16	Hard	64	People	25	Tiring	131	Can	42	Happy
38	Much	13	Rewarding	58	Can	23	Repetitive	118	People	41	Enjoyable
37	However	13	Dull	49	Time	19	Easy	106	Get	40	Exciting

Notes. N = Number of observations. * = The most frequently used stop words in the English language are omitted from the textual data (Salton, 1971).

6.2.2.2. Virtuous leadership

Virtuous leadership was measured using the 18-item Virtuous Leadership Questionnaire developed by Wang and Hackett (2016, α = 0.97; ω = 0.97). Answer categories ranged on a 7-point Likert scale from 1 (*never*) to 7 (*always*). An example question is "My supervisor expresses concern for the misfortunes of others".

6.2.2.3. P-O fit

P-O fit was measured using a 3-item scale developed by Cable and Judge (1996, $\alpha = 0.87$; $\omega = 0.89$). Answer categories ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). An example item is "my values match those of current employees in my organization."

6.2.2.4. OCB

OCB was measured using the 10-item short version of the Organizational Citizenship Behavior Checklist developed by Spector and colleagues (2010, $\alpha = 0.87$; $\omega = 0.87$). Response categories ranged from 1 (*never*) to 5 (*every day*). An example item is "How often have you lent a compassionate ear when someone had a work problem."

6.2.2.5. Flourishing

Flourishing was measured using the 8-item Flourishing Scale developed by Diener and colleagues (2010, $\alpha = 0.91$; $\omega = 0.91$). Answer categories ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). An example item is "I am optimistic about my future."

6.2.2.6. Life satisfaction

Life satisfaction was measured with a single item that read "All things considered, how satisfied are you with your life as a whole these days?" The question stems from the World Values Survey (2019), one of the largest and most comprehensive surveys that administers well-being questions across nations (Bjørnskov, 2010). Answer categories ranged from 0 (*not satisfied at all*) to 10 *(very satisfied*).

6.2.3. Analytical strategy

Data pre-processing and hypothesis testing was done in R (R Core Team, 2014). For reproducibility purposes, all scripts (S2 File) and data (S3 Dataset) will be made available in the supplementary information.

6.2.3.1. Sentiment detection

We used both independent manual coding by humans and computer-aided coding, i.e., LIWC 2015, SentimentR and SentiStrength. Summaries of the textual responses and descriptive statistics of the text-based measures can be found in Table 6.2. The histograms of the different ratings from wave 1 are displayed in Figure 6.1. and Figure 6.2. To be able to make fair comparisons between text-based measures, we re-coded or rounded sentiment scores into a categorical five-point scale: 1 (*very negative*), 2 (*negative*), 3 (*neutral*), 4 (*positive*) and 5 (*very positive*).

Human coding

Three coders were asked to independently rate all textual responses in terms of sentiment on a categorical five-point scale ranging from 1 (*very negative*) to 5 (*very positive*). Coders were asked to annotate all adjectives separately. The average time for coding 100 responses to the semi-open and open-ended question was 120 minutes. To code all textual responses (about 1100), coders spend 3960 minutes (120 minutes × 3 coders × 11). Coders were provided a detailed guideline to ensure rater consistency (S1 Protocol).

Figure 6.1 | Histograms of the sentiment measures based on the open-ended question

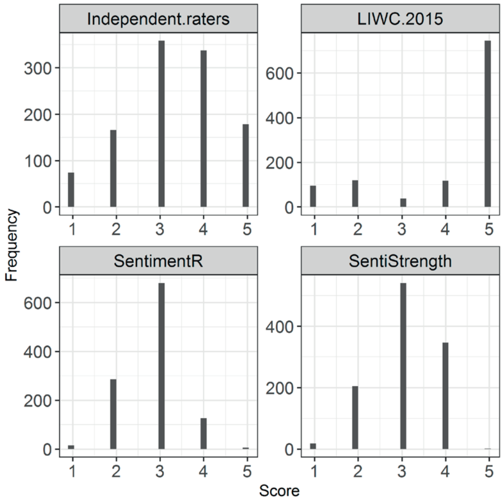
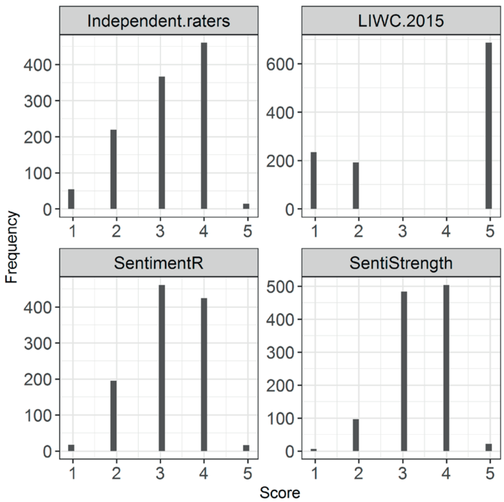


Figure 6.2 | Histograms of the sentiment measures based on the semi-open-ended question



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Following the recommendations of Hallgren (2012), we used a two-way model, average-measures unit interclass correlation to determine inter-rater reliability. We deemed an interclass correlation of 0.6 to be minimally acceptable (Boyer & Verma, 2000). For waves 1 and 2, respectively, the interclass correlation scores for the first adjective (0.994 and 0.920), second adjective (0.902 and 0.914), third adjective (0.904 and 0.936), fourth adjective (0.817 and 0.904), fifth adjective (0.903 and 0.916), complete semi-open text-based measure (0.934 and 0.936) and open text-based measure (0.921 and 0.951) exceeded this threshold. The human coding measure of the semi-open-ended question was created by first averaging the sentiment ratings of the individual adjectives provided by the individual independent coders, and then taking the mean of the aggregated sentiment ratings. The human coding measure of the open-ended question was generated by aggregating the sentiment ratings provided by the independent coders.

We verified the reliability of this independent coding procedure by correlating the generated measures with the evaluations from respondents themselves. We asked respondents the following question after they completed the open-ended questions: "How would you rate your previous answer in terms of sentiment/emotion?" The answer categories ranged from 1 (*very negative*) to 5 (*very positive*). The results showed that the semi-open measure based on independent coding correlated strongly with the respondent-generated semi-open measure ($r = 0.794$). We found the same pattern for the open text-based measures ($r = 0.785$).

Computer-aided coding

The LIWC 2015 measure originally ranged on a continuous scale from 1, extremely negative emotional tone, to 100, extremely positive emotional tone. SentimentR produced sentiment scores from -2 to 2. SentiStrength was not programmed to produce overall sentiment scores but was instead designed to generate scores for negative sentiment, range from -1 to -5, and positive sentiment, range from 1 to 5. The overall sentiment score was created by summing up the positive and negative scores.

6.2.3.2. Hypothesis testing

The guidelines provided by McKenny et al. (2018) were followed to assess measurement error in text-based measures. Pearson correlation analyses were used to assess specific factor error, i.e., examining the convergence between the individual text-based measures and the human ratings. The data from wave 1 and wave 2 were combined because the software packages analyze texts as independent observations. To test hypothesis 1a, we first conducted a Fisher (1915) *z*-transformation of all correlations between the individual text-based measures and the human-coded measures. Using a *t*-test, the correlations between the open text-based measures and the human-coded measures were compared with the average correlation between the semi-open text-based and the human-coded measures. To test hypotheses 1b and 1c, statistical differences in convergence between the separate text-based measures and the human-coded measures were assessed by means of Steiger's (1980) *z*. Algorithm error and the corresponding hypothesis 2 were assessed by computing Krippendorff's α among the text-based measures. Transient error was examined by correlating the text-based measure from wave 1 with the text-based measure from wave 2. The test of hypothesis 3 was based on the comparison of the test-retest reliability of the text-based measures with the test-retest reliability of the human-coded measures (H3a) and with the test-retest reliability of the general closed job satisfaction measure (H3b).

Moving on to construct validity, hypothesis 4a was tested by computing the correlations between the text-based measures and the closed job satisfaction measures. Hypothesis 4b was assessed by *z*-transforming all correlations and comparing the correlation between text-based measures and the general job satisfaction measures with the correlations between the text-based measures and the job facet satisfaction measures by means of a *t*-test. Hypothesis 5a was tested by examining the correlations between the job satisfaction measures and the measures of the related constructs. Hypothesis 5b concerned comparisons between two sets of correlations, i.e. correlations between text-based measures and closed job satisfaction measure vs. correlations between text-based measures and measures of related but distinct constructs. We used Steiger *z* tests to assess whether these differences were significant. Hypothesis 6a was supported if the closed question measures of job satisfaction correlated more strongly with the semi-open text-based measures than with the open text-based measures. We tested this hypothesis by *z*-transforming all correlations and comparing them using a *t*-test. Hypothesis 6b would be supported if the semi-open text-based measures' average deviation with measures of the other constructs was higher than the average deviation of the open text-based measures' deviation with these measures. The correlation analyses used for testing hypothesis 4 to 6 were based on the data from wave 1, as the job facet satisfaction questions and measures of the related constructs were not administered in wave 2.

6.3. RESULTS

6.3.1. Measurement error

The text-based measures suffered from specific factor error to different degrees, as demonstrated in a wide range of parallel forms reliability values (r_{min} = 0.189 to r_{max} = 0.775). The correlations between the open text-based measures and the human-coded measure were lower ($r_{average}$ = 0.508) than the correlations between the semi-open text-based and the human-coded measure ($r_{average}$ = 0.774), as shown in Table 6.4. and 6.5. We accepted hypothesis 1a because this difference was statistically significant (t = 0.563, p < 0.01). As hypothesized, in the analysis of the responses to the open-ended questions, the SentiStrength measure (r = 0.587) suffered less from specific factor error than the LIWC 2015 measure (r = 0.508, t = 3.38, p < 0.01) and the SentimentR measure (r = 0.532, t = 2.33, p < 0.05). Contrary to our expectations, the SentimentR measure did not suffer less from specific factor error than the LIWC 2015 measure (t = 1.00, ns). Therefore, we partially accepted hypothesis 1b. Regarding the semi-open-ended question, the results showed that the SentiStrength measure (r = 0.695) suffered more from specific factor error than the LIWC 2015 measure (r = 0.775, t = 5.63, p < 0.01) and the SentimentR measure (r = 0.772, t = 5.21, p < 0.01). In addition, our results suggested that the specific factor error in the LIWC 2015 measure and SentimentR measure are equivalent (t = 0.16, ns). These findings provided only partial support for hypothesis 1c.

Algorithm error was high, as Krippendorff's α was generally low, i.e., α < 0.65, confirming hypothesis 2. Notably, the algorithm error was lower for the semi-open text-based measures, i.e., $\alpha_{all\ CATA}$ = 0.506, $\alpha_{LIWC2015\text{-}SentimentR}$ = 0.471, $\alpha_{LIWC2015\text{-}SentiStrength}$ = 0.495 and $\alpha_{SentimentR\text{-}SentiStrength}$ = 0.631) than for the open text-based measures (i.e., $\alpha_{all\ CATA}$ = 0.187, $\alpha_{LIWC2015\text{-}SentimentR}$ = 0.010, $\alpha_{LIWC2015\text{-}SentiStrength}$ = 0.159. and $\alpha_{SentimentR\text{-}SentiStrength}$ = 0.434).

In our test of transient error, we discovered that the test-retest reliability of the open text-based measures (average r_{tt} = 0.255) was more than 0.2 lower than the human-coded measure (r_{tt} = 0.543). The test-retest reliability of the semi-open text-based measure (average r_{tt} = 0.268) deviated less than 0.2 from the test-retest reliability of its corresponding human-coded measure (r_{tt} = 0.314). In accordance, we could only partially accept hypothesis 3a. The test-retest reliability of the open and semi-open text-based measures diverged substantially from the test-retest reliability of the measure based on the closed job satisfaction question. As a result, we rejected hypothesis 3b.

Table 6.4 | Correlations between open text-based measures and closed job satisfaction question (N = 1113) and test-retest reliability (N = 116)

	Human coding	LIWC 2015	SentimentR	SentiStrength	Closed question
Human coding	0.543				
LIWC 2015	0.508	0.249			
SentimentR	0.532	0.512	0.329		
SentiStrength	0.587	0.510	0.487	0.189	
Closed question	0.726	0.393	0.407	0.464	0.502

Notes. Test-retest reliability values are displayed on the diagonal; All correlations significant at the level of p < 0.05; LIWC = Linguistic Inquiry and Word Count.

Table 6.5 | Correlations between semi-open text-based measures and closed job satisfaction question (N = 1113) and test-retest reliability (N = 116)

	Human coding	LIWC 2015	SentimentR	SentiStrength	Closed question
Human coding	0.314				
LIWC 2015	0.775	0.311			
SentimentR	0.772	0.708	0.244		
SentiStrength	0.696	0.704	0.665	0.250	
Closed question	0.628	0.576	0.593	0.547	0.502

Notes. Test-retest reliability values are displayed on the diagonal; All correlations significant at the level of $p < 0.05$; LIWC = Linguistic Inquiry and Word Count.

6.3.2. Construct validity of textual job satisfaction measures

To test convergent validity, we correlated the text-based measures with the closed job satisfaction question measures. These findings are presented in Table 6.6. We found support for hypothesis 4a because all text-based measures positively correlated with the closed questions ($r_{min} = 0.203$; $r_{max} = 0.579$). Hypothesis 4b was also supported, as an independent t-test showed that the correlations between the text-based measures and the general job satisfaction measure ($r_{average} = 0.532$) were consistently higher than the correlations between the text-based measures and the job facet satisfaction measures ($r_{average} = 0.356$; $t = 3.45$, $p < 0.05$).

We tested discriminant validity by correlating the text-based measures with closed question measures of P-O fit, virtuous leadership, life satisfaction, flourishing and OCB. As shown in Table 6.6, all correlations except for one (i.e., OCB – open text-based measure$_{LIWC2015}$) were positive and significant. Considering the evidence that the LIWC measure is much less reliable than the other CATA measures, we accepted hypothesis 5a. We also found support for hypothesis 5b, as the correlations between the text-based measures and the closed question measure of job satisfaction were consistently higher than the correlations between the text-based measures and the measures of the other constructs. As an illustration, the LIWC 2015 measure based on the open-ended question was the most at risk for poor discriminant validity, as its correlation with the closed question job satisfaction measure diverged the least from its correlations with other constructs ($\Delta r = 0.083$). Yet, a Steiger z test showed that this difference was still significant ($t = 3.22$, $p < 0.01$). The semi-open text-based measure had better convergent validity, as its correlation with the closed question measure of job satisfaction ($r_{average} = 0.510$) was higher than the correlation between the open text-based measure and the closed question job satisfaction measure ($r_{average} = 0.457$). This difference was statistically significant ($t = 5.70$, $p < 0.05$). Similarly, the semi-open text-based measure correlated significantly stronger with the job facet questions ($r_{average} = 0.413$) than the open text-based measure ($r_{average} = 0.300$; $t = 4.39$, $p < 0.01$). Hence, we accepted hypothesis 6a. The semi-open text-based measure also displayed better discriminant validity, as its average deviation with measures of the other constructs ($\Delta r_{average}$ = 0.267) was almost 0.09 higher than the average deviation of the open text-based measures' deviation with these measures ($\Delta r_{average}$ = 0.178). Hence, we found support for hypothesis 6b.

We conducted a robustness check that assess whether the reliability and validity of CATA measures differed across lowly educated (2-year degree or lower) and highly educated respondents (4-year degree or higher). A comparison of correlations showed that parallel-forms reliability was 0.05 higher and convergent validity was 0.06 higher for the lowly educated respondents. These differences were not significant though (t = 0.77 and t = 1.12, respectively, p = ns).

