

The well-being of high-skilled workers: Interplay of autonomy, learning, and creativity.

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Abstract

High-skilled workers are defined as individuals having a highly specialized education and working with complex, non-routine tasks. This dissertation investigates aspects of job control – autonomy, learning, and creativity – and their role as predictors of work-related well-being in the group of high-skilled workers. The thesis builds on three empirical studies aimed at investigating: 1) How do different aspects of high-skilled workers' work environment contribute, separately or together, to the sustainable development of worker well-being?; 2) What differences and similarities exist between subgroups of high-skilled workers in terms of working conditions and well-being at work?; and 3) Is there a way to improve the well-being of high-skilled workers, who as a group already have favorable working conditions?

The first, prospective exploratory study distinguished patterns of psychosocial working conditions, described their characteristics, and investigated how they changed over time. The working conditions of high-skilled workers (N=1,744) in Sweden, based on a representative sample of the working population, were empirically classified into four distinct patterns. Importantly, these patterns were associated with significant differences in worker well-being. In terms of aspects of job control, the study revealed that the levels of autonomy seemed to better differentiate between high-skilled workers than opportunities to be creative and to learn. Over time, workers tended to transition from patterns with high autonomy levels to patterns with low autonomy levels.

The second, comparative task level study examined mechanisms that lead to differences in work engagement between self-employed and organizationally employed high-skilled workers. Participants (N=167) assessed their job control and reported their work engagement during work tasks. Aspects of job control predicted work engagement, yet their role differed for the two groups of workers. Employees with more opportunities to be creative and autonomous were more engaged at work. Self-employed workers were more engaged when they had more learning opportunities. Overall, self-employed workers reported higher levels of job control and well-being than organizationally employed workers.

The third, experimental study tested how creative tasks may influence autonomous self-expression, and whether this in turn increases positive emotions. Participants (N=478) from the four language samples were randomly assigned to solve either creative or non-creative tasks. Tasks formulated in a way that encouraged creativity, i.e., tasks that had many different solutions, encouraged switching between semantic categories, and enabled individuals to approach a problem in a novel way, increased autonomy, which in turn increased the positive emotions of the participants. This indirect effect was replicated in all four language samples.

In sum, this thesis investigates the interplay of job control aspects as predictors of well-being within the group of high-skilled workers. The results imply that autonomy,

opportunities to be creative and to learn should be considered as separate predictors of worker well-being, which may at the same time relate and influence each other. Moreover, a large group of high-skilled workers was shown to be internally quite diverse, with significant differences between workers of different work sectors and forms of employment. Finally, the findings suggest that carefully targeted interventions for particular groups of workers, as well as task level interventions, may significantly improve the well-being of high-skilled workers. This thesis concludes with a call for a more nuanced view of work environment characteristics and their role in predicting the well-being of specific groups of workers.

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Chapter 1: Introduction

If you received a highly specialized education, your job requires mostly cognitive rather than physical effort, you typically deal with non-routine tasks at work, and you solve problems using your expertise in a given area - you are a high-skilled worker. If you also live in a developed country, that means you belong to one of the largest groups of workers. In Europe, about 35% of the workforce is employed as high-skilled professionals and technicians, and another about 7% works as managers (Eurofound, 2016).

As a high-skilled worker, you have probably received higher education - or a more specialized one - than your older colleagues. Every year more and more highly educated workers enter the labor market to take over an increasing number of jobs (Beaudry, Green, & Sand, 2016). It is also quite likely that your parents used to work in a more routine way than you do now. Employment in non-routine cognitive jobs has grown significantly over the last 20 years, compared to routine manual jobs that have decreased due to the rapid automatization of work (Dvorkin, 2016; Stuart, De, & Cole, 2014). In highly innovative and technologically advanced economies, the importance of high-skilled work is especially profound. For example in Sweden, employment in high-skilled occupations increased from 39% in 2001 to 43% in 2013 (Statistics Sweden SCB, 2015). If this growth trend continues, soon high-skilled workers will become a dominant group in the workforce and a main contributor to the country's economy. Therefore, it seems particularly important to study the working conditions and well-being of high-skilled workers in developed countries.

The structural transformations of the labor market are one of the indicators of a more general change in the character of work. Today's knowledge economies rely on the intellectual capabilities of workers, rather than physical inputs or natural resources (Powell & Snellman, 2004). Modern working practices, such as team work, knowledge management, and virtual working, aim at empowering workers and increasing their involvement in decision making and knowledge sharing (Holman, Wood, Wall, & Howard, 2005). Furthermore, individual career development planning, flexible employment schedules, and other current human resources practices result in many workers being expected to take responsibility for aspects of work that previously were under the control of their managers (Hellgren, Sverke, & Naswall, 2008). Finally, with computers taking over increasing numbers of algorithmic tasks, the creative skills of workers have become crucial for individual and organizational success (The Economist, 2014). For you as a high-skilled worker, these changes in the character of work mean getting more autonomy, more learning opportunities, and more creative tasks at work.

To date, the knowledge is still rather limited on the impact that these specific requirements of high-skilled work have on worker well-being in rapidly changing and technologically advanced sectors of business. The most popular theory of healthy work, namely the Job Demands-Control model (Karasek & Theorell, 1990), was developed at the time when the health of male blue collar workers was the main focus of interest, and in this population the JDC model found most empirical support (Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010; Johnson & Hall, 1988; Van der Doef & Maes, 1999). However, today's workforce has a much more diverse demographic profile, with more women, older, non-white, and immigrant workers (National Research Council, 1999). Moreover, typical working conditions have changed significantly. Following ever changing cus-

tomers demands, current businesses strive for increased flexibility through new forms of employment that focus on extreme specialization, cooperation, networking, and knowledge sharing (Eurofound, 2015). Finally, the tasks at work have changed from routine to creative, resulting in most workers in the EU having a job which involves a degree of creativity (Eurofound, 2012). Thus, it seems relevant to ask whether the same theoretical principles of healthy work can be applied to new ways of working in the growing and diverse population of high-skilled workers.

The main question raised in this dissertation is how working conditions, which are typical for high-skilled work, affect individual well-being. Therefore, the empirical studies included in this dissertation ask what differentiates work environments in which high-skilled workers either thrive or languish. More specifically, the following three general research questions are addressed in different ways in each of the empirical studies:

1. *How do different aspects of high-skilled workers' work environment contribute, separately or together, to the sustainable development of worker well-being?*
2. *What differences and similarities exist between subgroups of high-skilled workers in terms of working conditions and well-being at work?*
3. *Is there a way to improve the well-being of high-skilled workers, who as a group already have favorable working conditions?*

This introductory chapter provides definitions, background information, and an overview of the theoretical concepts discussed in this dissertation. First, the group of high-skilled workers is defined and described. Next, the theoretical background is discussed, starting from a description of an explanatory model that connects working conditions with worker well-being, and continuing with definitions of each of the key constructs as they are measured and analyzed in this dissertation. Finally, the overview of the studies discusses aspects of research designs and specifies the research questions investigated in the three empirical chapters of this dissertation.

The second chapter, entitled “Psychosocial working conditions among high-skilled workers”, aims at understanding the differences in working conditions within a large group of high-skilled workers. The main contribution of this study lies in describing how psychosocial working conditions interrelate, and determining what role such patterns of relations play in predicting worker well-being. To better understand the experience of an individual high-skilled worker, diverse subgroups need to be identified and compared. Thus, this study asks whether certain groups of workers (managers, technicians, engineers, education professionals, health care professionals, women, older workers) are more likely to have a specific pattern of working conditions. Finally, a longitudinal design of this study provides a unique insight into changes of working conditions over time.