6.4. DISCUSSION

In recent years, CATA is being used increasingly often within and outside the organizational sciences (Short et al., 2018). In the case of sentiment analysis, most studies have created measures based on collections of lengthy texts. Consequently, computer-aided sentiment analysis has rarely been used to construct measures from responses to open survey questions, while such questions can be an informative complement to closed survey measures. In our study, we have started to fill this gap by demonstrating the reliability of lexicon-based sentiment analysis methods for constructing text-based job satisfaction measures and looking at their validity. We tested our hypotheses on cross-sectional data from 997 workers in the US and the UK and longitudinal data from 116 workers. In particular, we constructed text-based measures from open and semi-open job satisfaction questions using three CATA techniques, LIWC 2015, SentimentR and SentiStrength, and a human coding procedure. As expected, measure construction by CATA methods took a negligible amount of the time (i.e., under half a minute). In sharp contrast, three manual coders required about 66 hours to annotate all texts. Next, we investigated the degree of measurement error in the different text-based measures (specific factor error, algorithm error and transient error) and examined their convergent and discriminant validity.

Concerning reliability, we demonstrated that specific factor error, the degree of convergence between the measures produced by CATA and the human coders, was lowest for the semi-open text-based measures and parallel forms reliability varied substantially across software packages. Algorithm error, the degree of disagreement between text-based measures, was generally high. This lack of agreement is likely to be related to our decision to recode the software programs' original sentiment ratings into comparable 5-point Likert scales. This decision was problematic for our LIWC 2015 measure, as the

Table 6.6 | Correlations between text-based measures and closed question measures ($N = 997$)

Text-based measure		Job facet satisfaction								Antecedents		Outcomes		
		General job satisfaction	Work environment	Work content	Team	Supervisor	Work-balance	Company	Pay	P-O fit	Virtuous leadership	Life satisfaction	Flourishing	OCB
Independent coder ratings	Open	0.703	0.503	0.598	0.445	0.512	0.412	0.582	0.355	0.539	0.482	0.413	0.400	0.168
	Semi-open	0.618	0.458	0.555	0.361	0.438	0.370	0.537	0.336	0.487	0.427	0.361	0.326	0.128
LIWC 2015	Open	0.373	0.303	0.333	0.230	0.244	0.233	0.337	0.200	0.290	0.234	0.233	0.233	*0.048*
	Semi-open	0.564	0.412	0.497	0.329	0.376	0.309	0.474	0.301	0.443	0.359	0.318	0.288	0.092
SentimentR	Open	0.382	0.301	0.345	0.256	0.305	0.245	0.342	0.229	0.279	0.292	0.220	0.194	0.078
	Semi-open	0.579	0.444	0.511	0.367	0.423	0.328	0.504	0.277	0.440	0.397	0.295	0.279	0.074
SentiStrength	Open	0.457	0.374	0.396	0.288	0.300	0.286	0.368	0.199	0.360	0.289	0.287	0.283	0.074
	Semi-open	0.541	0.402	0.480	0.348	0.368	0.288	0.475	0.282	0.422	0.359	0.302	0.272	0.070

Notes. P-O = Person-Organization; OCB = Organizational citizenship behavior; LIWC = Linguistic Inquiry and Word Count, N = Sample size; All *ps* < 0.05, except for the one in italic.

re-coding of its 1 to 100 scale resulted in a distribution of only very negative, moderately negative scores and very positive scores (see Figure 6.1). As the SentiStrength and SentimentR software produced ratings that were largely neutral or moderately positive, their agreement with the LIWC 2015 measures was very low and attenuated the average algorithm error. The transient error of the text-based measures was mostly in line with the transient error in the human-coded text-based measure, but consistently diverged from the transient error in the closed question job satisfaction measure.

Our initial test of construct validity showed that the open and, in particular, semi-open text-based measures have satisfactory convergent and discriminant validity. We found that the text-based measures based on the semi-open-ended question correlated more strongly with closed question measures of general job satisfaction and job facet satisfaction and diverged more strongly from related but distinct constructs than the text-based measure based on the open-ended question. This finding can be interpreted in various ways. If we assume that closed questions are the most suitable instrument for quantifying job satisfaction and consider the greater convergence and divergence of the semi-open text-based measure over the open text-based measure, we could argue that semi-open-ended questions should be preferred for measuring job satisfaction. Alternatively, if we assume that closed job satisfaction questions inevitably fail to measure the construct in its entirety, the lack of convergence and divergence between the open text-based measure and closed job satisfaction measures can also refer to the complementary nature of open-ended questions. Perhaps, the responses to open-ended questions contain information about job characteristics that are not measured by closed questions.

6.4.1 Limitations and future research

While our context-free sentiment dictionaries already produced reasonably reliable measures, future research would benefit from employing deductive and inductive dictionary-generation techniques to create a job satisfaction specific dictionary and thereby further boost reliability and, in turn, validity (Short et al., 2010). For example, researchers could look beyond unigrams, i.e., single words, and study the added value of multigrams, sequences of adjacent words (Taboada et al., 2011). Using the data from this study, researchers may discover that some words have different meanings in different contexts, e.g., the word ‘challenging’ may have very different connotations when it is used in combinations with words such as ‘gratifying’, ‘motivating’ and ‘engaging’ than with words such as ‘busy’, ‘stressful’ and ‘exhausting’. Furthermore, scholars could explore the added value of learning-based sentiment analysis methods (see Kobayashi et al., 2017 for practical text mining guidelines), for example, by training algorithms on our reliably labeled textual data. We note that high quality training data is costly to attain, as it usually involves tasking multiple coders to annotate texts. Survey researchers could ask respondents to rate their own textual responses in terms of sentiment toward the end of online surveys to have a reliable and time-saving alternative to a manual coding procedure. After all, respondents' own perceptions of sentiment are likely to come closest to the 'true', measurement-error-free sentiment score.

Our validation procedure suffered from several limitations. In our assessment of convergent validity, we, for example, did not examine the text-based measures' convergence with validated multiple-item job satisfaction scales or control for same-source variance. Therefore, we recommend future researchers to conduct an even more systematic validation of the new measures. The validation approach from Fisher et al. (2016) could be followed, because the open and semi-open-ended questions are single-item measures. In addition, future research could investigate whether the choice to produce text-based measures by means of sentiment analysis causes the measures to be more affect-oriented than cognition-oriented (Kaplan et al., 2009; E. R. Thompson & Phua, 2012). Scholars could test this by correlating the text-based measures with a closed question measure of job affect and a measure of job cognition (Bowling et al., 2018). Our examination of discriminant validity was limited, as the selection of constructs was small, all constructs were measured at one point in time and all measures were self-report. Future studies could look into the text-based measures' relationships with a wider range of antecedents, objective outcome variables such as sickness absence and turnover, and supervisor-rated performance constructs such as productivity and creativity. In light of this, it could prove useful to assess the incremental validity of the text-based measures over the closed question measures.

6.4.2 Conclusion

The initial evidence from our study has opened interesting research venues for mixed method research. Open-ended and, in particular, semi-open-ended questions show great promise for measuring job satisfaction because textual responses can reliably and swiftly be translated into text-based measures of job satisfaction, exhibit substantial convergence with closed question measures and display significant divergence with closed question measures of related but distinct constructs. We stress that semi-open-ended and open-ended questions should not just be regarded as another method to quantitatively measure a psychological construct. The information richness of the responses to open-ended questions and semi-open-ended questions can help scholars to unravel new insights about the sources and context of constructs. Whether used for cross-validation, contextualization or both, we believe that semi-open-ended and open-ended questions have the potential to further the science and practice of measuring and theorizing about psychological constructs.

7

Unpacking the potential of semi-open-ended job satisfaction questions

Based on paper: Wijngaards, I., Burger, M.J., & Van Exel, N.J.A. (2021). Unpacking the quantifying and qualifying potential of semi-open job satisfaction questions through computer-aided sentiment analysis. *Journal of Well-being Assessment*, 1-27.

7.1. INTRODUCTION

Job satisfaction, "a positive (or negative) evaluative judgment one makes about one's job or job situation" (H. M. Weiss, 2002, p. 175), continues to be closely monitored in corporate surveys (Macey & Schneider, 2008) and has a long history of scientific study (Judge et al., 2017). There are good reasons for its popularity; job satisfaction has proven to be a robust correlate of subjective well-being (Bowling et al., 2010), health (Faragher et al., 2005) and job performance outcomes (Judge et al., 2001b). Over the past few decades of scholarly and practitioner attention, a plethora of survey question instruments have been developed to cover conceptual nuances, e.g., affect-oriented vs. cognition-oriented scales (Kaplan et al., 2009; Organ & Near, 1985) and job facet satisfaction vs. general job satisfaction (Scarpello & Campbell, 1983; Spector, 1997; H. M. Weiss, 2002). Others have aimed at reducing response burden by shortening multiple-item scales (e.g., Russell et al., 2004) of developing single-item measures of job satisfaction (e.g., G. G. Fisher et al., 2016; D. G. Gardner et al., 1998; Wanous et al., 1997).

The majority of survey instruments share one commonality: they typically comprise of closed questions or items (e.g., "Overall, I am satisfied with my job.", G. G. Fisher et al., 2016, p. 8) rather than open-ended questions (e.g., "Please give us feedback or comments about your job." Gilles et al., 2017, p. 4; "How do you think about your job as a whole?", Wijngaards et al., 2019, p. 5) or semi-open-ended questions (e.g., "What three to five adjectives come to mind when you think of your job as a whole?", Wijngaards et al., 2019, p. 5). Closed questions have several advantages over open-ended questions, as they typically pose less burden for respondents than open-ended questions (Krosnick, 1999; Vinten, 1995; Zehner et al., 2016) and they prove to be more straight-forward to code and validate than open-ended questions (Maxwell & Delaney, 1985; Tausczik & Pennebaker, 2010).

The unpopularity of semi-open or open job satisfaction questions is unfortunate because semi-open or open-ended questions hold great potential as a complement to closed questions in surveys. A semi-open or open-ended question can, for example, be used to better *quantify* job satisfaction, as weaknesses of individual methods are likely off-set by the use of multiple methods (Bryman, 2006; Jick, 1979; Turner et al., 2017). Measuring job satisfaction with both closed and open-ended response formats in a single questionnaire could help mitigate common method error, as respondents are forced into different forms of cognitive processing (Podsakoff et al., 2003). Semi-open or open-ended questions can also be used to *qualify* job satisfaction and thereby obtain a more complete and deeper understanding of a construct (Fielding, 2012; Jick, 1979; Mauceri, 2016; Turner et al., 2017). Textual responses can be leveraged to contextualize responses to closed questions and obtain insights into the causes and sources of job (dis)satisfaction (Spector & Pindek, 2016; Taber, 1991). Moreover, they can illustrate and clarify the results from quantitative data analyses to non-expert audiences (Borg & Zuell, 2012; D. C. Zhang et al., 2019). Furthermore, the practical disadvantages of constructing textual job satisfaction measures are becoming increasingly obsolete, as computer-aided text analysis, which is a form of content analysis that facilitates the measurement of constructs by converting text into quantitative data based on word frequencies, make the creation of text measures more convenient than ever (McKenny et al., 2018; Short et al., 2010, 2018).

In this article, we aim to unpack the quantifying and qualifying potential of a semi-open job satisfaction question. We focus on a semi-open rather than a completely open job satisfaction question because semi-open-ended questions impose answering constraints on responses and therefore produce more structured texts than completely open-ended questions e.g., fewer meaningless words and less semantic nuance in textm (Glerum et al., 2014; Wijngaards et al., 2019). This makes text measures based semi-open-ended questions produced by computer-aided sentiment analysis methods probably more suitable for quantifying the level of job satisfaction than text measures based on completely open-ended questions produced by computer-aided sentiment analysis methods (Wijngaards et al., 2019). We investigate the semi-open-ended questions' quantifying potential by creating text measures using computer-aided sentiment analysis, the practice of automatically detecting opinions, sentiments, attitudes and emotions about certain objects in human-generated texts (R. Feldman, 2013; B. Liu, 2015), and validating this measure using standardized closed-ended questions. We investigate the semi-open-ended questions' qualifying potential by examining which sentiment ratings in sentiment-dictionaries are context-dependent and what unfavorable job characteristics are taken for granted if favorable job characteristics are present.

This study contributes to the literature by building on and extending existing methodological work on validation of textual job satisfaction measures. Previous studies on textual job satisfaction measures lack a systematic validation approach, neglecting content validity and using ad-hoc, single-item job satisfaction measures to test convergent validity (Borg & Zuell, 2012; Poncheri et al., 2008; Wijngaards et al., 2019), as well as discriminant validity (Borg & Zuell, 2012; Gilles et al., 2017; Poncheri et al., 2008). It is essential to systematically examine the validity of a text measure, as researchers with a preference for traditional survey measures are unlikely to accept text measures as fruitful complement to a closed question if there is no convincing evidence for their validity available. Therefore, we discuss the content validity of the semi-open job satisfaction question. Using correlational analyses and confirmatory factor analyses (CFAs), we also test its fit with a closed question job satisfaction scale. In addition, we assess the semi-open-ended question' correlations with variables falling within and outside job satisfaction's nomological network. As computer-aided text analysis techniques produce measures with attenuated reliability (McKenny et al., 2018), we benchmark the text measures generated by computer-aided sentiment analysis techniques with a text measure with the least possible measurement error, a text measure based on respondents' own sentiment annotations (henceforth: benchmark measure).[15]

The qualitative analysis on context-dependency of sentiment ratings help advance the field of computer-aided sentiment analysis, while the exploration on the weight of different job characteristics contributes to scientists and practitioners' understanding of job satisfaction and its causes.

7.1.1 Using computer-aided sentiment analysis to create a textual job satisfaction measure

Much of the research on constructing text measures from responses to semi-open-ended or open-ended job satisfaction questions have made use of computer-aided sentiment analysis techniques. The techniques' popularity is not surprising, as it is much faster than manual sentiment annotation (Wijngaards et al., 2019) and an individual's choice of words is a plausible manifestation of thoughts and opinions (Pennebaker et al., 2003; Short et al., 2010). As mentioned earlier, computer-aided sentiment analysis is particularly suitable for constructing a job satisfaction measure from text, as job satisfaction classifies as a job attitude and comprises cognitive appraisals, emotions, and beliefs (H. M. Weiss, 2002). Sentiment analysis software typically classifies respondents that mainly use positive words in their written responses as satisfied individuals, and classifies respondents that mainly use a negative tone as dissatisfied respondents (B. Liu, 2015; Poncheri et al., 2008).

To construct the text measure in this study, we use lexicon-based computer-aided sentiment analysis software, a type of sentiment analysis that annotates texts using dictionaries of words with pre-labelled sentiment orientation. Sentiment orientation concerns words' sentiment polarity (e.g., "good" vs. "bad") and sentiment strength (e.g., "good" vs. "great"). The lexicon-based sentiment analysis approach is characterized by two stages. In the first stage, software is used to pre-process raw textual data. Steps involved in pre-processing are removing stop words, such as "the", "from" and "as", correcting language mistakes, converting words to lowercase and removing punctuation and white spaces (Meyer et al., 2008; Pandey & Pandey, 2019). Once this has been done,

15 This measure is likely a more reliable measure of sentiment than measures produced by independent coders. Independent coders introduce unique measurement errors through individual differences in evaluation strategies (Mikhaylov et al., 2012) and in annotation experience and education (Snow et al., 2008) and, in the end, are mere forecasters of the sentiment rating a respondent would have decided upon.

software can be employed to classify words into sentiment classes, e.g., very negative (-2), negative (-1), neutral (0), positive (+1) and very positive (+2). Contemporary sentiment analysis software does not only consider an individual words' sentiment rating, but also considers words in the context that they are used in. For example, contemporary software considers negators, such as "not" and "never", as they reverse the semantic polarity and amplifiers, such as "very", and de-amplifiers, such as "reasonably", as they offer an indication of the sentiment strength. After this, the software automatically adds up (and weighs) all the individual ratings and computes an overall sentiment rating. The rating can, in turn, be used as a measure of job satisfaction.

To illustrate this two-stage procedure, we use a response from a semi-open-ended question and a response to an open job satisfaction question, both obtained from the open-access data from Wijngaards et al. (2019). The sample answer to the semi-open-ended question was a list of three adjectives: "Interesting", "Stressful" and "Helpful". The sample answer to the open-ended question was a statement: "I am extremely proud of the work I do and think I do it very well, but I don't enjoy how hard and tiring it is and the people I work with are difficult to work with".

The pre-processing of the response to the semi-open-ended question only involves converting all words into lowercase (i.e., "interesting", "stressful" and "helpful"). Then, the software searches in the pre-processed text for words that either contain non-zero sentiment ratings or sentiment strength and draws from its dictionary to assign sentiment ratings. As the semi-open-ended question asks respondents to come up with individual adjectives, it is important to treat the individual words as separate, de-contextualized textual instances. In this example, all words carry a non-zero sentiment loading: "interesting" (+1) "stressful" (-1) and "helpful" (+1). The three sentiment scores can be summed into a single score (i.e., 1 + -1 + 1 = 1) and the response would be classified as positive. As an illustration, SentimentR (Rinker, 2019), a sentiment analysis software program that by default uses a dictionary of words with 20 sentiment classes (e.g., -0.25, 0, 0.75, scale ranges from -2.0 to 2.0) and considers negators, amplifiers and deamplifiers in its algorithm, assigns the following sentiment ratings to each word: "interesting" (+0.75), "stressful" (-0.50) and "interesting" (+0.75). The final sentiment rating would be 1.0.

The pre-processing and sentiment calculation of the example response to the open-ended question is more complex. To pre-process the sentence, the software has to convert all words into lowercase, omit punctuation and remove stop words. The pre-processed text would then read "extremely proud do work think do very well but don't enjoy hard tiring people work difficult work". As the response is a sentence, it is important to consider the context in which words are used (e.g., valence shifters and amplifiers). In this text, the following terms do not have a non-zero sentiment score or sentiment strength score: “extremely proud” (+2), “very well” (+2), “don’t enjoy” (-1), “hard” (-1), “tiring” (-1) and “difficult” (-1). Finally, the software solves the equation (i.e., 2 + 2 + -1 + -1 + -1 + -1 = 0) and classifies the response as neutral. In accordance with this example, SentimentR would classify the response as slightly positive (0.3).

7.1.2. Quantifying job satisfaction

Now that we have explained how a textual response to a semi-open or open-ended question can be converted into a text measure, we move to a justification of the semi-open-ended question’s suitability as a job satisfaction measure. We discuss the measure’s theoretical validity and provide a description of our empirical validation procedure.

7.1.2.1. Theoretical validity

We use the following semi-open-ended question in our study: “What three to five adjectives come to mind when you think of your job as a whole?” (Wijngaards et al., 2019, p. 5). Being based on the fundamentals of the adjective generation technique, a psychological method initially used for personality assessment (Potkay & Allen, 1973), the question was designed to tap into both to the affective and cognitive component of job satisfaction and thus measure the construct as a whole (Judge et al., 2012; H. M. Weiss, 2002). The verb “think” likely spurs both affective and cognitive thoughts and is presumably more suitable than more specific verbs like “appraise”, “evaluate” and “feel”. The first two words would primarily elicit cognitive evaluations of the job, while the third word would likely tap more into the affective component of job satisfaction. The “as a whole” at the end of the question was included, as the semi-open-ended question is purported to measure general job satisfaction. The clause likely triggers respondents into thinking more inclusively (Scarpello & Campbell, 1983; H. M. Weiss, 2002). We restricted the number of words to (i) reduce required effort for respondents and (ii) get an idea of the most salient thoughts.

7.1.2.2. Empirical validity

Convergent validity

Turning to empirical validity, the text measure based on the responses to the semi-open job satisfaction question has to converge with an existing measure of job satisfaction (Edwards, 2003; Hinkin, 1998). However, we do not expect perfect convergence between the two types of job satisfaction measures because closed and open-ended questions have divergent epistemological foundations and introduce different sources of measurement error (Fielding, 2012; Mauceri, 2016; McKenny et al., 2018).

In line with this expectation, previous research on open comment boxes in surveys has demonstrated moderate correlations between sentiment ratings and overall job satisfaction. For example, in a study among military personnel, Poncheri et al. (2008)

documented a correlation of 0.41 between comments' affective tone and a closed question measure of general job satisfaction. Drawing upon data from a large corporate survey from an information technology organization, Borg and Zuell (2012) documented a correlation between affective comment tone and closed question job satisfaction measures of 0.38, on average. In a study by Wijngaards et al. (2019), similar correlations were found between the text measures based on a completely open-ended question and a closed question measure of general job satisfaction: $r_{average} = 0.40$. The average correlation between the text measures based on the responses to the semi-open-ended question and the closed question measure was significantly higher, $r_{average} = 0.56$. As we use a semi-open-ended question in this study, we expect that the text measures correlate positively with a closed question measure of job satisfaction. Even though neither of these studies provided factor analytic evidence for the convergent validity of the text measures, we expect that the text measures of job satisfaction fit well with closed question job satisfaction measures.

Discriminant validity

To have satisfactory discriminant validity, a text measure must fit within a constructs' nomological network, the abstract representation of constructs, their measures and the interrelationships among them (Cronbach & Meehl, 1955). In our case, discriminant validity could be demonstrated by testing the bivariate correlations between the text measures of job satisfaction and theoretically related antecedents, correlates and outcomes of job satisfaction, and looking into its relationship with constructs that fall outside the job satisfaction's broader theoretical context (Edwards, 2003; Shaffer et al., 2016). Drawing on the many nomological networks that have been developed in the many decades of job satisfaction research (e.g., Bowling & Hammond, 2008; Brief, 1998; Crede et al., 2007), we identify various antecedents, correlates, outcomes and unrelated constructs. Research suggests that skill variety, task autonomy and person-environment fit are pertinent examples of antecedents of job satisfaction. Theorists have argued that job variety, "the degree to which a job requires employees to perform a wide range of tasks on the job" (Morgeson & Humphrey, 2006, p. 1324), and job autonomy, "the extent to which a job allows freedom, independence, and discretion to schedule work, make decisions, and choose the methods used to perform tasks" (Morgeson & Humphrey, 2006, p. 1324), contribute to an employee's experienced meaningfulness and responsibility, respectively (Hackman & Oldham, 1976). They reasoned that the sense of meaningfulness and responsibility have the potential to boost intrinsic motivation, which in turn positively correlates with job satisfaction (Fried & Ferris, 1987; Hackman & Oldham, 1976). Person-organization fit refers to the fit between employees and organizations that occurs when one offers what the other wants, they share similar important characteristics, or both (Kristof, 1996). Therefore, person-organization fit is likely associated with job satisfaction (Kristof, 1996). Life satisfaction, "a global assessment of a person's quality of life according to his own criteria" (Shin & Johnson, 1978, p. 478), is among the most fundamental correlates of job satisfaction because job satisfaction contributes to a person's overall satisfaction with life, and vice versa (Judge et al., 2012; Judge & Watanabe, 1994; for empirical evidence, see Bowling et al., 2010). Organizational citizenship behavior and turnover intention are two relevant performance indicators for organizations (G. Cohen et al., 2016; Koys, 2001). Organizational citizenship behavior concerns supportive gestures from employees that are valued by organizations, but are not linked directly to individual productivity or their contractual role expectations (Organ, 1988). Theory suggests that satisfied employees exhibit organizational citizenship behavior to reciprocate the favorable job conditions organizations offer (Organ, 1988). Meta-analytical evidence supports this theoretical contention (Dalal, 2005; LePine et al., 2002). Turnover intention, the intention to willingly change jobs or companies (Schyns et al., 2007), is a likely outcome from job dissatisfaction, as employees tend to avoid unpleasant work situations by displaying withdrawal behaviors. When job dissatisfaction persists, individuals tend to withdraw for good and leave (Hanisch & Hulin, 1991). Indeed, previous research suggests that the relationship between job satisfaction and turnover intention is negative (Bowling & Hammond, 2008; Tett & Meyer, 1993). Personality traits are also related to job satisfaction (Judge et al., 2002), but empirical studies indicate that this is not the case for all traits (Bowling et al., 2018; Bui, 2017; Harvey & Martinko, 2009; Judge et al., 2002). Two examples are need for cognition, "the need to structure relevant situations in meaningful, integrated ways" (A. R. Cohen et al., 1955, p. 291), and openness, "the breadth, depth, and permeability of consciousness, and in the recurrent need to enlarge and examine experience" (McCrae & Costa Jr, 1997, p. 826). A plausible explanation for this nonsignificant correlation is that openness to experience and need for cognition are positively related to job satisfaction for some jobs (e.g., entrepreneurs and jobs where one can learn), while it may be negatively correlated to job satisfaction in other jobs (e.g., boring and uncreative jobs), rendering the overall correlation between the two personality traits and job satisfaction nonsignificant (Bui, 2017).

Taking theoretical justifications and empirical evidence into consideration, we expect that text measures of job satisfaction will significantly correlate with measures of task variety, job autonomy, person-organization fit, life satisfaction, organizational citizenship behavior and turnover intention, while we do not expect it to correlate significantly with measures of need for cognition and openness.

7.1.3. Qualifying job satisfaction

In this part of the study, we want to show that semi-open-ended questions can be used to obtain insights that closed questions may not provide. As respondents themselves know best what the sentiment in their responses is, we use their ratings for our analyses on qualifying job satisfaction.

7.1.3.1. Context-dependency of sentiment ratings

Can all words be assigned a single sentiment rating or are sentiment ratings generally context-dependent? Previous research indicates that the answer to this question is probably somewhere in the middle (McKenny et al., 2018; Short et al., 2010). Some words are likely to have a less ambiguous meaning across contexts, such as "love" and "enjoy". Other words evoke divergent sentiments depending on the sentiment of the words that they are used along with. As an illustration, the word "challenging" might evoke a positive meaning when it is used with adjectives, such as "engaging" and/or "satisfying", rather than when it is used with adjectives, such as "stressful" and/or "overwhelming". Following this reasoning, we expect that words will vary substantially depending on the extent to which they can reliably be assigned a single sentiment score.

7.1.3.2. Balancing job characteristics

Even if our semi-open-ended question does not produce detailed information about the cognitive appraisal of job facets, it may offer some ideas about the job characteristics that influence it. One avenue of research we found particularly interesting is: examining the unfavorable job characteristics that respondents are willing to accept in light of unfavorable job characteristics. For instance, respondents may accept the boring nature of their job if it gives them job security.

7.2. METHODS

7.2.1. Participants and data collection

We collected our data through Prolific, a virtual crowdsourcing platform where people get compensated to complete tasks Prolific workers tend to provide reliable data and turned out to be more honest and more diverse in terms in terms of geographical location and ethnicity than respondents from other crowdsourcing platforms, such as Amazon's Mechanical Turk (Peer et al., 2017). Using Prolific's filtering system, we selected people from the United States of America, who worked at least 20 hours a week and had an approval rate of 80% or higher. We followed recommendations from Prolific for the height of the respondent compensation and paid respondents an amount of $1.31 for 10 minutes of work. The data collection procedure resulted in 395 responses. Most respondents were male (56.0%). The large majority of respondents had at least some college experience (94.2%). Most respondents had a permanent employment contract (76.5%). The average age was 35.1 (SD = 10.2). The average number of work hours and number of years of experience within their organization were 37.7 (SD = 7.8) and 5.2 (SD = 5.0), respectively. Of all the respondents, 32.6% had a managerial position in an organization.

The research context classifies as a low-stake environment, which may have introduced the issue of careless responding in our data (Curran, 2016; Fleischer et al., 2015). To address this problem, we flagged careless respondents based on three criteria: average response time per item, item consistency on a semantic antonym and Mahalonobis distance (Curran, 2016; Meade & Craig, 2012). We adopted the cut scores set for 95% specificity from Goldammer et al. (2020) for average response time per item and the Mehalonobis distance. We considered responses to be inconsistent if the absolute difference between the two reverse-item scored items was equal or larger than 2. The criteria pointed towards three different samples of careless respondents. We constructed three reduced samples based on the omission of the three samples of careless respondents.

The first sample contained individuals who excluded respondents who took less than 5.56 seconds to complete a survey item, on average (N = 232). The second sample excluded respondents where the absolute difference in scores to the following two items measuring openness (i.e., "I tend to vote for liberal political candidates." and "I tend to vote for conservative political candidates."), each rated on a 5-point Likert scale, was higher or equal to 2 (N = 290). We deemed this item suitable for careless responding analyses, as the two items are antonyms and the bivariate correlation between the items in the whole sample was high (r = -0.79). The third sample excluded respondents with a Mehalonobis distance higher than 94.81, computed over 52 items (N = 381).

7.2.2. Measures

Internal consistency of the instruments was tested using McDonald's (1999) omega (ω) (Dunn et al., 2014). The closed question survey scales' internal consistency statistics were considered sufficient, as all the values were equal to or above 0.80 (Nunnally & Bernstein, 1994), see Table 7.3. We constructed measures by computing unweighted averages of all items, unless specified differently.

7.2.2.1. Job satisfaction

Job satisfaction was measured using the 3-item Michigan Organizational Assessment Questionnaire Job Satisfaction Subscale (MOAQ-JSS, Cammann et al., 1979). The MOAQ-JSS has been validated (Bowling & Hammond, 2008). The answer categories from the MOAQ-JSS ranged on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*). An example item is "All in all, I am satisfied with my job." In addition, we measured job satisfaction using a semi-open-ended question, which reads "Which three to five adjectives come to mind when you think of your job as a whole?"

7.2.2.2. Task variety

Task variety was measured using a 4-item scale from the Work Design Questionnaire (Morgeson & Humphrey, 2006), with response categories ranging from 1 (*strongly agree*) to 5 (*strongly disagree*). A sample item is "The job involves a great deal of task variety."

7.2.2.3. Job autonomy

Job autonomy was measured using a 3-item scale from the Work Design Questionnaire with response categories ranging from 1 (*strongly agree*) to 5 (*strongly disagree*). A sample item is "The job allows me to make a lot of decisions on my own."

7.2.2.4. Person-organization fit

Person-organization fit was measured using a 3-item scale developed by Cable and Judge (1996), with response categories ranging from 1 (*not at all*) to 5 (*completely*). A sample item is "My values match those of current employees in my organization."

7.2.2.5. Life satisfaction

Life satisfaction was measured using the 5-item Satisfaction With Life Scale (SWLS, Diener et al., 1985), with response categories ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The item scores were summed up into one aggregate measure. A sample item is "In most ways my life is close to ideal."

7.2.2.6. Organizational citizenship behavior

Organizational citizenship behavior was measured using the 10-item short version of the Organizational Citizenship Behavior Checklist (Spector et al., 2010). The scale had response categories ranging from 1 (*never*) to 5 (*every day*). A sample item is "I worked weekends or other days off to complete a project or task".

7.2.2.7. Turnover intention

Turnover intention was measured using the 3-item turnover intention subscale in the MOAQ (Cammann et al., 1979), where the questions had to be answered using categories ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). A sample item is "How likely is it that you will actively look for a new job in the next year?"

7.2.2.8. Need for cognition

Need for cognition was measured using the 10-item Need For Cognition Scale (Cacioppo & Petty, 1982). Answer categories ranged from 1 (*strongly disagree*) to 5 (*strongly agree).* A sample item is: "I like to solve complex problems".

7.2.2.9. Openness

Openness was measured using a 10-item scale from the NEO Personality Inventory (Costa & McCrae, 1985), and had response categories ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). A sample item is "I have a vivid imagination".

7.2.3. Data processing and statistical analysis

Data pre-processing and validity testing was done in the software program R (R Core Team, 2018). All scripts and the data are made available as supplementary material.