The third chapter, entitled “Work engagement of self-employed high-skilled workers”, focuses on differences in employment forms and their impact on worker well-being. Due to the increasing flexibility of employment conditions, more and more high-skilled workers decide to work as self-employed freelancers or become entrepreneurs (Barley

& Kunda, 2006; Kunda, Barley, & Evans, 2002). Thus, this study asks how working conditions of the self-employed differ from those of the organizationally employed high-skilled workers. The main contribution of this study lies in explaining the mechanisms due to which the self-employed and employees differ in their levels of well-being. To fully explain worker well-being, this study introduces a multilevel perspective, which allows for testing both fairly stable person-level differences as well as varying task-level fluctuations.

The fourth chapter, entitled “Creative tasks and positive emotions”, focuses in even more detail on task-level differences in well-being, investigating specifically tasks that require creativity and provide high levels of autonomy. This study asks how tasks based on problem solving, which are typical for high-skilled workers, may influence worker well-being. The main contribution of this study lies in providing an explanation of whether and why creative problem solving tasks may have a special role in shaping the momentary well-being of a high-skilled worker. The experimental design of this study enables a causal interpretation of its findings, and a cross-national comparison helps to generalize its findings to a wide spectrum of high-skilled jobs across Europe.

Finally, the fifth chapter summarizes and integrates the results from the three empirical studies. The final chapter also discusses the strengths and limitations of the three studies, highlights the methodological contribution brought by the innovative research designs of the studies, and clarifies the contribution of the dissertation to the theoretical models of work-related well-being.

1.1 High-skilled workers

In recent years the growing group of high-skilled workers attracted significant attention from researchers. The profound role this group plays in the modern knowledge economy has even been acknowledged by distinguishing a new class of workers called “the creative class” (Florida, 2002). Members of this new class may be defined using three main criteria: an engagement in complex problem solving, a requirement for a great deal of independent judgement, and a demand for high-levels of education and human capital. This definition corresponds with the approach taken by other authors who studied new occupations or forms of work as representing “the knowledge economy” or “the new rules of work” (Cooper & Burke, 2002; De Spiegelaere, Van Gyes, Benders, & Van Hootegem, 2015; Eurofound, 2015; Powell & Snellman, 2004). There are many examples of such groups in the current workforce that are considered prototypical for the changes in the ways that we work. Engineers in high-tech organizations are commissioned to solve challenging design problems using sophisticated, state-of-the-art technology (Kunda et al., 2002). Entrepreneurs deal with a wide variety of tasks using a balanced set of skills on a daily basis (Åstebro & Thompson, 2011; Lazear et al., 2005). Narrowly qualified freelancers perform highly specified tasks in flexible conditions - with regard to both time and location (Kunda et al., 2002). Knowledge workers hold jobs that focus on the creation, distribution, and application of knowledge (Davenport, 2005). Even though significant differences between these groups certainly exist, all these new types of workers may fall under the one umbrella term of “high-skilled workers”.

In this dissertation, high-skilled workers are defined as individuals having a highly specialized education and working on complex, non-routine tasks. Defining a group of interest based on occupation, rather than on the sector of business or typical job requirements, has a clear practical value. The International Standard Classification of Occupations (International Labour Organization, 2010) is widely used in international reporting, making it easy to find and compare information about high-skilled workers from different sources. Moreover, the system takes into consideration both the education level of a worker, as well as the tasks and duties undertaken in the job. Having a group of interest clearly distinguished from other populations of workers minimizes the variability in demographic and structural variables, and thus helps investigating the differences in variables representing psychological experiences at work, such as working conditions and well-being.

High-skilled workers are typically classified into three occupational groups: managers, professionals, and technicians (Eurofound, 2014a). Not surprisingly, high-skilled workers are the most educated group in the workforce. In Europe, over 80% of professionals hold a university degree. Among managers and technicians about a half have a university degree, which is still significantly higher than in a group of service workers (Eurofound, 2014a).

As this dissertation focuses mainly on Swedish high-skilled workers, it is important to bear in mind that currently 42% of the workforce in Sweden is classified as high-skilled workers (Statistics Sweden SCB, 2014), which is slightly higher than the EU average of 39% (Eurofound, 2014a). Furthermore, an estimated 35% of workers is engaged in creative types of occupation (Tinagli, Florida, Ström, & Wahlqvist, 2007). Policies that ensure high education levels, for example free access to university education, contribute to the growing number of high-skilled workers. Sweden has a well-educated population and a high level of skills relative to other developed countries (OECD, 2015). Moreover, unlike in most other countries, in Sweden labor unions play an important role in ensuring that workers have good generic skills and are adaptable over the course of their career (OECD, 2015). Thus, the large amount and the relative importance of high-skilled workers make Sweden a potentially interesting case for the study of knowledge work.

The entire group of high-skilled workers in Sweden consists of 51% women, yet gender balance varies significantly depending on the position in the organization. Only 37% of managers are women, compared to 60% of professionals and 41% of technicians (Statistics Sweden SCB, 2014). This is a consequence of a segregated labor market in which men and women work not only in different sectors, but also different occupations (Eurofound, 2012). Most high-skilled workers are over 30, and the largest group (around 30%) is between 40 and 50 years old (Statistics Sweden SCB, 2014).

High-skilled workers can be found across all types of industries, yet some industries employ a significantly larger proportion of them. In Sweden, the majority of high-skilled workers are employed in educational establishments (18%), human health and social work establishments (15%), and professional, scientific, and technical companies (13%; Statistics Sweden SCB, 2014). Generally across Europe, high-skilled workers are more commonly employed by the public sector than other occupational groups (Euro-

found, 2014a). Professionals and managers are also more likely than other groups to be self-employed without employees, which means they are likely freelancing or work project-based (Eurofound, 2014a).

According to the report from the European Foundation for the Improvement of Living and Working Conditions (Eurofound, 2014a), working conditions of high-skilled workers are significantly better than in the other occupational groups. High-skilled workers enjoy high salaries and report higher increases in their wages (particularly professionals and managers). Over 50% of high-skilled workers report the recent introduction of new processes and technologies at their workplace, which is much less common for service or sales workers. About a half of high-skilled workers have undergone training paid for by the employer in the past 12 months, and they are also more likely than other occupational groups to participate in training paid by themselves (Eurofound, 2014a). Moreover, they more often take part in on-the-job training. Even though high-skilled workers have more training and learning opportunities than other groups, they are still the ones reporting the highest need for training. Thus, not surprisingly, high-skilled workers most often acknowledge that their jobs involve learning new things. Technology use, especially regarding information and communication technology, is also much higher among high-skilled workers compared to other occupational groups (Eurofound, 2012). Due to the character of high-skilled work, they mainly face intellectual challenges rather than physical risks (Eurofound, 2012).

Due to favorable working conditions, high-skilled workers report fewer health problems than workers in mid-skilled and low-skilled manual occupations (Eurofound, 2014a). Managers, professionals and technicians are also the most informed about health and safety risks at work, which may of course help prevent health problems from occurring (Eurofound, 2012). Apart from this advantage regarding physical health, high-skilled workers score high on a number of psychological well-being indicators, including feeling calm, relaxed, vigorous, and rested (Eurofound, 2014a). Professional and technical workers often indicate higher satisfaction with their working environment, compared to other groups of workers (Eurofound, 2012). The highest level of mental well-being is reported by managers. Professionals and managers also find their jobs more fulfilling and meaningful, compared to technicians and other occupational groups (Eurofound, 2014a).

High skilled workers enjoy the highest levels of procedural autonomy at work (Eurofound, 2012). Around 80% of managers and professionals, as well as around 70% of technicians, are able to choose or change the order of their tasks, methods of work, and speed of work (Eurofound, 2014a). Their work arrangements are often flexible, with about a half of professionals and technicians, and about 70% of managers, being able to adapt their working hours or choose between several working schedules. Only skilled agriculture and forestry workers enjoy higher flexibility in working hours. Apart from high levels of autonomy and flexibility, high-skilled workers are also given more opportunities to influence important decisions in their organizations. Between 60% (technicians) and 80% (managers) of high-skilled workers are able to meet with their supervisors to express their views (Eurofound, 2014a). In sum, workers in high-skilled occupations enjoy relatively high average values on almost all job quality indicators (Eurofound, 2014a).