7.2.3.1. Analyses for text measure construction

In our study, we used SentimentR (Rinker, 2019) and Linguistic Inquiry and Word Count (LIWC) 2015[16] (Pennebaker, Boyd, et al., 2015) to compute the sentiment ratings of the semi-open-ended questions. We selected these software packages, as Wijngaards et al. (2019) found that sentiment scores from these software packages most closely resembled the sentiment scores produced by independent human coders ($r_{\text{SentimentR}}$ =.77 and r_{LIWC2015} = 0.78).

SentimentR is a freely available sentiment analysis package written in R (R Core Team, 2018). It uses, by default, the English sentiment dictionary of Jockers (2017), which contains 10,739 annotated words. This software package has been successfully deployed in several studies outside the survey methodology domain (e.g., Ikoro et al., 2018; Naldi, 2019; Rinker, 2019; Weissman et al., 2019). As SentimentR software incorporates the context of words in its sentiment ratings and the semi-open-ended questions ask respondents about three to five disconnected adjectives, we constructed the SentimentR measure in three steps: (1) classifying the individual adjectives in terms of sentiment, (2) re-coding these individual sentiment scores onto a scale from 1 (*very negative*), 2 (*negative*), 3 (*neutral*), 4 (*positive*) to 5 (*very positive*), and (3) averaging the scores into a final sentiment score.

The LIWC software is one of the most widely used computer-aided text analysis techniques in the organizational sciences (Short et al., 2018), and has been validated across a large number of studies (Pennebaker, Boyd, et al., 2015). LIWC2015 draws from an English dictionary of 620 positive words and 744 negative words. LIWC2015 does not explicitly contextualize the valence loadings of individual words. As we wanted to maximize the comparability of the LIWC2015 measure and SentimentR measure, we adopted the aforementioned three-step sentiment calculation procedure to create the LIWC2015 measure.

16 The Emotional Tone summary variable from LIWC 2015 was used (Cohn et al., 2004).

We tested the reliability of the SentimentR measure and the LIWC2015 measure in the current data by examining their convergence with text measures produced by humans (i.e., parallel-forms reliability, McKenny et al., 2018). We used the benchmark measure for this procedure. At the end of the survey, we asked respondents to separately annotate all adjectives they previously used on a scale from 1 (*very negative*), 2 (*negative*), 3 (*neutral*), 4 (*positive*) to 5 (*very positive*). The question read: "How would you rate your previous answer in terms of sentiment/emotion?"

7.2.3.2. Analyses for empirical validation

Correlational analyses and single-factor CFAs were used to test the convergent validity of the text measures. The fit of a single-item CFA was considered adequate if the χ^2-test is significant, the comparative fit index (CFI) value was above 0.95 and the standardized root mean square residuals (SRMR) and root mean square error of approximation (RMSEA) values were less than 0.06 (T. A. Brown, 2014; L. Hu & Bentler, 1999; Kline, 2015). Standardized factor loadings of the text measures should exceed 0.6 to be satisfactory (Matsunaga, 2010). Correlational analyses were used to test discriminant validity.

7.2.3.3. Analyses for contextualization of job satisfaction

For this part of the study, we only used the responses to the semi-open-ended question and the benchmark measure. For the analyses concerning the context-dependency of sentiment ratings, we computed the frequency of individual words and calculated the mean and *SD* of the sentiment ratings associated with each individual word. This dictionary allowed us to discover which words had divergent sentiment connotations depending on the sentiment of the other words provided by the respondent. We produced three sub-dictionaries by splitting the complete dictionary based on the average sentiment rating by respondents: negative (mean < 2.5), neutral ($2.5 \leq$ mean ≤ 3.5) and positive (mean > 3.5).

For the analyses on the antecedents of job satisfaction, we concentrated on individual respondents' word use and associated sentiment ratings. In specific, we averaged the individual sentiment ratings for each respondent and calculated the *SD* for each mean score. To illustrate this, let us consider two hypothetical respondents that responded with two adjectives. Respondent A used the adjectives "Bored" and "Safe" and, at the end of the survey, classified them as 1 (*very negative*), and 4 (*positive*), respectively. Respondent B used "Bored" and "Unhappy" and classified them as 1 (*very negative*) and 2 (*negative*), respectively. The mean sentiment (and *SD*) for rating for Respondent A and B would be 2.5 (2.12) and 1.5 (0.71), respectively. A high *SD*, in this context, thus points towards the use of both positive and negative words in a single answer. In our study, we reported findings based on a threshold for *SD* of 1.5, but checked the sensitivity of our findings for a *SD* threshold of 1.0 and 2.0. We manually qualified the responses to the semi-open-ended question to map the job conditions that respondents with a high *SD* generally had to deal with and discussed its relationship with job satisfaction.

7.3. RESULTS

7.3.1. Construction of textual job satisfaction measures

The semi-open-ended question was generally understood well, as 61.6% of all words provided by respondents were adjectives. Nouns and verbs were the second and third most popular word categories, which is 22.0% and 12.8% of the total words, respectively. We did not omit any textual data, as many verbs and nouns have affective loadings too. The mean number of words per respondent was 4.5 with a *SD* of 1.2 words. The median was 5 words. Table 7.1 presents the fifteen most common words used by respondents who are dissatisfied with their job (MOAQ-JSS ≤ 3) as well as the respondents who are satisfied with their jobs (MOAQ-JSS ≥ 5).

Table 7.1 | Most frequently used words amongst satisfied and dissatisfied respondents

Dissatisfied with their job		Satisfied with their job	
Word	*N*	Word	*N*
Boring	28	Fun	57
Stressful	13	Interesting	46
Tedious	9	Challenging	41
Annoying	8	Rewarding	28
Frustrating	6	Stressful	27
Demanding	5	Easy	21
Dull	5	Flexible	20
Exhausting	5	Fulfilling	17
Pointless	4	Helpful	17
Repetitive	4	Good	15
Underpaid	4	Busy	15
Slow	4	Important	14

Notes. *N* = Sample size.

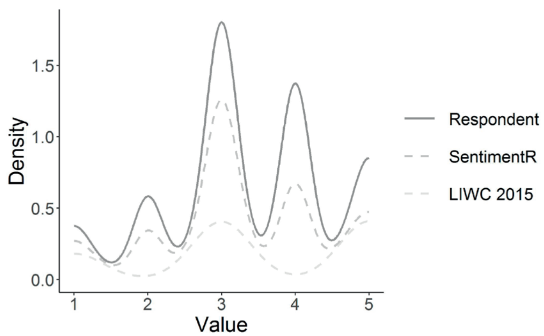
To test whether SentimentR and LIWC2015 are appropriate software packages for sentiment analysis in our context, we compared the text measures based on the two algorithms and the benchmark measure. Parallel-forms reliability for both the SentimentR measure ($r = 0.80$) and the LIWC2015 measure turned out to be satisfactory ($r = 0.62$). As apparent in the 0.18 difference in correlation coefficient and as visualized in Figure 7.1, the SentimentR measure more closely resembles the density plot from the benchmark measure than the LIWC2015 measure. Table 7.2. shows twenty examples of responses with corresponding sentiment scores.

Table 7.2 | Examples of responses and coding

Response to semi-open-ended question	SentimentR measure[a]	LIWC2015 measure [a]	Benchmark measure [a]	MOAQ-JSS[b]
Exciting, fun, cool, interesting, hard	3.60	4.80	4.00	3.33
Positive, caring, interested, fun, engaging	3.60	5.00	4.80	6.33
Boring, tedious, important, relaxed	2.75	3.00	3.25	5.67
Temporary, part, time, underpaid, remote, flexible	3.00	4.00	3.20	5.67
Interesting, frustrating, focused	3.33	1.80	3.00	6.00
Cold, stringent, red	2.33	2.20	2.67	6.00
Good, decent, well paying, nice, tiring	3.40	4.80	3.80	6.00
Rewarding, interesting, enjoyable, fun, pleasurable	4.20	5.00	5.00	7.00
Beautiful, nice, wonderful, predictable, awesome	3.80	4.80	5.00	7.00
Fun, stressful, tired, happy, strong	3.20	3.80	3.80	6.00
Uninteresting, fast, paced, pointless, obligatory	2.75	2.80	2.50	2.67
Necessity, relaxed, nonflexible, boring, annoying	2.80	3.40	2.60	4.00
Hard, flexible, demanding, creative, frustrating	2.80	4.00	3.20	3.00
Creative, hands on, fast, paced, positive, interesting	3.80	4.20	4.20	6.00
Fulfilling, challenging, hectic, rewarding	2.75	3.80	3.50	5.33
Rewarding, flexible, challenging	3.00	3.40	4.33	5.33
Personal, educational, artistic, interesting	4.00	3.40	3.75	6.00
Boring, tedious, dull	1.67	1.00	1.00	2.67
Slow, tedious, surprising, relaxed, calm	3.00	3.80	2.60	3.67
Customer, service, fast pace, stressful, food, serving	3.20	2.60	4.60	7.00

Notes. LIWC = Linguistic Inquiry and Word Count; MOAQ-JSS = Michigan Organizational Assessment Questionnaire - Job Satisfaction Subscale; [a] Scale ranges from 1 (*very negative*) to 5 (*very positive*); [b] Scale ranges from 1 (*strongly disagree*) to 7 (*strongly agree*).

Figure 7.1 | Density plot of the benchmark measure, SentimentR measure and LIWC2015 measure



7.3.2. Empirical validation

The results of our correlation analyses, shown in Table 7.3, indicated convergence between the MOAQ-JSS and the text measures in varying degrees: the SentimentR measure ($r = 0.70$, $p < 0.01$), the LIWC2015 measure ($r = 0.55$, $p < 0.01$) and the benchmark measure ($r = 0.80$, $p < 0.01$). The CFAs further corroborated convergent validity because the CFA model that included the SentimentR measure (χ^2 [2] = 3.70, p = ns, CFI = 1.00, SRMR = 0.01, RMSEA = 0.05), the LIWC2015 measure (χ^2 [2] = 0.54, p = ns, CFI = 1.00, SRMR = 0.00, RMSEA = 0.00) and the benchmark measure (χ^2 [2] 0.45, p = ns, CFI = 1.00, SRMR = 0.00, RMSEA = 0.00) fitted the data very well. The standardized factor loadings of the SentimentR measure ($\lambda = 0.72$) and the benchmark measure ($\lambda = 0.83$) exceeded 0.60, while the standardized factor loading of the LIWC2015 measure did not ($\lambda = 0.57$). Notably, the factor loadings of the SentimentR measure and, in particular, the benchmark measure were generally in line with the loadings of the MOAQ-JSS items (CFA model including the SentimentR measure: $\lambda_{\text{MOAQ-JSS1}} = 0.93$, $\lambda_{\text{MOAQ-JSS2}} = 0.85$, $\lambda_{\text{MOAQ-JSS3}} = 0.92$; CFA model including the benchmark measure: $\lambda_{\text{MOAQ-JSS1}} = 0.94$, $\lambda_{\text{MOAQ-JSS2}} = 0.84$, $\lambda_{\text{MOAQ-JSS3}} = 0.92$). The factor loading of the LIWC2015 measure diverged quite substantially ($\lambda_{\text{MOAQ-JSS1}} = 0.94$, $\lambda_{\text{MOAQ-JSS2}} = 0.84$, $\lambda_{\text{MOAQ-JSS3}} = 0.92$). Taken together, the convergent validity analyses showed that the SentimentR measure has better properties than the LIWC2015 measure, and that neither measure performed as well as the benchmark measure.

With respect to discriminant validity, the results indicated that the relationships between the text measures and their hypothesized antecedents (i.e., skill variety, autonomy and person-organization fit), correlate (i.e., life satisfaction), and outcomes (i.e., turnover intention and organizational citizenship behavior) were significant and in the expected direction (e.g., positive association with life satisfaction and negative association with turnover intention). The data also suggested that the SentimentR measure, the LIWC2015 measure and the benchmark measure only marginally correlated with need for cognition and openness measure. All convergent correlations were higher than the average discriminant correlations. The results remained robust when testing our hypotheses on survey data from respondents who have not been flagged as careless.

7.3.3. Contextualizing job satisfaction

7.3.3.1. Context-dependency of sentiment ratings

The descriptive statistics in Table 7.4 show that words vary in the extent to which their sentiment rating is context dependent. Eight words, “overwhelming”, “uncertain”, “underpaid”, “complex”, “academic”, “official”, “educational”, and “rewarding”, had a *SD* of 0, and thus an unequivocal meaning. Put differently, we can be quite certain that these words can have a single sentiment rating assigned to them: positive, neutral or negative. Other words had much higher *SD*s, such as “demanding”, “exhausting”, “repetitive”, “different", "variable" and "easy", implying that the meaning, and thus the sentiment rating of these words depend on the words they are used in conjunction with.

To illustrate this point, let us consider the word "easy". With a mean score of 3.72, it was generally rated as positive. When we focused on individual responses and considered the *SD* of 0.96, we noticed that the word was rated as negative when combined with words such as "boring", "repetitive", "unchallenging", "tedious" and "monotonous". When used in conjunction with words such as "stress-free", "easy-going", "fun", "safe", "relaxing" and "slow", it was rated more positively.

7.3.3.2. Balancing job characteristics

For this part of the analysis, we were interested in respondents who provided words with varying sentiment meanings, as demonstrated in a *SD* of 1.5 to the average sentiment rating.[17] Two examples of responses with high *SD*s were "Boring, Easy, Slow, Secure" and "Flexible, Challenging, Unpredictable, Stressful". The respondent that provided the first example indicated that the first and third word are negative, the second word is neutral, and the fourth word is positive. The respondent that provided the second example indicated that the first two words are positive and the last two are negative. The mean (and *SD*) sentiment ratings for the two responses were 2.75 (1.48) and 3.00 (1.58), respectively. Looking at word frequencies, we noticed that certain words were used particularly often. Organized from the most to the least frequently used (count between brackets), respondents used the following positive words: "interesting" (15), "fun" (15), "challenging" (14), "rewarding" (10), "flexible" (9), "easy" (9), "creative" (7), "engaging" (5), "social" (5), "fast" (5), "helpful" (5), "important" (4), "fulfilling" (4), "exciting" (4), "technical" (4) and "satisfying" (4).

The following negative words were most often used: "stressful" (23), "boring" (13), "frustrating" (10), "tiring" (9), "underpaid" (6), "exhausting" (5), "demanding" (5), "slow" (4) and "repetitive" (4).

A qualitative analysis of these instances suggests that the common factor behind a substantial part of the most frequently occurring positive words is intrinsic motivation (Hackman & Oldham, 1976). People either enjoy doing their work tasks (e.g., "fun", "interesting", "challenging" and "engaging") or believe that their work is important (e.g., "rewarding", "fulfilling", "important" and "helpful").

The negative words can also be categorized into higher-order categories. Except for the word "underpaid", all words have either a connotation with a job that is too demanding or a job that is not demanding enough. Overall, these findings suggest that a segment of

17 A sensitivity analysis for other *SD* cut-off values (i.e., 1.0 and 2.0) did not alter the results.

Table 7.3 | Means, standard deviations, internal consistency statistics and bivariate correlations (N = 395)

Variable	*M*	*SD*	ω	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Job satisfaction (SentimentR measure)	3.14	0.73	0.54												
2. Job satisfaction (LIWC2015 measure)	3.31	1.01	0.66	0.60											
3. Job satisfaction (benchmark measure)	3.51	1.07	0.84	0.80	0.62										
4. Job satisfaction (MOAQ-JSS)	5.13	1.64	0.93	0.70	0.55	0.80									
5. Task variety	3.79	1.03	0.93	0.19	0.18	0.29	0.35								
6. Job autonomy	3.80	0.99	0.91	0.31	0.28	0.48	0.53	0.50							
7. Person-organization fit	3.34	1.00	0.93	0.53	0.46	0.65	0.68	0.37	0.52						
8. Life satisfaction	21.87	7.72	0.92	0.39	0.34	0.47	0.50	0.21	0.33	0.42					
9. Turnover intention	2.77	1.34	0.92	-0.50	-0.39	-0.60	-0.73	-0.28	-0.39	-0.53	-0.41				
10. Organizational citizenship behavior	2.79	0.78	0.85	0.19	0.15	0.29	0.25	0.37	0.27	0.32	0.16	-0.15			
11. Need for cognition	3.85	0.57	0.82	*0.02*	*0.10*	*0.10*	0.12	0.11	0.11	*0.09*	0.14	*-0.07*	0.19		
12. Openness	3.93	0.62	0.80	*-0.05*	*0.06*	*-0.03*	*0.02*	*0.06*	*0.01*	*0.06*	*-0.07*	0.10	*0.08*	0.54	

Notes. All correlations significant at the level of $p < 0.05$ (2-tailed), except for the ones in italic; LIWC = Linguistic Inquiry and Word Count; MOAQ-JSS = Michigan Organizational Assessment Questionnaire - Job Satisfaction Subscale; M = mean; SD = standard deviation, ω = McDonald's omega.

7

respondents deal with both favorable and unfavorable job conditions at the same time. For example, respondents seem to take boredom or stress for granted when their tasks are sufficiently enjoyable or important. To test whether this combination of favorable and unfavorable job conditions in the responses was also manifested in less extreme (and thus more neutral) scores on the closed job satisfaction measure, we regressed the *SD* variable against the MOAQ-JSS. As shown in Figure 7.2, we found an inverted U-curve. This suggests that respondents with a relatively high *SD* generally had moderate levels of job satisfaction. Respondents with relatively low *SD*s tended to respond more extremely to the job satisfaction question.

Table 7.4 | Context-dependent sentiment ratings

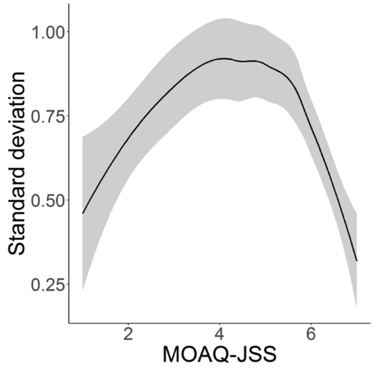
Negative (N_{words} = 36)				Neutral (N_{words} = 13)				Positive (N_{words} = 58)			
Word	*M*	*SD*	N_{obs}	Word	*M*	*SD*	N_{obs}	Word	*M*	*SD*	N_{obs}
Overwhelming	1.00	0.00	4	Complex	3.00	0.00	3	Educational	5	0.00	5
Uncertain	2.00	0.00	3	Academic	3.00	0.00	3	Rewarding	6	0.00	4
Underpaid	1.30	0.48	10	Official	3.00	0.00	3	Productive	5.8	0.45	5
Frustrating	1.56	0.51	19	Fine	3.25	0.50	4	Freedom	4.8	0.45	5
Long	2.33	0.51	6	Detailed	3.33	0.57	3	Important	4.8	0.45	5
Annoying	1.50	0.52	12	Difficult	2.83	0.81	6	Stimulating	1.2	0.45	5
…				Intense	3.00	0.89	4	…			
Repetitive	2.14	0.66	14	Routine	2.60	0.89	5	Necessary	3.60	0.89	5
Exhausting	1.70	0.67	10	Busy	3.18	0.95	17	Calm	4.14	0.89	7
Demanding	2.20	0.92	10	Hard	2.60	0.67	10	Great	4.25	0.96	4
Temporary	2.00	1.00	3	Work	3.33	1.15	3	Different	3.75	0.96	4
Cheap	2.00	1.00	3	Unpredictable	2.66	1.15	3	Variable	3.75	0.96	4
Stress	1.67	1.15	3	Slow	2.50	1.17	12	Easy	3.72	0.96	29

Notes. M = mean; *SD* = standard deviation; N_{words} = total number of words that fitted the filtering criteria; N_{obs} = total number of observations per word, … = words that do fall in the top six of words with the most varying sentiment ratings and bottom six of words with the least varying sentiment rating, i.e., 23 in the "Negative"-category and 45 in the "Positive"-category, please contact the first author for the complete table.

7.4. DISCUSSION

Throughout this study, we investigated the quantifying and qualifying potential of a semi-open-ended job satisfaction question. We showed that computer-aided sentiment analysis is a time-saving method to produce text measures. In less than five seconds, LIWC2015 and particularly SentimentR produced text measures that converged strongly with our benchmark measure ($r_{SentimentR}$ = 0.80, $r_{LIWC2015}$ = 0.62). Furthermore, the text measures showed promise as quantitative measures of job satisfaction. The text measures correlated strongly with a closed question measure of job satisfaction ($r_{SentimentR}$ = 0.70 and $r_{LIWC2015}$ = 0.55) and CFA models that included the text measure showed adequate

Figure 7.2 | The relationship between the MOAQ-JSS and SD in sentiment rating and pointwise 95% confidence interval on the fitted values



Notes. MOAQ-JSS = Michigan Organizational Assessment Questionnaire - Job Satisfaction Subscale.

fit. Concerning discriminant validity, we found that the text measures had logical associations with closed question measures of constructs that fall within and outside job satisfaction's nomological network. Finally, we demonstrated that the responses to a semi-open job satisfaction question can act as a means to fine-tune sentiment analysis dictionaries and unravel antecedents of job satisfaction. Taken together, we conclude that semi-open-ended questions have the potential to quantify and qualify job satisfaction and that computer-aided sentiment analysis is a valuable tool to help researchers to unpack this potential. The theoretical and practical contributions of our study, its limitations and future research directions are discussed below.

7.4.1. Theoretical implications

Our study has several theoretical implications. First, we add to the field by illustrating that computer-aided sentiment analysis is not an absolute panacea, as the psychometric qualities of the SentimentR and LIWC2015 measure were inferior to those of the benchmark measure. For instance, the internal consistency score of the benchmark measure ($\omega = 0.84$) was much higher than the internal consistency scores of LIWC2015 measure ($\omega = 0.66$) and the SentimentR measure ($\omega = 0.54$). This limited inconsistency between adjectives, as suggested by the respondents, suggests that the LIWC2015 and SentimentR measure introduce measurement error. This measurement error is likely because the computer-aided sentiment analysis techniques do not explicitly consider the context-dependency of words. The correlation analyses and CFAs showed that the benchmark measure converged more strongly with the MOAQ-JSS than the text measures generated by computer-aided sentiment analysis. These attenuated correlations may be driven by the substantial measurement error in the text measures. Thus, even though the results generally support the appropriateness of text measures produced by computer-aided sentiment analysis as a job satisfaction measure, our findings also suggest that its reliability still has considerable room for improvement.

Secondly, to the best of our knowledge, we are among the first to systematically test the content, convergent, and discriminant validity of text measures of job satisfaction. Most previous research investigated the convergence between text measures and the responses to ad-hoc job satisfaction measures (e.g., Borg & Zuell, 2012; Poncheri et al., 2008; Taber, 1991; Wijngaards et al., 2019) or did not consider convergent validity at all (e.g., Jung & Suh, 2019; Moniz & Jong, 2014; Young & Gavade, 2018). In our study, we adopted a traditional instrument validation approach. We tested the text measures' validity with well-established multiple-item survey instruments and employed techniques that control for same-source variance. Based on our findings, we tentatively argue that semi-open-ended questions can be used to measure the level of job satisfaction.

Finally, we examined the qualitative value of semi-open-ended questions over closed question measures. We found that the responses to our semi-open-ended question could be used to fine-tune the reliability of a computer-aided sentiment analysis dictionary. Analyses showed that words differ in the degree to which they can be labelled with a single sentiment rating. More specifically, certain words can have both positive and negative connotations depending on the words they are used in conjunction with. For instance, words such as "stressful" and "busy" often do not represent stressors that are harmful for well-being if they are combined with more positive words such as "enthusiastic" and "fulfilling". By contrast, words such as "underpaid" and "overwhelming" always have negative connotations. This finding supports the proposition that stressful job demands such as job complexity and work pressure do not necessarily lead to reduced subjective well-being (Bakker & Demerouti, 2017; Van den Broeck et al., 2010). These results highlight the importance of transforming context-free dictionaries into domain-specific dictionaries to guarantee optimal reliability of text measures (e.g., treating "challenging" as a slightly positive word, McKenny et al., 2018; Short et al., 2010). Finally, the semi-open-ended question allowed us to discover that respondents who use both positive and negative words are often striking a balance between experiencing boredom or stress, on the one hand, and intrinsic motivation, on the other. This illustrates the intricate ways in which job characteristics contribute to employee well-being, for example, some occupations might be deemed highly meaningful, but at the same time have unfavorable job characteristics (Allan et al., 2018), e.g., nursing (Zangaro & Soeken, 2007).

7.4.2. Practical implications

In today's competitive and fast-paced economy, organizations are compelled to maximize employee well-being (Guest, 2017). To design high-quality well-being interventions, organizations must first obtain adequate insights about their employees' work-related well-being and its drivers (Macey & Schneider, 2008). To obtain this information, human resource practitioners typically request employees to complete surveys about their work experience and job attitudes (Gerrad & Hyland, 2020). In the design of such surveys, they typically face a challenging trade-off between information richness and the minimization of respondent burden (G. G. Fisher et al., 2016; Fuchs & Diamantopoulos, 2009). For example, practitioners may be reluctant to administer surveys containing multiple, lengthy closed question scales with good measurement quality because they are associated with considerable opportunity costs and provide no opportunity for contextualization (Krosnick, 1999). On the other hand, practitioners may be hesitant to use open-ended questions that may provide valuable context to a survey because converting raw textual data into reliable text measures is a challenging task and may feel daunting to many. We argue that the semi-open job satisfaction question has the promise to quantify and qualify job satisfaction, and that it therefore functions as a valuable addition to an employee survey. Practitioners can leverage existing code (e.g., our code included in the supplementary materials) and well-established sentiment analysis software to construct text measures, which can be used both as a valid quantitative measure of job satisfaction, as well as input for the qualification of other quantitative measures. As an illustration of the latter, responses can be used to identify the most pertinent antecedents of job satisfaction in a particular group of employees (e.g., Table 7.1). Additionally, responses to the semi-open-ended question may help organizational researchers to communicate research findings to individuals with limited experience with quantitative analysis (Borg & Zuell, 2012). An anecdote obtained from a semi-open-ended question can, for example, provide an intuitive illustration of improvement areas and make abstract research findings feel more relatable (Glaser et al., 2009; Rynes, 2012).

7.4.3. Limitations and future research

This study has several limitations that should be noted. For instance, even though the correspondence of the text measures were substantial, the validation evidence generally corresponded with the evidence of the benchmark measure, as reliability of text measures produced by computer-aided sentiment analysis was not perfect. Considering the importance of the accuracy of a computer-aided text analysis technique in the validity of a text measure (McKenny et al., 2018; Short et al., 2010), we recommend researchers to develop more reliable techniques to construct text measures and come closer to the measurement-error-free sentiment measure. One approach would be to tailor generic dictionaries like the one of Jockers (2017) or the LIWC (Pennebaker, Boyd, et al., 2015), so that text measures better align with the construct they intend or context of study (Taboada et al., 2011; for guidelines, see Short et al., 2010). The results of our study indicate that certain words will inherently differ in their sentiment rating depending on their context. Therefore, it would therefore be valuable to move beyond lexicon-based sentiment analysis and to employ machine learning approaches to sentiment analysis (Zehner et al., 2016). Such approaches leverage pre-labeled texts to train algorithms, with the purpose of predicting (i.e. classifying) unlabeled textual instances, and are particularly useful for recognizing context-specific nuances (Taboada et al., 2011; for guidelines, see Kobayashi et al., 2017). Our data, which is included as supplementary material, can be used as training data for such endeavors. Alternatively, researchers could use publicly available self-rated job reviews from online platforms like Glassdoor (Jung & Suh, 2019; Moniz & Jong, 2014) or manually annotated texts as training data (Sheehan, 2018).

We did not leverage the full potential of the textual data, as we only constructed a measure of job satisfaction from the textual responses. We expect that the information derived from texts could also be used to measure other constructs, such as work engagement, job affect or emotional exhaustion. For example, theory-driven or data-driven dictionaries of particular job affect dimensions can be created (Short et al., 2010). A theory-driven lexicon could be produced by reviewing items taken from the Job-related Affective Well-being Scale (Van Katwyk et al., 2000) and consulting a thesaurus to create emotion-specific dictionaries. The Job-related Affective Well-being Scale's boredom dimension could, for instance, be measured using a dictionary containing words such as "bored", "monotonous", "tedious", "pointless", "dull" and "dreary". Using a more qualitative and data-driven approach, a dictionary could be generated by looking at the most frequently used words, and manually assigning them to word categories or themes. Software programs such as ATLAS.ti, NVivo and CAT Scanner can be used to help researchers annotate texts and create custom dictionaries (Short et al., 2018).

Furthermore, we cannot generalize our conclusions to open-ended questions in general. It is plausible that different kinds of open-ended questions provide different kinds of insights. Our study showed that a semi-open-ended question seems useful for measuring the level of job satisfaction, arguably more suitable than a completely open-ended question (Wijngaards et al., 2019). We expect that the responses to our semi-open-ended question are more suitable for quantifying job satisfaction than responses to an open-ended question, as they are more straightforward to process and analyze. However, the lack of complexity in responses to semi-open-ended questions concurrently functions as its most important limitation compared to responses to entirely open-ended questions: they do not allow respondents to fully contextualize their responses. We, therefore, encourage researchers to investigate the qualifying and quantifying potential of completely open-ended questions and examine the reliability of computer-aided sentiment analysis techniques.

While entirely open-ended questions may be more useful for qualitative research, we expect that semi-open-ended questions could have additional potential for helping researchers quantify and qualify well-being. For example, our semi-open job satisfaction question could easily be reframed into a semi-open life satisfaction question (change 'job as a whole' to 'life as a whole'). Questions, such as "What five aspects of your job contribute the most to your job satisfaction and how do they rank?" and "What words do you associate with work engagement?" could help organizational researchers unravel the constituents of multi-dimensional constructs such as work engagement (Briner, 2014; Purcell, 2014) and job satisfaction (Hsieh, 2012; Mastekaasa, 1984). A question like "In a best-case scenario, what job function would have in this organization in five years?" could aid practitioners to map the preferences of employees and design policies aimed at improving well-being.

Our validation procedure is subject to certain limitations. Even though some initial evidence suggests that text measures of job satisfaction have sufficient test-retest reliability (Wijngaards et al., 2019), we did not address it in this study. In addition, our reliance on self-report cross-sectional data is likely to have introduced measurement error, although mixing up different answering formats in theory mitigates the risk for common method bias (Podsakoff et al., 2003) and CFA helps control for same-source variance. Therefore, we recommend future researchers to combine self-report data with other-report data, like supervisor ratings of organizational citizenship behavior, and adopt a longitudinal research design. This data can be used to more robustly test the hypotheses from this study and explore other components of validity, such as predictive and incremental validity.

Our choice to collect data through Prolific limits the generalizability of our research findings. First and foremost, respondents did not come from the same professional context or company. The findings are therefore not generalizable to a typical employment survey context. Second, respondents from online survey platforms such as Prolific often are very experienced survey takers and thus may have lost their naivety (Peer et al., 2017). This issue may not have biased our results too much because the purpose of our study was not immediately obvious for Prolific workers and employees in organizations are increasingly often asked to complete employee surveys (Gerrad & Hyland, 2020). Third, the motivation of the respondents in our sample to provide high-quality data may be unrepresentative for an average sample in a traditional employee survey. In our study, we did not have any item non-response because we paid Prolific workers to answer all questions and only considered workers with a high approval rating. In a traditional (corporate) survey context where respondents are not financially compensated, there is likely a higher risk of missing (text) data (Anseel et al., 2010; Scholz & Zuell, 2012). For these reasons, it would be interesting to replicate our validation study in other, more natural contexts, such as an employee satisfaction survey in an organization, and investigate the generalizability of our results in subpopulations (e.g., blue-collar vs. white-collar workers, different industries) and across nations.