In general, and compared with service and blue-collar workers, high-skilled workers seem to hold occupations with more favorable conditions, and usually report higher well-being and fewer health problems. However, in recent years many high-skilled workers have experienced an intensification of psychosocial demands at work, which in turn increases the risk of exhaustion (Eurofound and EU-OSHA, 2014; Kelliher & Anderson, 2010) and decreases job satisfaction (Lopes, Lagoa, & Calapez, 2014). Moreover, in technologically advanced economies high-skilled workers account for almost half of the current workforce (Eurofound, 2012). This suggests that the large and growing group of high-skilled workers is likely to be more internally diverse than researchers usually assume. Therefore, a more thorough exploration is needed to understand the similarities and differences between types of working conditions in high-skilled work, and the consequences they have on worker well-being.

In sum, the term “high-skilled workers” refers to a large group of highly educated and specialized professionals. These workers usually enjoy more favorable working conditions than other groups, and report higher well-being levels. However, this group may account for up to half of the entire workforce, including diverse subgroups such as managers, educational professionals, engineers and health care professionals. Thus, this dissertation aims at investigating which aspects of a work environment differentiate happier and healthier individuals within the group of high-skilled workers, rather than in comparison to the other groups.

1.2 Theoretical background

Over the last decades, researchers have uncovered the relationships between working conditions and well-being. They identified a number of work-related health problems, such as burnout, depression and cardiovascular disease, and also discussed theoretical models that explain their outset (Hakanen, Schaufeli, & Ahola, 2008; Maslach, Schaufeli, & Leiter, 2001; Rozanski, Blumenthal, & Kaplan, 1999). They defined indicators of well-being at work, including work engagement and job satisfaction, and developed interventions to promote healthy work (Bakker, Demerouti, & Sanz-Vergel, 2014; Bowling, Hendricks, & Wagner, 2008; Dronavalli & Thompson, 2015; Fisher, 2010; Nielsen & Abildgaard, 2013). Even though individual factors, such as personality or coping strategies, play a significant role in explaining differences in the well-being of workers, the majority of researchers have looked at work environment factors as main predictors of well-being at work. Identifying certain characteristics of the psychosocial work environment as energy-depleting demands marks an important breakthrough in occupational health research. In most jobs psychosocial demands are malleable, rather than inevitable, and thus extensive demands may be addressed by job redesign and other interventions. However, some demands at work are unavoidable, especially when adopting a productivity point of view (Karasek & Theorell, 1990). Moreover, reducing demands completely will likely result in boredom and lack of challenges. Thus, simply eliminating job demands is neither sufficient nor doable, and a more sophisticated solution needs to be prescribed to ensure the well-being of workers.

Current theoretical approaches to stress at work suggest that the concept of balance between negative (stressors) and positive (control, support, resources, rewards) aspects of the work environment may be such a solution. The interaction effect, also known as the buffer hypothesis or the strain compensation process, stands out as the central point of many healthy work theories. Karasek and Theorell in their Job Demands-Control (JDC) model were the first to suggest that the negative effects of demands may be “neutralized” when coupled with sufficient control (Karasek, 1979; Karasek & Theorell, 1990). Later, the model was expanded into the Job Demands-Control-Support (JDCS) model, which includes an additional buffering role of social support to better explain the differences in well-being between workers (Häusser et al., 2010; Johnson & Hall, 1988; Van der Doef & Maes, 1999). The interaction hypothesis was specified even further by the Demand-Induced Strain Compensation model to reflect compensation processes provided by specific resources on specific stressors (de Jonge & Dormann, 2006). Moreover, the idea of balance between the positive and the negative aspects of work environments was also broadly applied in other models of stress at work, for example the Person-Environment Fit model (French, Caplan, & Harrison, 1982) and the Effort-Reward Imbalance model (Siegrist, 1996).

Despite the popularity of the interaction hypothesis, researchers rarely provide a theoretical mechanism that is able to explain its functioning. Some speculate that a lack of control at work constrains an individual by blocking his or her optimal response in a demanding situation (Karasek & Theorell, 1990). This means that even though a person is still able to learn and cope with demands, a constraint presented by a lack of sufficient control will trigger a stress reaction. Another functional explanation of the interaction hypothesis is based on the homeostatic regulation process. In this view, when facing demands at work an individual experiences psychological imbalance that needs to be regulated by corresponding job-related resources (de Jonge, Dormann, & van den Tooren, 2008). A failure to regulate an imbalance induces a stress reaction. Apart from these biologically inspired explanations, the balance hypothesis may also be viewed as a social process. As suggested by the rule of reciprocity, which is explained in detail by the social exchange theory, an effort invested at work should be met by an appropriate reward (Cropanzano & Mitchell, 2005; Siegrist, 1996). In conditions characterized by high demands and lack of resources, an individual must invest a lot of energy to get a relatively small reward. As a consequence, an energy depleting stress reaction is triggered. In sum, the health of a worker depends greatly on the availability of positive psychosocial factors at work that are supposed to ‘neutralize’, in one way or another, unavoidable demands of work.

A broad category of positive factors at work not only buffer against the harmful effect of demands, but also have an intrinsic and motivating value (Gorgievski, Halbesleben, & Bakker, 2011). In the Job Demands-Resources (JDR) model, researchers extended the definition and role of the positive aspects of work environment by labelling them as job resources. The main role of job resources is to facilitate an achievement of work goals and to promote personal development (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). According to the JDR model, a motivational process, in which job resources energize a worker leading to higher work engagement, interacts with an energy depleting process triggered by job demands in predicting worker well-being (Bakker et al., 2014; Demer-

outi et al., 2001). Even though the role of job demands and the interaction hypothesis may help to explain the sources of occupational stress, classifying the positive aspects of work environment as resources and identifying the mechanisms of their functioning provides a better framework for understanding work-related well-being. However, the functional definition of resources allows researchers to create a varying list of positive characteristics of the work environment depending largely on the context of a particular study. Typically, job resources refer either to factors related to the organization of work i.e., job control, potential for qualification, participation in decision making, and task variety, or factors related to social interactions i.e., support from colleagues, groups, and managers (Demerouti et al., 2001). In practice, however, different aspects of the work environment may be called resources, depending on the target group's occupation, education, employment form, position in the organization, and other contextual variables. Such inclusive approaches make it difficult to create a complete list of resources that would be relevant and sufficient across occupational contexts. Instead, it requires taking a more specific approach that will match a group of interest.

Given that the defining feature of high-skilled work is its cognitively demanding character, providing support in this area will likely be the most valid for high-skilled workers. Moreover, a great level of responsibility and a flexible work environment suggest that job control may play a particularly crucial role for the well-being of high-skilled workers. Thus, this thesis focuses mainly on the importance and functionality of positive aspects of the work environment, as defined by the job control concept and when applied to the group of high-skilled workers. The following section of this introductory chapter reviews the meaning and the role of the job control concept, and also discusses its most important aspects - autonomy, creativity, and learning - when applied to research on working conditions.

1.2.1 Job control

In the Job Demands-Control model, Karasek and Theorell proposed decision latitude, more commonly labeled as job control, to be the positive counterpart to job demands (Karasek & Theorell, 1990). According to these authors, psychosocial demands become bearable when workers have a chance to shape and influence their working environment. Feeling in control over one's work assignments opens up a box of possibilities: from simply rearranging tasks in space and time to reinterpreting given assignments so they will become less (or more) challenging. Thus, high job control encourages engagement and prevents stress by allowing workers to react to a situation in the best possible way, or in other words by not constraining their optimal reaction. Such an approach inherently assumes that workers are competent individuals, able to react in a healthy way if only the environment does not prevent them from doing so.