7.4.4. Conclusion

We want to emphasize that closed questions are likely still the best strategy for quantifying well-being because the comparability of closed question measures is high, non-response is relatively low and validation is straightforward. However, we believe that semi-open (and open) survey questions can be asked alongside closed questions to fully realize the closed questions' potential. As complements of closed questions, semi-open-ended questions could serve as a source of qualitative insights and means to cross-validate closed questions. Opportunely, computer-aided text analysis has the promise to mitigate the traditional obstacles, such as labor-intensiveness, that are typically associated with using textual data to study psychological constructs. We expect that the rapid advances in computational linguistics and its applications in psychological science will make computer-aided text analysis more reliable and spur new research avenues on the parallel use of the different types of survey instruments. It is not expected that any particular multiple-item survey scale will soon be labelled the gold standard for measuring all aspects of a psychological construct, such as job satisfaction, in every context. Therefore, we expect that "opening up of standardized surveys" (Singer & Couper, 2017, p. 128) and looking at constructs from different epistemological angles (Mauceri, 2016) will eventually allow researchers and employers to capture employees' job evaluations and feelings more validly, and to generate better insights into what employees really thinking influences their job attitudes. This could be crucial for the development of more context-specific and allegedly more effective strategies to improve employee well-being.

8

General discussion

Worker well-being is a hot topic in organizations and academia. More and more organizations have a well-being strategy in place and invest in programs to improve worker well-being, giving rise to a billion-dollar industry. The scientific literature on worker well-being dates back more than a century, but is expanding rapidly. In particular, the popularity of survey assessment systems that capture well-being and its drivers is spiking. Perhaps unsurprisingly, a prerequisite for an effective worker well-being survey is the rigorous measurement of the concept of worker well-being *itself*. After all, without sound data on worker well-being, data-driven insights on well-being problems, outcomes and interventions will be biased and, thus, be of limited value for evidence-based decision making. Three principles of rigorous worker well-being measurement were identified: (i) the examination of a broad selection of worker well-being constructs (or variables), (ii) the use of valid closed survey questions and (iii) the consideration of open-ended survey questions.

Yet, scholars and practitioners concerned with well-being assessment in organizations, such as experts from consultancy firms, in-house organizational behavior specialists and HR professionals, do not seem to invariably adhere to these principles, often focusing on a very narrow range of constructs, not using valid closed questions and disregarding open-ended questions. There is a practical and a technical challenge that may explain this discrepancy. The practical challenge for scholars and practitioners is that organizations are regularly disinclined to administer surveys that put a heavy burden on their workers' time and, therefore, obligate researchers to focus on a limited set of constructs and prioritize time-efficient measurement over valid measurement. The technical challenge is that scholars and, in specific, practitioners lack the training to navigate the vast and scattered literature on the definition, operationalization and measurement of worker well-being, lack access to this literature, or both. The goal of this thesis is to offer scholars and practitioners conceptual and empirical guidance on how to deal with these practical and technical challenges and, thereby, improve the rigor of their worker well-being measurement in organizations. This guidance is organized around four research questions.

(1) How can the concept of worker well-being be defined and operationalized into constructs?
(2) Which worker well-being constructs should be focused on in a survey?
(3) What kind of closed survey questions are suitable for measuring worker well-being constructs in organizations?
(4) How can open-ended survey questions contribute to measuring worker-well-being in organizations?

In this chapter, I use the insight from Chapters 2 to 7 to formulate an answer to these research questions. The answers to the first three research questions are based on conceptual insights from Chapter 2 and empirical examples from Chapter 3 to 7. The answer to the fourth research question is based on theoretical overviews and empirical results from Chapters 6 and 7. After discussing the main findings, I reflect on this thesis' strengths and limitations and discuss implications for scholars and practitioners in organizations. I conclude with a general conclusion.

8.1. MAIN FINDINGS

8.1.1. How can the concept of worker well-being be defined and operationalized into constructs?

Chapter 2 offered help with overcoming the technical challenges of navigating the scattered and vast literature on the definition and operationalization of worker well-being. This was done by offering two pieces of conceptual guidance.

First, Chapter 2 drew up conceptual boundaries of the term worker well-being and offered a holistic definition. It proposed that, at the most inclusive level, worker well-being can be understood as the general well-being of working people. It discussed the differences between worker well-being and other related concepts, such as employee well-being, well-being at work, work-specific well-being and general individual-level well-being. For example, worker well-being differs from employee well-being, as not all working people are employed by organizations. And, although most well-being constructs are relevant for both employees and non-employed working people, there may be some exceptions. For instance, the construct of satisfaction with supervisor will be irrelevant for independent contractors and chief executive officers.

Second, Chapter 2 developed a comprehensive construct taxonomy that can be used to navigate the wide assortment of related, but distinct constructs that fall under the conceptual umbrella of worker well-being. This construct taxonomy distinguishes four construct dimensions: philosophical underpinning (hedonic vs. eudaimonia), temporal stability (trait-like vs. state-like), scope (context-free vs. domain-specific) and valence (positive vs. negative). For example, life satisfaction would classify as a hedonic, trait-like, context-free and positive worker well-being construct, while negative job emotions at work, such as anger and fear, would classify as a hedonic, domain-specific, state-like and negative worker well-being constructs.

Chapters 3 to 7 – summarized in terms of population, survey research design and studied well-being constructs and measures in Table 8.1 – illustrated how many faces worker well-being has, studying a total of nine worker well-being constructs, i.e., job satisfaction, job facet satisfaction, work engagement, emotional exhaustion, perceived stress at work, mood, life satisfaction, self-reported health and flourishing. In addition, these chapters exemplified that worker well-being constructs are empirically distinct, but related. For example, Chapter 3 and Chapter 7 reported a positive significant correlation between measures of life satisfaction and job satisfaction of $r = 0.38$ and $r = 0.42$, respectively. Linear regression analyses in Chapter 4 revealed that a person's momentary mood on the day of completing the survey is a robust predictor of general work engagement ($B = 0.36$, $SE = 0.06$, $p < 0.01$). Chapter 6 showed that correlations between measures of general job satisfaction and measures of satisfaction with work content, pay, colleagues and other job facets ranged between $r = 0.34$ and $r = 0.70$.

8.1.2. Which worker well-being constructs should be focused on in a survey?

Chapter 2 reiterated the importance of maximizing the number and diversity of well-being constructs to unravel well-being trade-offs and offered readers conceptual guidance in overcoming the practical and technical challenges that complicate this maximization process. With an extremely broad operationalization being unfeasible in most organizational settings, Chapter 2 argued in favor of conceptual focus. It explained that this focus should be based on the careful analysis of the study objectives, the research questions and the employment situation of the workers of study as well as a thorough search for relevant constructs in scientific literature. Once a list of relevant constructs is composed, Chapter 2 recommended the selection of only those constructs that are conceptually and empirically distinct and could theoretically uncover well-being trade-offs. The proposed construct taxonomy could be a useful tool for unraveling the conceptual distinctiveness of worker well-being constructs and making a deliberate choice. For example, when evaluating the well-being enhancing potential of a new coffee machine, it would be logical to consider domain-specific constructs, such as satisfaction with facility management, and state-like constructs, such as momentary happiness while drinking coffee, in addition to broader constructs, such as job satisfaction.

Chapters 3 to 7 offered practical examples of how an evaluation of the research context and an analysis of established theory can be used to select relevant well-being constructs. In addition, several of these chapters offered support for the existence of well-being trade-offs. For example, drawing upon different strands of literature in occupational and cognitive psychology, Chapter 5 selected perceived email interruptions as proximal well-being outcome variable, and emotional exhaustion and work engagement as distant well-being outcome variables. The analysis showed that the treatment – an intervention that stimulated participants to check their email only three times a day – had a significant effect on perceived email interruptions and emotional exhaustion, but not on work engagement. Chapter 7 made use of previous measure validation research and well-established nomological networks to identify relevant determinants, outcomes and correlates as well as unrelated constructs. A correlational analysis showed that turnover intention was more strongly related to job satisfaction (r = -0.73) than to life satisfaction (r = -0.41), while the bivariate correlations between organizational citizenship behavior and the two well-being constructs differed only marginally (r = 0.24 and r = 0.16, respectively).

8.1.3. What kind of closed survey questions are suitable for measuring worker well-being constructs in organizations?

Chapter 2 underlined the importance of selecting valid closed survey questions and validating collected survey data, and provided readers conceptual guidance on how to do this in practice. With lengthy multiple-item scales and intense longitudinal surveys being impractical in most settings, Chapter 2 recommended the reader to be pragmatic and search the literature for validated, time-efficient alternatives to the more time-consuming and costly measures. For example, if one wants to measure job affect using the experience sampling method, and an organization suggests a cross-sectional survey to do this, researchers can suggest the day reconstruction method as a valid alternative. If one wants to use well-established multiple-item scales to measure certain well-being constructs, and an organization rejects this idea because they want to keep the survey as short as possible, researchers might want to suggest validated single-item measures or shortened scales. As the literature on well-being measurement is not easily accessible to many practitioners and difficult to oversee for scholars, Chapter 2 composed a list of potentially useful closed question survey measures. In addition, as some may not be comfortable with survey data validation, Chapter 2 elucidated a number of important terms relating to measurement error, e.g., social desirability and careless responding, and validity testing, e.g., content, convergent, discriminant, predictive and incremental validity.

Chapters 3 to 7 contained examples of time-efficient, but valid measures of worker well-being constructs and different validation procedures. Readers can use the code and data, as provided in the Online Supplementary Materials of the published versions of the chapters, to learn about and experiment with data validation. As an illustration, Chapters 4 and 5 measured work engagement using the 3-item Utrecht Work Engagement Scale, a short and valid survey scale that matched the operational definition of work engagement used in the two studies. The use of a shortened scale was a necessity. Chapter 4 took place in the healthcare sector during the COVID-19 pandemic. The participating hospital demanded that the survey had to be as short as possible to keep the burden on the already heavily burdened workforce to a minimum. Chapter 5 required remote workers to report their work engagement in multiple bi-weekly surveys. The participating financial services organization desired a very brief survey because it feared substantial survey fatigue.

8.1.4. How can open-ended survey questions contribute to measuring worker-well-being in organizations?

Chapters 6 and 7 offered readers technical guidance on how to process textual data collected through open-ended survey questions and illustrated their relevance for measuring job satisfaction. Chapter 6 provided a rationale for why open-ended survey questions are a useful complement to closed questions for quantifying job satisfaction, discussed the differences between a completely open and a semi-open survey question and elaborated on the pros and cons of lexicon-based and learning-based computer-aided sentiment analysis techniques. Furthermore, it reflected on the various kinds of measurement error that may be introduced when constructing a textual measure (algorithm error, transient error, specific factor error). Chapter 7 zoomed in on the added value of the semi-open survey question for quantifying and qualifying job satisfaction and provided a basic introduction on how lexicon-based sentiment analysis works.

The empirical findings reported in the two chapters confirmed the hypothesized added value of open-ended questions. The textual measures based on completely open-ended and, in particular, semi-open-ended survey questions contained little measurement error and seemed to be valid measures of job satisfaction. Notably, the comparison of human-generated and computer-generated textual measures presented in Chapter 6 revealed that, although the human-generated measures are relatively more robust, computer-generated measures are sufficiently robust in absolute terms. This finding is encouraging, as readily available and relatively easily deployable lexicon-based sentiment analysis techniques were used in the analyses, and the creation of a computer-generated measure is much less time-consuming that the production of a human-generated measure. In addition to verifying the quantifying potential of a semi-open survey question, Chapter 7 illustrated that the responses to this type of question can be used to tailor sentiment lexicons to particular study contexts and inductively examine sources of job satisfaction.

8.2. STRENGTHS AND LIMITATIONS

This thesis has several strengths. This thesis in its entirety features a vast number of worker well-being operationalizations, measurement instruments and validation procedures and, thereby, exemplifies that rigorous well-being measurement is possible in real-life, dynamic organizational settings. Below, the strengths of the individual chapters are discussed.

Table 8.1 | Overview of worker well-being constructs and measures in this thesis

Chapter	Population	Survey research design	Validation procedures	Well-being construct	Measure
3	Truck drivers	Cross-sectional survey and experience sampling study (time lag: 3-4 hours)	Bivariate correlations	Momentary happiness	1 closed question, *"How happy did you feel in the last hour?"*
				Job satisfaction	1 closed question (G. G. Fisher et al., 2016; Wanous et al., 1997) *"How satisfied are you with your current job?"*
				Life satisfaction	1 closed question (Abdel-Khalek, 2006; G. G. Fisher et al., 2016) *"Taking all into consideration, how satisfied are you with your life?"*
				Self-reported health	1 closed question (Macias et al., 2015) *"In general, how is your health?"*
				Feelings of stress at work	1 closed question *"In the last 4 weeks, how often did you experience feelings of stress during work?"*
4	Hospital workers	Cross-sectional survey	Bivariate correlations, internal consistency	Work engagement	3 closed questions (Schaufeli et al., 2019) *e.g., "I am enthusiastic about my job."*
				Mood	1 closed question *"How happy do you feel today?"*

Table 8.1 | Continued: Overview of worker well-being constructs and measures in this thesis

Chapter	Population	Survey research design	Validation procedures	Well-being construct	Measure
5	Remote office workers in a financial service organization	Between-person experimental design with five repeated survey (time lag: 1-2 weeks)	Bivariate correlations, internal consistency	Emotional exhaustion	4 closed questions (Maslach & Jackson, 1981) *e.g., "I am used up at the end of the workday."*
				Work engagement	3 closed questions (Schaufeli et al., 2019) *e.g., "I am enthusiastic about my job."*
6	Heterogenous sample of workers spanning multiple industries and countries	Cross-sectional survey and follow-up survey (time lag: 1 year and 3 months)	Bivariate correlations, internal consistency	General job satisfaction	1 semi-open-ended question *"Which three to five adjectives come to mind when you think of your job as a whole? Adjective 1: […] – Adjective 5 […]"*
					1 open-ended question *"How do you think about your job as a whole?"*
					1 closed question *"How satisfied are you with your job?"*
				Job facet satisfaction	7 closed questions (Nagy, 2002) *e.g., "How satisfied are you with your salary?" "So your salary?"*
				Flourishing	8 closed questions (Diener et al., 2010) *e.g., "I am optimistic about my future."*
				Life satisfaction	1 closed question (World Values Survey, 2019) *"All things considered, how satisfied are you with your life as a whole these days?"*
7	Heterogenous sample of workers spanning multiple industries and countries	Cross-sectional survey	Bivariate correlations, internal consistency, confirmatory factor analysis	Job satisfaction	1 semi-open-ended question *"Which three to five adjectives come to mind when you think of your job as a whole? Adjective 1: […] – Adjective 5 […]."*
					3 closed questions (Cammann et al., 1979) *e.g., "All in all, I am satisfied with my job."*
				Life satisfaction	5 closed questions (Diener et al., 1985) *e.g., "In most ways my life is close to ideal."*

First, Chapter 2 adopted a particularly inclusive approach towards synthesizing the vast and ever-expanding literature on definition, operationalization and measurement of worker well-being. Most previous research aimed at synthesizing this literature either restricted itself to a specific subfield, focused on either definition or measurement issues, or ignored the practical and ethical considerations surrounding the study of worker well-being. By adopting this broad, multi-disciplinary scope, Chapter 2 serves as a comprehensive guidebook of the most important considerations for selecting worker well-being constructs and closed question measures and points to dedicated references on specific topics.