Even though job control refers specifically to the work context, a feeling of being in control over the environment is hardly a new concept in psychology. Definitions of job control may be tracked down to parallel ideas that form the foundation of personality and motivational theories. Self-efficacy, intentionality, locus of control, and self-

determination all refer to similar phenomenon broadly described as a feeling that one's decisions are causing one's own actions (Ajzen, 2002; Bandura, 2001; DeCharms, 1968; Deci, 1980; Deci, Olafsen, & Ryan, 2017; Parkes, 1989). The main difference between the job control concept and other notions lies within the specification of the subject. According to personality and motivational theories, control is mainly a feature of an individual and thus varies between people in a way typical for individual differences. On the other hand, job control defines the ability to shape and influence one's work as a feature of the work environment that may be provided to a worker to differing degrees. Such an approach results in job control being an umbrella term for a set of work environment characteristics gathered under the same function: they all increase workers' feeling of control.

The original concept of job control does not specify why certain characteristics of a situation may increase feelings of control. It simply assumes that a combination of two opportunities available to workers - skill discretion and decision authority - can prevent stress (Karasek & Theorell, 1990). However, the cognitive evaluation theory (CET), initially formulated to explain the sources of intrinsic motivation (Deci, 1980; Ryan & Deci, 2002), may provide an answer as to why skill discretion and decision authority may be particularly important protective factors. CET postulates that perceptions of causality and competence (i.e., control) depend on two characteristics of a situation. The first aspect refers to the presence of external factors influencing workers' behavior. The salience of an external reward and/or the threat of punishment undermine workers' feeling of control. For example, in situations where goals are imposed, deadlines are strict, and evaluation or managerial surveillance are threatening, intrinsic motivation to act may be undermined (Ryan & Deci, 2002). Thus, job control is diminished. In other words, such situations prevent a worker from behaving in an optimal way, and instead force a certain types of expected reactions. The second aspect refers to available information. The amount of knowledge one has about a given situation plays a significant role in raising intrinsic motivation, and thus feelings of being in control. When provided with sufficient information and adequate feedback, workers are more likely to perceive a situation as controllable. Thus, they are more likely to use their skills and knowledge to act in an optimal way. Consequently, skill discretion and decision authority may characterize work environments in which workers feel competent to deal with the demands of their jobs. Such environments present little or no obstacle for high engagement and well-being to occur.

Even though high job control has been repeatedly shown to relate to worker well-being (Häusser et al., 2010; Van der Doef & Maes, 1999), further distinctions within the two aspects of job control may reveal more subtle differences between healthy and unhealthy work environments. For example, skill discretion may be diversified into learning and creativity. Opportunities to learn reflect the extent to which a worker is presented with challenging tasks. On the other hand, opportunities to be creative at work reflect a possibility to freely specify and solve problems. Furthermore, decision authority provides a worker with a possibility to decide on both what to do at work (decision autonomy) and how to complete specific work assignments (procedural autonomy). These examples show that autonomy, creativity, and learning are not only different aspects of the job control construct, but they are also separate features of work environments. Specifically for high-skilled workers, job control as a global construct may not be fine-

grained enough to successfully distinguish between working conditions that lead to better or worse well-being outcomes.

This dissertation focuses on different aspects of the job control concept – autonomy, learning, and creativity – in order to distinguish between the roles they may play in building and sustaining the well-being of high-skilled workers. Thus, three types of relationships are discussed in this thesis: the separate effects of each of the job control aspects on workers' well-being, the joint effects that job control aspects have on workers' well-being, and finally the effects that job control aspects may have on each other.

1.2.2 Autonomy

Autonomy is probably the most important aspect of the job control concept. In fact, workers value freedom to control their own actions higher than the ability to control and influence others (Lammers, Stoker, Rink, & Galinsky, 2016). Being able to choose one's own actions in a way that makes a worker feel in control of her work tasks may be viewed as a prerequisite for other aspects of job control, such as learning and creativity. Workers who enjoy high autonomy may shape their work tasks according to their needs and preferences. Thus, a sense of autonomy relates strongly to worker well-being (e.g., Alarcon, 2011; Loher, Noe, Moeller, & Fitzgerald, 1985), and many organizational interventions were developed to increase autonomy at work (e.g., Hardré & Reeve, 2009; Semmer, 2006). Autonomy may be a characteristic of a person or an environment, and the two are difficult to distinguish in self-reported research. Dispositional autonomy refers to “a feeling” or “a tendency” of a person, while situational autonomy refers to a choice a person has in a given situation (Xiao, Wang, Chen, Zheng, & Chen, 2015). Even though autonomy is sometimes defined as a positive personality trait (i.e., autonomous functioning; Weinstein, Przybylski, & Ryan, 2012) or a skill that develops with age (Sheldon, Housermarko, & Kasser, 2006), autonomy is above all a characteristic of an action (Ryan & Deci, 2011). Therefore, in the context of work environments autonomy may be studied primarily in reference to different tasks performed by workers.

Task autonomy means either an opportunity to decide how a given task will be performed or a choice of what tasks to perform in general. Thus, two dimensions of task autonomy may be distinguished: a regulative one and a constitutive one (Alvin, 2008). The first type refers to how given tasks at work are performed (i.e., procedural autonomy), and the second type refers to what tasks are executed in the first place (i.e., decision autonomy). Typically, a worker will enjoy both types of autonomy, yet the extent of each type may vary in different occupations and work situations. For example, a freelancer may be commissioned to prepare a report without strict guidelines on how to do it. She will have a high level of procedural autonomy as to when and how to complete the job, even though she didn't have a say in deciding that this particular report is needed. On the other hand, when a manager sets up a creative team to solve a problem, she enjoys decision autonomy when deciding which problem should be solved by the team. However, she typically doesn't have much procedural autonomy over the way in which this job will be completed (Grabner & Speckbacher, 2016).

In this dissertation, both decision and procedural autonomy are studied as an experience of being given a choice and freedom of self-expression during tasks at work. In the prospective and the comparative task level studies, participants were asked how often they typically experience both decision and procedural autonomy in their jobs, while in the experimental study participants assessed their perceived autonomy in reference to a specific task.

1.2.3 Creativity

The majority of studies on the creativity of workers investigate creative behaviors - such as problem solving, divergent thinking, and idea generation - as outcomes of a certain work environment. For example, environments that facilitate autonomy, freedom, playfulness, flexibility, and offer a variety of challenges, tend to increase the creative achievements of workers (Hunter, Bedell, & Mumford, 2007; Ma, 2009). However, creativity may be defined not only as a behavioral outcome, but also as a characteristic of work tasks. Specifically for high-skilled workers, job descriptions are filled with tasks that require creative self-expression, problem solving, and abstract reasoning (Cohen, 2005; Fincham, 2006).

Opportunities to be creative at work fall into the category of skill discretion in the definition of job control, and are usually measured using an item worded as “my job requires me to be creative” (Fransson et al. 2012). Creativity requirement, defined as the perception that one is expected or needs to generate work-related ideas, facilitates the creative achievements of workers (Unsworth, 2005), and also increases job satisfaction and reduces intentions of leaving (Shalley, Gilson, & Blum, 2000). Moreover, several researchers have hypothesized the existence of a gain spiral, where creative activities improve emotional well-being and positive emotions in turn facilitate creative achievement (Amabile, Barsade, Mueller, & Staw, 2005; Bar, 2009; Richards, 2010). Thus, creativity may be studied both as an outcome of a supportive work environment, but also as a predictor of worker well-being (Anderson, De Dreu, & Nijstad, 2004).

In this dissertation, opportunities to be creative are measured as a characteristic of a work environment, or more specifically of a task at hand. In the prospective and the comparative task level studies, participants were asked how often they are required to, or have a possibility to, express themselves in a creative way. In the experimental study, the creativity of a task was an independent variable that was manipulated by randomly assigning participants to solve a creative or a non-creative task.

1.2.4 Learning opportunities

High-skilled workers need to constantly learn not only to stay productive in the world of rapid technological advances, but also to sustain high levels of well-being. Learning opportunities build effectiveness and increase a feeling of control over every day work

challenges (Noe, Clarke, & Klein, 2014). Thus, a key aspect of job control refers to skill discretion in terms of challenges and learning occasions, during which workers may apply their skills and build their confidence. In fact, increased self-efficacy is a valid indicator of training effectiveness on the individual level (Bell, Tannenbaum, Ford, Noe, & Kraiger, 2017).

Challenges are necessary for the development of work engagement. As frequently demonstrated by research on the concept of flow – which is a psychological state of happiness, high energy and cognitive efficiency – challenging tasks may increase well-being when accompanied with a high skill level (Fong, Zaleski, & Leach, 2014; Keller, Ringelhan, & Blomann, 2011; Lambert, Chapman, & Lurie, 2013; Moneta, 2012a). Moreover, challenging aspects of work environments seem to bring more energy and vigor rather than trigger exhaustion (Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). Opportunities to learn and gain resources for the future may even compensate for unfavorable working conditions in the present (Schmitt, Zacher, & de Lange, 2012). In other words, high learning opportunities prevent a loss in work engagement during challenging and difficult times at work.

In this dissertation, opportunities to learn at work refer to the extent to which workers are provided with challenging tasks that allow them to learn new things. In the prospective and the comparative task level studies, participants assessed how often they are given a possibility to learn new things and take on difficult tasks. In the experimental study, the perceived difficulty of a task was controlled for when analyzing the effect of a creative task on well-being.

In sum, there is significant evidence available to assume that the three aspects of the job control concept – autonomy, learning, and creativity – are related to worker well-being. The following part of this introductory chapter reviews how well-being is understood and measured in this dissertation.

1.2.5 Well-being

In this dissertation, positive aspects of the work environment are assumed to play a crucial role in sustaining high-skilled workers' well-being. This assumption builds on current approaches to health as a state of well-being and an ability to adapt, and not merely the absence of disease or dysfunction (Huber et al., 2011; World Health Organization, 1948). In line with this, researchers should focus their attention on these aspects of the work environment that not only prevent stress-related health problems, but also increase and promote well-being. Therefore, worker well-being is a key outcome variable in organizational research. Interventions, work environment arrangements, quality of management, and many other aspects of work environments are nearly always validated against changes in work well-being (often together with or as an alternative to work performance). This means that the well-being of a worker needs to be effectively and precisely measured. Thus, the issue of well-being measurements has been a subject of lively discussion (Fisher, 2010; Kahneman, 1999; Kashdan, Biswas-Diener, & King, 2008; Pavot & Diener, 2008; Straume & Vittersø, 2015; Waterman, 2008). Among the various operationalizations of well-being, two stand out as the most common: job satisfaction and job engagement.

Job satisfaction is defined as a pleasurable emotional state resulting from one's job (Cranny, Smith, & Stone, 1992; E. Locke, 1969). This classic definition has been criticized for suggesting that job satisfaction reflects mainly an affective state, which does not seem to be entirely correct (Weiss, 2002). More appropriately, job satisfaction reflects a cognitive judgement of one's job. Satisfaction scores build largely on an evaluation of work in terms of aspects one finds adequate and sufficient to one's expectations (Warr & Inceoglu, 2012). In other words, workers are satisfied with a job when it fits their expectations. However, the cognitive nature of such judgement does not mean that job satisfaction has no emotional component. An experience of satisfaction is characterized by positive affect with moderate to low arousal (Warr & Inceoglu, 2012). Individual differences in affectivity are responsible for 10 to 25% of variance in job satisfaction (Connolly & Viswesvaran, 2000). Thus, the affective component of job satisfaction seems to reflect mainly stable dispositional traits, given that job satisfaction scores show considerable test-retest stability (Dormann & Zapf, 2001). In general, job satisfaction represents a fairly stable evaluation of one's job in terms of both a cognitive appraisal and an affective reaction resulting from such appraisal. The emotional component, however, reflects only a moderately positive experience of having one's expectations met, and does not seem to capture the short-term fluctuations of affect as it varies from day to day or even from task to task.

Job engagement, in its most parsimonious definition, refers to a positive affective state characterized by high arousal and involvement in a task (Bakker, Albrecht, & Leiter, 2011b; Inceoglu & Warr, 2011). Thus, engagement represents an active psychological state rather than a set of behaviors (Parker & Griffin, 2011). Even though several other constructs have been previously included under the umbrella of employee engagement (Hallberg & Schaufeli, 2006; Kahn, 1990; Macey & Schneider, 2008), an ongoing discussion has stripped down the definition to its core, i.e. to an affective state (Bakker, Albrecht, & Leiter, 2011a; Bakker et al., 2011b; Bakker & Demerouti, 2008). When embedded into the wider nomological net, the concept of engagement brings a unique contribution to the existing well-being measurement mainly due to its ability to capture short term fluctuations of worker well-being, and because it includes a motivational component directed to present and future actions (Bledow, Schmitt, Frese, & Kühnel, 2011; Breevaart, Bakker, & Demerouti, 2014; Tadić, Bakker, & Oerlemans, 2015).

Apart from the two indicators of well-being, this dissertation also measures one of many possible indicators of ill-being. Emotional exhaustion refers to a feeling of chronic fatigue, and is a central quality of burnout syndrome (Maslach et al., 2001). Even though emotional exhaustion is strongly associated with job engagement, they are distinct constructs rather than opposite sides of the same dimension (Demerouti, Mostert, & Bakker, 2010). While job engagement changes from tasks to task, and thus emerges during the process of working, exhaustion refers to a chronic state with little fluctuation from one day to the other (Sonnentag, 2017). Therefore, increased exhaustion is considered a symptom of the chronic ill-being of a worker, and the first indicator of the burnout syndrome (Gustavsson, Hallsten, & Rudman, 2010).

In this dissertation, well-being is studied mainly as an experience of engagement that varies from one activity to the other. The reason for this relates to the momentary character of engagement, and its responsiveness to change in working conditions. Thus,

two studies included in this dissertation, which focus on the well-being experience on the task level, use momentary engagement as an operationalization of well-being. In the prospective study, the time perspective is broader, and the results are aggregated to a group level. Thus, in this study an evaluative aspect of well-being is measured through job satisfaction, and symptoms of ill-being are measured through emotional exhaustion.

1.3 Overview of the studies

The main research question of this dissertation refers to the interplay of specific aspects of job control – autonomy, creativity, and learning – and their relations to the well-being of high-skilled workers. The three studies included in the thesis explore how and why these aspects of work environment may bring increased well-being to a worker. Thus, the main focus here is to identify mechanisms that can explain whether and why certain combinations of positive work environment characteristics would bring beneficial outcomes to high-skilled workers. To achieve this goal, different research designs were used in the three empirical studies included in this dissertation.