Second, Chapters 3 to 5 exemplified the value of scholar-practitioner collaborations. For example, Chapter 3 originated from a research collaboration between our research team and the Dutch Sector Institute of Transportation and Logistics. This institute struggled with attracting new truck drivers and a major outflow of current drivers and wished for a deeper understanding of the problems in the workforce. Our collaboration resulted in a win-win situation: We were able to leverage the institute's extensive network to recruit study participants and the sector instituted could benefit from our experience with studying well-being in organizations. Chapter 5 was based on a successful collaboration with a financial services organization that wanted to facilitate better working conditions for their remote workforce during the COVID-19 pandemic but lacked the capability to develop an adequate research methodology and intervention. With the help of our research team, the organization was able to implement an established intervention and make a well-informed decision on its effectiveness in their specific organizational context.

In addition, Chapters 3 to 5 offered robust evidence for the significance of considering moderators in the relationship between worker well-being and other variables. This is in line with recent propositions that suggest scholars should move from answering the question "what works?" to "what works for whom in which circumstances?" to instigate positive change in organizations (Nielsen & Miraglia, 2017, p. 40; Nielsen & Noblet, 2018; Nielsen, Randall, et al., 2010). Specifically, Chapter 3 showed that the degree to which driving the road contributes to the momentary happiness of truck drivers depends on traffic conditions. Chapter 4 revealed that cognitive crafting, a form of bottom-up work design, positively relates to the work engagement of remote healthcare workers, but not to the work engagement of frontline healthcare workers. Chapter 5 concluded that email batching – processing online messages only at certain times of the day – will only be beneficial for the well-being of remote office workers that receive many emails during the week.

Third, Chapter 6 and 7 introduced the reader to a potentially fruitful way of measuring worker well-being that is not yet widely embraced. Scholars can use this work to answer calls "to take measurement more seriously and to devote more attention to the creation of better well-being measures" (Schneider & Schimmack, 2009, p. 374; Brulé & Maggino, 2017; Diener, 2012). Practitioners in organization can use the insights from these chapters as inspiration to put the textual data that is already available in their organization to work.

This thesis also has various limitations that are worth mentioning. It has proven to be extremely challenging to follow all the thesis' recommendations for rigorous worker well-being measurement in the individual chapters. An explanation for this is that individual chapters were written as journal articles and thus had narrow research scopes and were subject to strict word limits. Additionally, my research practice has taught me that organizations are often not keen on fulfilling all scholars' methodological desires (e.g., longitudinal or experimental research design, comprehensive well-being measurement). For example, Chapters 3, 4, 6 and 7 did not use the available data on different well-being constructs to unravel well-being trade-offs. Chapters 4, 5 and 6 only evaluated the internal consistency of the multiple-item measures but ignored other forms of validity testing; Chapter 7 was the only chapter that looked at careless response tendencies. Certain aspects of validity, such as measurement invariance and incremental validity, were not considered at all. Chapters 6 and 7 did not get around investigating the potential of learning-based sentiment analysis techniques.

Furthermore, the survey designs used in Chapters 3 to 7 were subject to a range of limitations. The first limitation concerns the use of different kinds of convenience samples, each subject to specific limitations (Landers & Behrend, 2015). The samples in Chapters 3 to 5 were drawn from single organizations or specific industries in the Netherlands, which limits the generalizability of results to other organizations, industries and countries. After all, research suggests that worker well-being differs significantly between countries, sectors and organizations, and that the importance of work characteristics differs across people (De Neve et al., 2018). Chapters 6 and 7 made use of Prolific, a virtual crowdsourcing platform where people can complete paid tasks, to obtain survey data. The fact that respondents are paid for their (complete) response is atypical for a traditional worker well-being survey in an organization, where survey participation is voluntary (Aguinis et al., 2020). Furthermore, Chapters 3 to 5 faced some of the methodological issues that were introduced in Chapter 1, such as survey non-response, panel attrition and careless responding. In Chapter 3, for example, 24% of the truck drivers participating in the baseline survey participated in the subsequent experience sampling method study. In Chapter 4, 12% of the invited healthcare workers completed the survey. In Chapter 5, 51% of the selected employees completed both the pre- and the post-test. In Chapter 7, one analysis flagged 41% of the respondents as careless responders.

8.3. IMPLICATIONS FOR SCHOLAR AND PRACTITIONERS IN ORGANIZATIONS

This thesis has several implications for scholars and practitioners in organizations. The implications for both stakeholders are combined because the substantial practical and technical challenges associated with the rigorous measurement of worker well-being can most effectively be overcome if scholars and practitioners collaborate (D. J. Cohen, 2007; Huffman & Benson, 2021). For example, with scholars being trained and incentivized to stay informed about the latest conceptual developments in the scientific literature and to enrich and deploy their methodological toolboxes, practitioners will likely have to depend on scholars to ensure rigor in their measurement efforts (C. Gill, 2018; Marler & Boudreau, 2017). Practitioners' time and resource investments, on the other hand, will remain indispensable to put worker well-being and data-driven decisions on organizations' strategic agendas, to ensure that surveys are sufficiently time-efficient and tailored to the study context, but also to motivate workers to participate in survey research (Aguinis et al., 2014; Banks et al., 2016; Lapierre et al., 2018).

Against this background, I propose two specific areas for future scholar-practitioner collaborations that directly follow from this thesis. First, this thesis demonstrated that the field of worker well-being is rife with constructs and closed question measures and that their suitability in a worker well-being survey depends on a large variety of factors, such as the research question, population of study and research design. This suggests that a gold standard for measuring worker well-being is and will probably remain lacking and that researchers should therefore take a 'best fit' approach. In practice, this means that scholars and practitioners are advised to leverage previous research to select feasible and valid closed questions and validate the data once collected and administer multiple measures in parallel. After the research, the parties are encouraged to share study results publicly so that individuals in the research community can learn from each other. In the end, these efforts will help well-being researchers to understand which constructs and measures are relevant in specific research contexts and uncover well-being trade-offs. As an additional benefit, these efforts offer opportunities to examine the empirical distinctiveness of worker well-being constructs and address the pervasive issue of construct proliferation, "research streams are built around ostensibly new constructs that are theoretically or empirically indistinguishable from existing constructs" (Shaffer et al., 2016, p. 81), that characterizes the worker well-being field (Shuck et al., 2013, 2017). As an illustration, research suggested that employee engagement is not clearly distinct from constructs like job burnout (Cole et al., 2012) and job satisfaction (Christian et al., 2011).

Second, future research is encouraged to replicate the results about the quantifying and qualifying value of open-ended questions in Chapters 6 and 7 in more natural contexts, such as an organizational survey, and look into other functions of open-ended survey questions. Two additional functions are already hinted upon in Chapters 3 to 5. Open-ended questions can help researchers to make the survey results more actionable for decision-makers (Borg & Zuell, 2012; Gilles et al., 2017; Stoneman et al., 2013). For example, an analysis of job activities and momentary happiness in Chapter 3 showed that the job category "Other" brought respondents the least happiness of all job activities. It is plausible that the inclusion of an open-ended question that asked respondents to label the job activities that were not mentioned in the fixed response categories would have helped decision-makers to get a better idea of the issues in truck drivers' job description and develop more relevant interventions. The conclusion of Chapter 4 that cognitive crafting behavior is positively associated with remote workers' work engagement, would probably have been more actionable for decision-makers if an open-ended question allowed respondents to specify the kinds of cognitive crafting behaviors they displayed at work. In addition, open-ended questions can help researchers to communicate survey results. Research from communication sciences suggests that narrative evidence – "the use of case stories or examples to indicate that the conclusions offered by the communicator is true" (Allen & Preiss, 1997, p. 125) – may be more effective for changing attitudes than statistical evidence (Dunlop et al., 2010; Zebregs et al., 2015), especially when recipients are skeptical about the evidence in the first place (Slater, 2002). Anecdotes from open-ended questions may therefore be used to convince decision makers of the importance of acting on survey results (Borg & Zuell, 2012) and sharing research findings with the mainstream media (Silber et al., 2020; D. C. Zhang, 2018). This point is illustrated by the interview quotes in the first paragraphs of Chapters 3 and 5 and the open-ended question responses in the Results section of Chapter 5.

There are two areas of research that were not explicitly covered in this thesis but are not less important for future research. Foremost, research is urged to also pay attention to the other prerequisites for effective worker well-being survey studies. For example, in most survey studies, it is not necessarily worker well-being per se that is of interest, but rather its relationship with other variables (e.g., well-being over time or across departments, well-being in relation to job characteristics). As a result, a typical worker well-being survey contains questions on work experience, work behaviors, preferences, suggestions and complaints (see the Method sections in Chapters 3 to 7 for examples). The selection of these measures arguably is even more challenging than the selection of well-being measures, as worker well-being measures are most often relevant for all populations while measures on work experiences are not. For example, research shows that Utrecht Work Engagement Scale is a highly stable indicator of occupational well-being across occupations (Seppälä et al., 2009) and cultures (Balducci et al., 2010), while general questions about work experience may be open to interpretation (Choi et al., 2012) and may be perceived as irrelevant by certain workers (Nielsen et al., 2014). In addition, the choice of non-well-being measures may heavily affect the overall survey duration and burden on workers. For example, the time savings from using a brief well-being survey will be completely negated, if a researcher decides to also include a 100-item battery of questions asking about job characteristics and personality of workers. Furthermore, the actions that follow the design, collection and validation of survey data are pivotal in making a survey study count (Gerrad & Hyland, 2020). For example, survey data should be analyzed with state-of-the-art analytical techniques to ensure the robustness of research findings. Additionally, it is important to pay attention to the translation of the findings into policy proposals and encouragement of organizations to use these proposals for their policy making.

Furthermore, research can benefit from examining the complementary value of non-survey measures for capturing worker well-being. The triangulation of multiple measures will enable researchers to offset the weaknesses of a single measure and obtain a more complete, deeper understanding of their constructs of study (Turner et al., 2017). For example, experience sampling produces measures of emotional well-being that are subject to careless response tendencies (Eisele et al., 2020), but not to recollection bias (Beal, 2015). In contrast, by their very nature, physiological indicators of emotional well-being, such as heart rate and blood pressure, are immune to response tendencies, but distorted by irrelevant variables, such as physical activity, coffee intake and alcohol consumption (Ilies et al., 2010). As another example, open-questions will, to a certain extent, be subject to social desirability biases (Silber et al., 2013; Vinten, 1995), while anonymous textual data published on job review websites are not (Jung & Suh, 2019; Moniz & Jong, 2014). Compared to open survey questions, the relevance of the anonymous job reviews for identifying specific well-being problems in an organization and formulating relevant policies to solve them is debatable. The overview of measures in Chapter 2 describes a wide range of word, behavioral and physiological measures that may be used for future research and points the reader to relevant validity and feasibility considerations.

8.4. GENERAL CONCLUSION

The already widespread interest in worker well-being and its measurement in organizations is expected to grow in the years to come. In this thesis, I argued that it is important to rigorously measure the concept of worker well-being itself, but that this is often challenging in practice. This thesis was dedicated to helping scholars and, in specific, practitioners to overcome their challenges and, thereby, improve the rigor of their well-being assessment. Specifically, this thesis offered a general definition of worker well-being, a tool for understanding conceptual nuances of individual well-being constructs and a strategy for selecting a limited, but sufficiently diverse set of constructs. In addition, it provided a list of validated closed question survey measures, guidance for selecting appropriate measures, and an introduction to survey data validation. Finally, it demonstrated how these principles and measures could be put into practice. This thesis hopefully helps future worker well-being survey research to contribute more effectively and efficiently to protecting and improving the well-being of workers.

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B

Acknowledgements

Four years ago, straight from university, I ambitiously joined an interdisciplinary 4-year research project called The New Science of Existential Well-being (NEWEL): Concepts, Ethics and Responsible Algorithms. For me, the NEWEL project ticked every box. I would be able to collaborate with bright researchers from the Erasmus University Rotterdam, the University of Twente and the University of Amsterdam, studying a range of academic discplines, such as artificial intelligence, philosophy, economics and psychology. In addition, I would be able to conduct practically relevant scientific research within Ahold Delhaize, a multinational grocery retail company employing over 400,000 employees.

The goals of my research track were ambitious from the start. I was tasked to "explore and predict what the labor force of tomorrow looks like", "identify significant elements of work-related well-being from survey and multisource performance data collected by Ahold's HR department" and "find causal relationships between organizational and job characteristics, well-being, and performance in the context of intervention experiments".

As the years went by, I learned that I would not able to achieve all these objectives. Interdisciplinary collaboration turned out to be very difficult in practice. Large-scale field experiments were mostly infeasible. Existing datasets were rarely suitable for scientifically relevant research. Privacy regulations complicated the collection of high-quality data.

Does this mean that NEWEL was a failure for me? No, on the contrary. It allowed me to become a pragmatic, confident and resilient researcher. For a large part, my successes can be attributed to the people that helped me along the way.

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About the author

Indy Wijngaards (1994) holds a BSc (with distinction) and MSc in Human Resource Studies (cum laude) from the School of Social and Behavioral Sciences, Tilburg University, and a MSc in Data Science (with distinction) from the School of Humanities and Digital Sciences, Tilburg University. He worked as a PhD candidate at the Erasmus School of Health Policy & Management (ESHPM) under the supervision of prof. dr. Job van Exel, prof. dr. Jan van Ours and prof. dr. Martijn Burger. During his PhD, Indy was affiliated to the Erasmus Happiness Economics Research Organisation (EHERO) and conducted empirical field experiments in Ahold Delhaize. Indy's research interest is in the field of worker well-being studies, with a specific focus on the definition and measurement of worker well-being. His work has been published in the following peer-reviewed journals: PLoS ONE, Applied Research in Quality of Life, Frontiers in Psychology, Transportation Research Part A: Policy and Practice, Journal of Well-being Assessment and Health Care Management Review. Indy has a keen interest in communicating scientific research to the general public, for example, in the form of workshops, lectures, blogs and interviews. Upon completion of his PhD, Indy starts a career as human resources consultant at Capgemini Invent, in which he will advise companies to use data-driven decision making to make a positive impact.

Portfolio

PEER-REVIEWED PUBLICATIONS

Wijngaards, I. Pronk, F.R., Bakker, A.B., & Burger, M.J. (2021). Cognitive Crafting and Work Engagement: A Study among Remote and Frontline Healthcare Workers during the COVID-19 Pandemic. *Health Care Management Review.*

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CONFERENCES, WORKSHOPS AND PRESENTATIONS

Happy and Productive Remote Working, AIRLab, 2020, virtual (workshop).

Effective coping in times of crisis: Evidence from the COVID-19 pandemic, 18th Annual Conference of the International Society for Quality-of-Life Studies, 2020, virtual (workshop).

Unpacking the quantifying and qualifying potential of semi-open job satisfaction questions through computer-aided textual analysis, 18th Annual Conference of the International Society for Quality-of-Life Studies, 2020, virtual (oral presentation).

Geluksonderzoek EBS, European Business Services, 2020, virtual (oral presentation).

Geluk @EBS, European Business Services, 2019, Zaandam, the Netherlands (oral presentation).

Steering towards happiness: An experience sampling study on the momentary happiness of truck drivers, 17th Annual Conference of the International Society for Quality-of-Life Studies, 2019, Granada, Spain (oral presentation).

How to measure employee well-being: A taxonomy of constructs and review of measures, 19th EAWOP Congress, 2019, Turin, Italy (oral presentation).

Steering towards happiness: An experience sampling study on the momentary happiness of truck drivers, 19^{th} EAWOP Congress, 2019, Turin, Italy (oral presentation).

Evidence-based HR, Etos, 2018, Utrecht, the Netherlands (workshop)

Evidence-based HR and Associate Well-being, Ahold Delhaize, 2018, Brussels, Belgium (workshop)

Steering towards happiness: An experience sampling study on the momentary happiness of truck drivers, Erasmus Happiness Economics Research Organization, 2018, Rotterdam, the Netherlands (oral presentation).