First, the phenomena in question were studied on three levels of analysis. In the prospective study (chapter 2), perceptions of the work environment as reported by individual workers were aggregated into patterns of typical experiences as shared by a group. In this study, different configurations of work environment characteristics predicted the well-being and ill-being of diverse groups of workers. In the comparative task level study (chapter 3), aspects of job control were included as predictors of task level outcomes. Worker well-being was measured on the task level, and analyzed on both task and person levels. In general, the task level is considered a baseline level on which the well-being of a worker emerges. In the experimental study (chapter 4) aspects of job control (mainly creativity and autonomy) as well as positive emotions were studied in reference to a specific task. Thus, the research results presented in this dissertation range from a macro level i.e., population perspective and longitudinal changes over several years, to a micro level i.e., differences in work tasks and changes of momentary well-being. Figure 1.1 presents a summary of the levels of analysis discussed in this dissertation. Second, in addition to differences in levels of analysis, each of the studies referred to

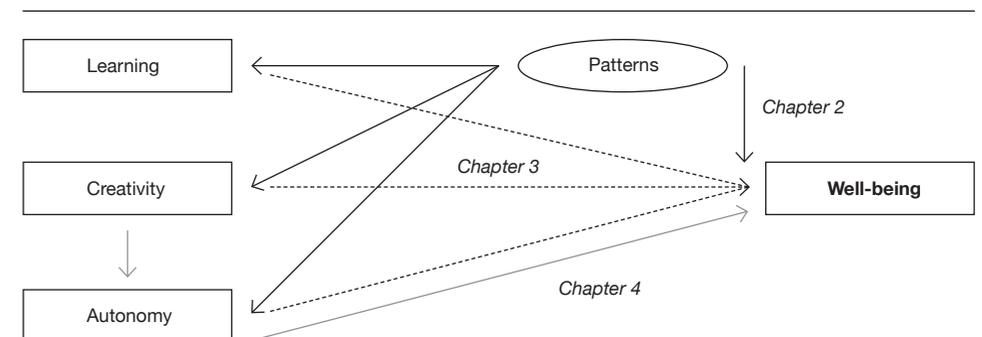
Figure 1.1 Overview of levels of analysis of the three studies presented in this dissertation.

Group level Patterns of a typical individual experience as shared by a group	Chapter 2	Chapter 3
Person level Typical work experiences of an individual		
Task level Momentary work experiences of an individual	Chapter 4	

a different time frame, starting from a long-term perspective and ending with a momentary experience. In the prospective study, changes in working conditions and well-being were studied over a six year period with three measurement occasions. In the comparative task level study, an experience of a worker was measured in reference to a typical day at work. In the experimental study, momentary changes in well-being were analyzed in reference to a specific task. Thus, this dissertation discusses mechanisms of change in well-being from both long-term and short-term perspectives.

Third, relationships between the aspects of job control and worker well-being were modelled using three different perspectives. In the prospective study, participants were classified into groups based on the availability of autonomy, learning, and creativity, as well the prevalence of job demands, in their work environments. Next, the groups were compared in terms of their well-being and ill-being. In the comparative task level study, each aspect of job control was specified as a separate predictor of worker well-being. In the experimental study, a mediation model was tested where creative task predicted well-being indirectly through an increase in autonomy. Figure 1.2 presents simplified models of the relationships between aspects of job control and worker well-being described in this dissertation. The solid lines represent the model from the longitudinal study (chapter 2), the dashed lines represent the model from the multilevel study (chapter 3), and the grey lines represent the model from the experimental study (chapter 4).

Figure 1.2 Relationships between aspects of job control and well-being in three studies.



Fourth, specific groups were compared in each of the three studies to determine whether the findings may be generalized across diverse types of high-skilled workers. In the prospective study, a large sample (N = 1,744) was derived from a representative population of high-skilled workers in Sweden, and the analyses empirically divided the sample into four groups of workers characterized by different patterns of working conditions. In the comparative task level study, two matching samples of high-skilled workers were recruited from the creative sector in Sweden - one group was self-employed (n = 86) and the other was organizationally employed (n = 81). In the experimental study, four samples of highly-educated adults were recruited in different countries, including English speaking participants (n = 159), Italian speaking participants (n = 106), Polish speaking participants (n = 123), and German speaking participants (n = 90). Thus, this dissertation

provides an overview of differences and similarities across multiple groups of high-skilled individuals.

Fifth, each of the study designs allowed for a certain degree of cause-effect investigations. In the prospective study, well-being variables were measured with a two-year time lag from the measurement of working conditions, suggesting time referenced causality. In the comparative task level study, a general experience of working conditions was specified as a predictor of task level well-being, assuming that general well-being arises from task to task fluctuations of emotions. In the experimental study, creativity of a task was manipulated, implying the causal effect of creative tasks on well-being, mediated by a change in perceived autonomy levels. Thus, this dissertation attempts to discuss the causality of relationships between work environment characteristics and the well-being of high-skilled workers.

In sum, the empirical studies included in this dissertation attempt to present a comprehensive overview of the relationships between work environment characteristics of high-skilled work and the well-being of workers: across levels of analyses, over long and short time frames, across diverse groups of workers, and through three explanatory models that allow for different levels of cause-effect investigation. Importantly, this dissertation was planned in the form of a stepwise exploration: starting from a prospective study of the work environment in a large sample of high-skilled workers, through an investigation of the differences between the self-employed and the organizationally employed high-skilled workers, and ending with an experimental test of the momentary effects that tasks typical for high-skilled workers may have on worker well-being.

Chapter 2: Psychosocial working conditions among high-skilled workers

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Abstract

Theories of psychosocial working conditions assume an interaction of different work environment characteristics. Most studies detail various aspects of such interactions, while fewer investigate the comprehensive patterns of interrelated variables. This exploratory study distinguishes patterns of psychosocial working conditions, describes their characteristics, and investigates their change over six years. The working conditions of 1,744 high-skilled workers in Sweden, of a representative sample of the working population, were empirically classified into four distinct patterns: 1) the Supporting pattern with a very low workload, very low time pressure, medium learning opportunities, high creativity requirements, and very high autonomy; 2) the Constraining pattern with a very low workload, very low time pressure, low learning opportunities, medium creativity requirements, and very low autonomy; 3) the Demanding pattern with a high workload, high time pressure, medium learning opportunities, high creativity requirements, and very low autonomy; 4) the Challenging pattern with a high workload, high time pressure, very high learning opportunities, very high creativity requirements, and very high autonomy. Importantly, these patterns were associated with significant differences in worker well-being. From an individual perspective, working conditions most often changed from patterns with a high workload and time pressure to patterns with lower levels of these demands. Over time, the prevalence of the Constraining pattern increased while that of the Challenging pattern decreased. To conclude, a person-centered approach broadens the understanding of the complex interplay between psychosocial working conditions and their longitudinal change, which can improve the tailoring of occupational health interventions.

2.1 Introduction

Undoubtedly, working conditions are more favorable in some occupations than in others. High-skilled workers, defined as individuals having a highly specialized education and working with complex, non-routine tasks, typically hold occupations that include favorable characteristics, such as high earnings, good future prospects, good training opportunities, and high work autonomy (Eurofound, 2014a). Also, high-skilled workers consistently report better well-being and fewer health problems than mid- or low-skilled workers (Batinic, Selenko, Stiglbauer, & Paul, 2010; Eurofound, 2014a). However, in recent years, many managers, professionals, and technicians have experienced an intensification of psychosocial demands at work, which in turn increases the risk of exhaustion (Eurofound and EU-OSHA, 2014; Green, 2001; Kelliher & Anderson, 2010) and decreases job satisfaction (Lopes et al., 2014). To understand these seemingly contradicting phenomena, this paper applies the perspective of an individual to identify typical patterns of interrelations of working conditions and their prevalence within the large and expanding group of high-skilled workers.

To date, few studies have investigated the heterogeneity of the apparently privileged group of high-skilled workers. Yet, due to their occupational position or a given sector of work, it is likely that some high-skilled workers are more prone to report a certain pattern of working conditions. Moreover, the prevalence of specific patterns in the population of high-skilled workers may vary over time since individuals may have to, or actively seek to, transition between them. The broad and comprehensive methodology of this study, seldom used in previous research, makes important contributions to the existing knowledge by demonstrating how working conditions can be grouped into distinct patterns, how prevalent such patterns are among various groups of high-skilled workers, and how individuals transition between them over time. Going beyond current variable-oriented interaction frameworks, this study will contribute to opening up a discussion regarding the role of specific working conditions. Specifically, our approach allows for flexible modeling of complex patterns that extends the prevailing analysis of a number of two-way interactions. Grouping individuals into such complex patterns provides a unique opportunity for studying work environments and their change over time.

Studies employing person-centered approaches, clustering methods (Brusco, Steinley, Cradit, & Singh, 2012) and latent class procedures (Wang & Hanges, 2011), have become increasingly popular in organizational research (Bernhard-Oettel, Isaksson, & Bellaagh, 2008; Kam, Morin, Meyer, & Topolnytsky, 2013; Merez & Andysz, 2014; Van den Broeck, Lens, De Witte, & Van Coillie, 2013). This study applies such a person-centered approach to identify patterns of individual experiences at work. While variable-centered approaches focus on associations between variables in a population, person-centered approaches use variability between individuals to distinguish unique subpopulations (Collins & Lanza, 2010; Wang & Hanges, 2011). For example, in this study, instead of describing relationships among variables representing job characteristics, we aim to distinguish a latent mixture of subpopulations characterized by different patterns of working conditions within a larger group of high-skilled workers. Such patterns provide an exploratory description of the interplay between different aspects of working conditions. Besides providing an empirical and exploratory distinction among the patterns, we aim to validate these patterns by investigating the stability of the classification over time along with the relationships of different patterns to worker well-being. Thus, another important contribution of this study lies in its identification of the ways that different patterns of working conditions relate to worker well-being.

2.1.1 Identifying patterns of psychosocial working conditions

Psychosocial factors at work refer to the way in which the work is organized, the content of the job, the workload, and working time arrangements (Eurofound and EU-OSHA, 2014). The main theories of psychosocial working conditions assume an interaction among various aspects of the work environment. For instance, different types of combinations have been identified based on the interrelations between job demands and different dimensions of job control, such as high-strain jobs characterized by high demands and low control, low strain jobs involving low demands and high control, and active-learning jobs with high demands and high control (Karasek, 1979; Karasek &

Theorell, 1990). Others have investigated working conditions in which both job demands and job resources (including job control and other factors) are high, particularly when compared to conditions where demands are high but resources are low (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007; Bakker, van Veldhoven, & Xanthopoulou, 2010). Despite the many studies that have investigated the interaction effects of two or three types of job demands and job resources (Häusser et al., 2010; Van Vegchel, De Jonge, & Landsbergis, 2005), research identifying complex multivariate patterns of psychosocial working conditions remains scarce. Specifically, this means that previous studies have mainly focused on investigating the degree to which a specific interaction of variables predicts various outcomes. In contrast, a person-centered methodology investigates how individuals differ in types that may incorporate the more complex interplay among the various aspects of a work environment. Consequently, such a person-centered approach allows for estimating the prevalence of each type (i.e., pattern) and for investigating changes among patterns over time. This important information is typically omitted in studies focusing on the strength of prediction rather than the prevalence of patterns of working conditions.

Only few studies have applied a person-centered approach. Yet, these studies have demonstrated that investigating unique combinations of several variables representing a pattern in working conditions can further knowledge beyond what is already known. Similarly to previous person-centered research, in this study indicators of psychosocial working conditions, such as time pressure or workload (typically referred to as job demands) and learning opportunities, creativity, and autonomy (often classified as job resources), are allowed to vary independently from one another and thus forming a unique pattern of working conditions. Previously, three types of such patterns have been distinguished: 1) healthy patterns characterized by high resources and low demands, 2) risky patterns with matching levels of resources and demands, and 3) unhealthy patterns characterized by low resources and high demands (Berntson, Wallin, & Härenstam, 2012; Härenstam et al., 2003; Vanroelen, Louckx, Moors, & Levecque, 2010). Typically, the healthy patterns are the most prevalent. Studying a full range of occupations, clusters of low-skilled workers have been found to differ from clusters of high-skilled workers. Specifically, the latter have been characterized by higher psychological demands, rather than physical demands, at work. These healthy, unhealthy, and risky patterns also emerged for the high-skilled group (Härenstam et al., 2003). In the current study, we expected to find a similar composition of at least three types of patterns, with healthy patterns being the most prevalent. However, the substantial heterogeneity of indicators, in addition to the diversity of workers in the samples of previous research, leads to a significant variability in the number and type of patterns identified. For example, together with dimensions of resources and demands respectively, previous studies have used different other indicators such as client conflicts and client recognition (Berntson et al., 2012), work-life balance (Härenstam et al., 2003), as well as overtime work and physical demands (Vanroelen et al., 2010). The target population has also varied greatly. Some studies have included a very narrow sample e.g., only managers in the public sector (Berntson et al., 2012) while others have studied a large group of workers from various occupations (Vanroelen et al., 2010). Thus, the clusters identified in previous studies have been rather different from each other and difficult to compare systematically across samples. Also, the limited use of the person-centered approach in previous research makes it difficult to

a priori define which and how many of the patterns of psychosocial working conditions to distinguish, particularly in the group of high-skilled workers. Thus, we adopted an exploratory study approach in which neither the number nor the prevalence of patterns was specified beforehand (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). To reflect typical aspects of the work environment, our choice of indicators was guided by the Job Demands-Control model (Karasek, 1979; Karasek & Theorell, 1990). The operationalization of this model includes the most parsimonious and commonly used set of indicators. Furthermore, these indicators can be combined in various ways in subpopulations of high-skilled workers. This means that the opportunity to make decisions concerning daily work, the work pace, the intensity of work, and requirements to be creative or to continuously learn new things may vary considerably among diverse occupational groups of highly-skilled professionals. To explore such variability, working conditions were not grouped in general terms of control and demands. Instead, they were investigated as separate indicators of unique work environment characteristics. Accordingly, we formulated the following research question:

Research Question 1: Which patterns of working conditions can be distinguished among high-skilled workers and how prevalent are these patterns?

2.1.2 Explaining differences in working conditions

Patterns of working conditions are likely to be associated with occupational differences among workers and as relating to an individual's occupational level and sector of work. However, these patterns also correspond to individual characteristics including gender and age. For instance, technicians and lower-level professionals typically have less decision autonomy regarding the ordering of both their job tasks and methods used (Eurofound, 2014a). As for managers, they seem to work more intensively, with demands being particularly high for women (Eurofound, 2014a; Gadinger et al., 2010). Not having enough time to get the job done also seems more prevalent among managers and technicians (Eurofound, 2012). Moreover, working conditions may vary considerably among different work sectors. For example, engineers more often encounter new processes and technologies (Eurofound, 2014b) and may thus have more learning opportunities at work than other high-skilled workers. Moreover, healthcare professionals tend to experience low levels of autonomy at work (Linzer, 2009; Lu, Barriball, Zhang, & While, 2012), while education professionals often report a high workload (Ballet & Kelchtermans, 2009; Bauer et al., 2007). As for individual characteristics, women often report their work as more demanding (Theorell et al., 2014) and experience lower job control than men (Niedhammer, Sultan-Taieb, Chastang, Vermeylen, & Parent-Thirion, 2012). In particular, women professionals report less decision autonomy and higher time pressure (Eurofound, 2012; Schütte et al., 2014). Finally, older workers at the later stage of their careers often report having less stressful working conditions (Vanroelen et al., 2010). In general, younger workers are more likely to have jobs with multiple disadvantages, as compared to workers over 50 years of age (Eurofound, 2014a). Another factor involves workers gaining mastery and experience over time, which means that the older they get, the less complicated and demanding they may perceive their jobs. This perception relates to career development:

over time, workers often reach a professional position involving lower demands (Eurofound, 2014a). In view of these findings, there is reason to believe that the patterns of working conditions will be linked to occupational differences and individual characteristics. However, since person-centered studies of working conditions are rare, we formulated a research question instead of a hypothesis:

Research Question 2: Are certain groups of workers (managers, technicians, engineers, education professionals, healthcare professionals, women, older workers) more likely to have a specific pattern of working conditions?