Break it open – the validity of open and semi-open job satisfaction questions, 16^{th} Annual Conference of the International Society for Quality-of-Life Studies, 2018, Hong Kong, Hong Kong (oral presentation).

Work to Well-Being, Albert, 2018, Prague, Czech Republic (workshop).

How to measure and boost happiness at work, People Analytics Academy Conference, 2018, Tilburg, the Netherlands (poster presentation).

COURSES

Analytic Storytelling training, Analytic Storytelling, 2019, Rotterdam, the Netherlands.

Masterclass the Secrets of Employee Engagement & Happy Workplaces, Erasmus School of Accounting & Assurance, Erasmus University Rotterdam, 2019, Garderen, the Netherlands.

Field Experiments, Faculty of Science, University of Copenhagen, 2018, Copenhagen, Denmark.

Basic Didactics, Risbo - Research-Training-Consultancy, Erasmus University Rotterdam, 2018, Rotterdam, the Netherlands.

Professionalism and integrity in research, Erasmus Graduate School of Social Sciences and the Humanities, Erasmus University Rotterdam, 2018, Rotterdam, the Netherlands.

DATA COLLECTIONS

Two-wave survey among 1937 individuals to unravel the effects of the COVID-19 crisis on happiness in the Netherlands, 2020.

Cross-sectional survey among 20 academics to tailor a workshop on productive and happy remote working to the audience, 2020.

Two-wave survey among 112 office workers to identify well-being problems in the organization, 2019-2020.

Cross-sectional survey among 1768 workers working in a retail organization to map well-being levels across departments, functions and stores, 2019.

Cross-sectional survey among 84 office workers to evaluate a participatory office refurbishment intervention, 2019.

Two-wave survey in 20 stores to evaluate the effectiveness of a break room renovation, 2019.

Two-wave survey among 82 store managers to evaluate the effectiveness of an e-coaching program, 2019.

Cross-sectional survey among 395 workers using Prolific to test the hypotheses in Chapter 7, 2019.

Semi-structured among eight senior leaders to obtain a better understanding of the importance of worker well-being in the organization, 2019.

Cross-sectional survey among 997 workers using Prolific to test the hypotheses in Chapter 6, 2018.

TEACHING

Minor Quality of Life and Happiness Economics (Bachelor 3 program, Erasmus School of Economics) - Module 3 'Quality of Life & Work', 2019-2020.

Supervision of various master's theses at the Erasmus School of Economics, 2019-2020.

ACADEMIC DEGREES

MSc Data Science: Business and Governance, Tilburg University, 2016-2017.

MSc Human Resource Studies, Tilburg University, 2015-2016.

BSc Human Resource Studies, Tilburg University, 2012-2015.

Summary

"What we measure affects what we do; and if our measurements are flawed, decisions may be distorted."

- Stiglitz et al. (2009, p. 7)

Worker well-being is a hot topic in organizations and academia. More and more organizations have a well-being strategy in place and invest in programs to improve worker well-being. The scientific literature on worker well-being is expanding rapidly and the popularity of surveys that capture well-being and its drivers is rapidly increasing. A prerequisite for an effective worker well-being survey is the rigorous measurement of the concept of worker well-being *itself*. Rigorous worker well-being measurement encompasses (i) the examination of a broad selection of well-being constructs, (ii) the use of valid closed survey questions, and (iii) the consideration of open-ended survey questions. After all, data-driven insights on well-being problems, outcomes and interventions will be biased and, thus, of limited value for evidence-based decision making, if data on the concept of worker well-being is unreliable or incomplete.

In practice, however, rigorous well-being measurement comes with significant practical and technical challenges. The practical challenge is that organizations are often reluctant to administer surveys that put a heavy burden on their workers' time and, therefore, demand scholars and practitioners to focus on a limited set of constructs and prioritize time-efficient measurement over valid measurement. The technical challenge is that scholars and, in specific, practitioners lack the training to navigate the vast and scattered literature on the definition, operationalization and measurement of worker well-being, or lack access to this literature. The main aim of this thesis is to provide conceptual and empirical guidance to scholars and practitioners on how to deal with these challenges and, thereby, contribute to the rigor of worker well-being measurement in organizations.

I organize this thesis around four research questions and provide answers to these questions in six chapters. The first chapter provides the conceptual foundation for this thesis (Chapter 2); the five subsequent chapters report on empirical studies on the determinants, outcomes and measurement of worker well-being. The empirical studies span a wide range of academic strands of research and target different study populations, i.e., truck drivers (Chapter 3), healthcare workers (Chapter 4), workers in financial services (Chapter 5) and crowdsourced workers (Chapters 6 and 7).

First, I address the question "How can the concept of worker well-being be defined and operationalized into constructs?" I find that, at the most inclusive level, worker well-being can be defined as the general well-being of working people, and that it differs from concepts, such as works-specific well-being and well-being at work. After reviewing the state-of-the-science, I propose a conceptual taxonomy that can be used to navigate the wide assortment of related, but distinct constructs that fall under the conceptual umbrella of worker well-being. In the following five empirical chapters, I illustrate the many faces of worker well-being, studying a total of nine worker well-being constructs. Overall, I find support for the idea that worker well-being constructs are empirically distinct, but related.

Second, I address the question "Which worker well-being constructs should be focused on in a survey?" I conclude that, even though it is essential to maximize the number and diversity of well-being constructs to uncover well-being trade-offs, it is often impossible to measure a multitude of constructs in organizations. Against this background, I argue in favor of a well-justified conceptual focus. Specifically, I suggest that the initial list of relevant constructs should be based on a careful analysis of the study objectives, the research questions, and workers' employment situation as well as a thorough scanning of the scientific literature. Furthermore, the eventual selection should contain constructs that are conceptually and empirically distinct, are directly related to the study object, and could theoretically uncover well-being trade-offs. In five empirical chapters, I exemplify how this conceptual focus can be attained in practice and, in three chapters, I find support for the existence of well-being trade-offs.

Third, I explore the question "What kind of closed survey questions are suitable for measuring worker well-being constructs in organizations?'" I conclude that, despite their methodological superiority, lengthy multiple-item scales and intense repeated survey designs are impractical in many organizational settings and that, therefore, a measure's time-efficiency should be considered as important selection criterion next to traditional criteria, such as reliability and validity. To help with the selection, I compose a list of promising survey measures of ten popular worker well-being constructs and introduce several procedures that play a central role in the validation of survey measures. In the empirical chapters, I illustrate the use of time-efficient, but valid closed well-being questions and several validation procedures.

Fourth, I address the question "How can open-ended survey questions contribute to measuring worker-well-being in organizations?" I explain how different sentiment analysis techniques can be utilized to produce measures from responses to open-ended survey questions and what kinds of measurement error they introduce. Furthermore, I develop a rationale for using open-ended survey questions as means of quantifying and qualifying well-being constructs. I find that completely open-ended and, in specific, semi-open-ended survey questions contain little measurement error and can safely be used to measure job satisfaction. In addition, I find that, although the human-generated measures are relatively more robust compared to their much more time-efficient computer-generated counterparts, computer-generated measures are robust by absolute standards. Finally, I find that the responses to a semi-open-ended question can be used to improve the performance of sentiment analysis techniques and to study the determinants of job satisfaction.

In sum, this thesis contributes to the promotion of worker well-being survey research that is both rigorous *and* realistic. Next to offering conceptual guidance to scholars and practitioners on defining, operationalizing and measuring worker well-being, this thesis offers a comprehensive showcase of how these guidelines can be applied in applied research contexts and reflects on the typical challenges in empirical work. Improved methodological rigor combined with an eye for practice will help scholars and practitioners to make their well-being measurements count and, in the end, contribute to evidence-based decision making in organizations that protects and improves the well-being of workers.

Samenvatting

> "Wat we meten beïnvloedt wat we doen; en als onze metingen gebrekkig zijn, kunnen beslissingen verslechteren."
>
> - Stiglitz et al. (2009, p. 7)

Het welzijn van medewerkers is een hot topic in organisaties en de academische wereld. Steeds meer organisaties hebben een strategie omtrent medewerkerswelzijn en investeren in programma's om het te verbeteren. De wetenschappelijke literatuur over het welzijn van medewerkers breidt zich snel uit. De populariteit van vragenlijsten om welzijn en de drijvende krachten daarachter in kaart brengen, neemt gestaag toe. Een voorwaarde voor een effectieve vragenlijst is een grondige meting van het concept medewerkerswelzijn zelf. Een goede meting wordt gekenmerkt door het gebruik van (i) een brede selectie van welzijnsconstructen, (ii) valide multiple-choice-vragenlijsten, en (iii) open vragen. Als gegevens over het welzijn onbetrouwbaar of onvolledig zijn, zullen data-gedreven inzichten over problemen, gevolgen en interventies op het gebied van het medewerkerswelzijn immers vertekend zijn en dus van beperkte waarde zijn voor empirisch onderbouwde besluitvorming.

In de praktijk brengt een grondige meting van het welzijn van medewerkers aanzienlijke praktische en technische uitdagingen met zich mee. De praktische uitdaging is dat organisaties vaak terughoudend zijn met het uitsturen van tijdrovende vragenlijsten naar hun medewerkers. Hierdoor moeten wetenschappers en mensen in de praktijk zich focussen op een beperkte set constructen en prioriteit geven aan tijdsefficiënte meting boven valide meting. De technische uitdaging is dat wetenschappers en, in het bijzonder, mensen in de praktijk niet opgeleid zijn om de uitgebreide literatuur over de definitie, operationalisering en meting van medewerkerswelzijn te doorgronden of hier geen toegang tot hebben. Het hoofddoel van dit proefschrift is om wetenschappers en mensen in de praktijk conceptuele en empirische richtlijnen te bieden over hoe om te gaan met deze uitdagingen en zo bij te dragen aan de nauwkeurigheid van welzijnsmetingen in organisaties.

In dit proefschrift ga ik in op vier onderzoeksvragen en baseer mijn antwoorden op zes hoofdstukken. Het eerste hoofdstuk biedt de conceptuele basis voor dit proefschrift (hoofdstuk 2); de vijf daaropvolgende hoofdstukken doen verslag van empirische studies naar de determinanten, de gevolgen en het meten van het welzijn van medewerkers. De empirische studies bestrijken een breed scala aan academische onderzoeksvelden en hebben verschillende onderzoekspopulaties, namelijk vrachtwagenchauffeurs (hoofdstuk 3), ziekenhuismedewerkers (hoofdstuk 4), kantoormedewerkers in de financiële dienstverlening (hoofdstuk 5) en individuen die werken voor een crowdsourcing platform (hoofdstukken 6 en 7).

Ten eerste ga ik in op de vraag "Hoe kan het concept medewerkerswelzijn worden gedefinieerd en geoperationaliseerd in constructen?" Ik ontdek dat medewerkerswelzijn in de meest algemene zin zou moeten worden begrepen als het algemene welzijn van werkende mensen, en dat het verschilt van concepten, zoals werk-specifiek welzijn en welzijn op het werk. Op basis van een analyse van de wetenschappelijke literatuur presenteer ik een conceptuele taxonomie die kan worden gebruikt om overeenkomsten en verschillen tussen de constructen die onder de conceptuele noemer van medewerkerswelzijn vallen, te duiden. In de vijf daaropvolgende empirische hoofdstukken illustreer ik de vele gezichten van medewerkerswelzijn door in totaal negen concepten te bestuderen. In het algemeen vind ik bewijs voor het idee dat welzijnsconstructen empirisch van elkaar verschillen, maar verwant zijn.

Ten tweede beantwoord ik de vraag "Op welke welzijnsconstructen moet in een vragenlijst de nadruk worden gelegd?" Ik concludeer dat het vaak onmogelijk is om een groot aantal constructen in organisaties te meten, ondanks het belang om het aantal en de diversiteit van welzijnsconstructen te maximaliseren om dilemma's op het gebied van welzijn bloot te leggen. Daarom pleit ik voor een goed onderbouwde conceptuele focus. Meer specifiek stel ik voor dat de initiële lijst met relevante constructen gebaseerd zou moeten worden op een zorgvuldige analyse van de studiedoelen, de onderzoeksvragen, de werksituatie van medewerkers en een grondige scan van de wetenschappelijke literatuur. Ik beargumenteer dat de uiteindelijke selectie constructen zou moeten bevatten die conceptueel en empirisch van elkaar verschillen, een direct verband houden met het studieobject en theoretisch welzijnsdilemma's aan het licht kunnen brengen. In vijf empirische hoofdstukken illustreer ik hoe deze conceptuele focus in de praktijk kan worden bereikt, en in drie hoofdstukken vind ik bewijs voor het bestaan van welzijnsdilemma's.

Ten derde onderzoek ik de vraag: "Welk soort multiple-choice-vragenlijsten zijn geschikt om welzijnsconstructen in organisaties te meten?" Ik concludeer dat, ondanks hun methodologische superioriteit, lange multiple-choice-vragenlijsten en intensief longitudinaal vragenlijstonderzoek onpraktisch zijn in veel organisatiecontexten. Om deze reden stel ik dat de tijdsefficiëntie van een instrument moet worden meegenomen als een belangrijk selectiecriterium naast traditionele criteria, zoals betrouwbaarheid en validiteit. Om te helpen bij de selectie stel ik een lijst samen met geschikte instrumenten voor tien populaire constructen en introduceer ik verschillende procedures die belangrijk zijn bij de validatie van vragenlijstmetingen. In de empirische hoofdstukken illustreer ik het gebruik van tijdsefficiënte, maar valide gesloten welzijnsvragen en verschillende validatieprocedures.

Ten vierde ga ik in op de vraag "Hoe kunnen open vragen in een vragenlijst bijdragen aan het meten van het welzijn van medewerkers in organisaties?" Ik leg uit hoe verschillende sentiment-analysetechnieken gebruikt kunnen worden om maatstaven te creëren op basis van antwoorden op open vragen en met welke soorten meetfouten zij gepaard gaan. Verder beargumenteer ik hoe open vragen gebruikt kunnen worden als middel om welzijnsconstructen te kwantificeren en te kwalificeren. Ik vind bewijs dat volledig open vraag en, in het bijzonder, een semi-open vraag over baantevredenheid weinig meetfouten introduceren en veilig gebruikt kunnen worden om het construct te meten. Verder ontdek ik dat, hoewel de door mensen gegenereerde maatstaven robuuster zijn dan hun veel tijdsefficiëntere door de computer gegenereerde tegenhangers, de door de computer gegenereerde maatstaven robuust zijn naar absolute maatstaven. Tenslotte concludeer ik dat de antwoorden op een semi-open vraag over baantevredenheid gebruikt kunnen worden om de prestaties van sentiment-analysetechnieken te verbeteren en om de determinanten van baantevredenheid te bestuderen.

Kortom, dit proefschrift draagt bij aan de verbetering van vragenlijstonderzoek naar medewerkerswelzijn. Naast het bieden van conceptuele richtlijnen over het definiëren, operationaliseren en meten van medewerkerswelzijn, biedt dit proefschrift een uitgebreide illustratie van hoe deze richtlijnen kunnen worden toegepast in organisatiecontexten en reflecteert dit proefschrift op de typische uitdagingen van empirisch werk in organisaties. Wanneer wetenschappers en mensen in de praktijk een methodologische nauwkeurigheid en oog voor de praktijk combineren, zullen hun welzijnsmetingen beter worden en bijdrage aan de verbetering van medewerkerswelzijn in organisaties.

Worker well-being is a hot topic in organizations and academia, causing the interest for its measurement using surveys to spike. However, scholars and practitioners are struggling to rigorously measure well-being in the workplace. The main aim of this thesis is to provide conceptual and empirical guidance on how researchers can deal with the technical and practical challenges they are facing and, thereby, contribute to the rigor of worker well-being measurement in organizations.

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