2.1.3 Validating the patterns of working conditions

To ensure a meaningful interpretation of empirically identified patterns, we attempt to validate them with external variables (Bergman, Magnusson, & El-Khouri, 2003). Given the consistent findings showing that working conditions are linked to worker well-being and ill-being, this study included the validation variables of job satisfaction and emotional exhaustion. Job satisfaction scores reflect not only a pleasurable state resulting from the job but also relate to levels of positive affect and general life satisfaction (Bowling, Eschleman, & Wang, 2010; Connolly & Viswesvaran, 2000). Emotional exhaustion represents a key dimension of the burnout construct (Maslach & Leiter, 2008). Also, the emotional exhaustion subscale has been found to be the most robust and reliable dimension of burnout (Schaufeli & Enzmann, 1998). Moreover, recent findings suggest that exhaustion first occurs as an early symptom of burnout and then develops further in individuals with dysfunctional coping strategies (Gustavsson et al., 2010). Thus, the chosen variables represent important core constructs of well-being and ill-being, respectively.

According to the Job Demands-Control model (Karasek, 1979; Karasek & Theorell, 1990) and its extensions (the Job Demands-Control-Support model, Johnson & Hall, 1988; the Job Demands-Resources model, Demerouti et al., 2001), psychosocial working conditions relate to health and well-being in two primary ways. First, the so-called strain hypothesis assumes an increased likelihood of poor health and reduced well-being for individuals in highly demanding jobs (Häusser et al., 2010). Thus, individuals having to deal with high demands are expected to be more exhausted and less satisfied with their jobs than those with low demands. Specifically, the combination of high demands and low resources is expected to be the most detrimental to worker well-being (e.g., Härenstam et al., 2003; Lopes et al., 2014). Second, the so-called buffer hypothesis assumes that positive work characteristics attenuate the impact of high demands on worker well-being (Bakker et al., 2014; Van der Doef & Maes, 1999). This means that high demands, when combined with corresponding and sufficiently adequate resources, are considered neutral for well-being (Bakker et al., 2010; de Jonge & Dormann, 2006). Thus, in general, patterns with high intensity and a fast work pace, combined with opportunities to decide and learn, seem more likely to yield lower exhaustion and higher satisfaction than patterns that do not couple demanding aspects of work with such opportunities (Karasek & Theorell, 1990). For those with chronic exposure, the detrimental effects of stressors on well-being tend to accumulate over time (Ford et al., 2014). Thus, one of the

questions explored in this study investigates how different patterns relate to outcomes reflecting worker well-being over a two-year time lag.

Research Question 3: How do patterns of working conditions differ in terms of worker well-being after a two-year time lag?

2.1.4 Investigating changes over time

Variations in work characteristics are related to both organizational and individual factors. Negative aspects of the working environment, such as high job demands, seem to fluctuate more over time than positive aspects, such as job resources (Brauchli, Schaufeli, Jenny, Fülleman, & Bauer, 2013). Demands may also fluctuate as job requirements in project-based work vary (Pinto, Dawood, & Pinto, 2014) or change due to career transitions within organizations (Rigotti, Korek, & Otto, 2014). Also, individuals seem to modify independently their working conditions through job crafting (Tims, Bakker, & Derks, 2012). In particular, workers have been found to try to increase their job control and reduce organizational constraints (Li, Fay, Frese, Harms, & Gao, 2014). Thus, over time, the patterns of working conditions may undergo certain changes.

To date, no study has investigated whether and how the prevalence of patterns changes over time (structural stability) and whether and how workers transfer from one pattern to another (individual stability). The structural stability over time mainly contributes to the methodological validity of identified patterns, which confirms that the same patterns may be found at different time points (Bergman et al., 2003). However, it is even more interesting to investigate individual stability, which includes the prevalence and directions in which individuals transfer from one working condition pattern to another. Such an exploratory analysis of longitudinal transitions among the patterns of working conditions stands out as the main contribution of this study. We aim to explore whether individuals transfer between patterns, how common such transitions are, and whether the same types of transitions can be detected over the two-year periods between measurement occasions of this study.

Research Question 4: How do individuals transfer from one working conditions pattern to another over time?

2.2 Method

2.2.1 Participants and data collection

Participants came from the Swedish Longitudinal Occupational Survey of Health (SLOSH), a nationally representative longitudinal cohort survey (Magnusson Hanson, Theorell, Oxenstierna, Hyde, & Westerlund, 2008). Respondents recruited into SLOSH were originally drawn from the entire Swedish population after their stratification by

county, citizenship, and inferred employment status. As part of the Swedish Work Environment Survey (SWES), a group of gainfully employed individuals, aged 16 to 64, were invited to respond to supplementary questionnaires (Magnusson Hanson, Chungkham, Ferrie, & Sverke, 2015). Through SLOSH, a successively increasing number of participants in SWES 2003-2011 who fulfilled the above criteria responded to self-report questionnaires in year 2008 (n = 11,441), 2010 (n = 11,525), and 2014 (n = 20,316). Ethical approval was obtained from the Swedish Central Ethical Review Board (Ref no #2014/2046-31).

The current analysis included a subsample (N = 1,744) of workers who fulfilled the three inclusion criteria: 1) responded to the SLOSH questionnaires in 2008, 2010, and 2012, 2) worked at least 30% of full-time during the past three months at all of the measurement occasions, and 3) were classified as high-skilled workers according to the Swedish Standard Classification of Occupations (SSYK; Statistics Sweden SCB, 2012). Regarding the last inclusion criterion, high-skilled workers were defined as those categorized into three occupational groups of the SSYK: 1) legislators, senior officials or managers, 2) professionals, and 3) technicians and associated professions. This classification was based on the job titles provided by the participants. The Table A.2 in the Appendix presents detailed information about the representativeness of the analytic subsample. The general response pattern in the SLOSH panel involves more women, older, married or cohabiting, born in Sweden, with a university degree, and from the governmental sector responding to the questionnaire over time. These differences tend to become more substantial in later follow-ups; and so, we decided against modeling the data from the last wave. Thus, we only used well-being and ill-being scores from time 4 (2014) to represent differences in these measures over a two-year time lag.

At the baseline measurement in 2008, the mean age of participants was 47.4 (SD = 8.5), ranging from 25 to 65 years. The study sample included more women (60.8%) than men (39.2%). The majority of the participants were born in Sweden (93.9%), held a university degree (72.5%), were married or cohabiting (60.8%), and had children living at home (59.7%). Governmental institutions (57.7%) and private companies (37.6%) were primarily their employers. About half of the sample worked at enterprises employing fewer than 50 individuals (43.5%). The majority had a day job (87.4%) while others worked shifts (7.0%) or had non-regulated working hours (4.4%).

2.2.2 Measures

Psychosocial working conditions were measured with seven items based on the Swedish version of the Demand Control Questionnaire (Sanne, Torp, Mykletun, & Dahl, 2005). Indicators represented learning opportunities (“Do you have the opportunity to learn new things through your work?”); opportunities to be creative at work (“Does your work require creativity?”); decision autonomy (“Do you have a choice in deciding what you do at work?”) and procedural autonomy (“Do you have a choice in deciding how you do your work?”); time pressure (“Do you have to work very fast?”); intensification of work (“Do you have to work very intensively?”) and extensive workload (“Does your work demand

too much effort?”). In the analysis, the items were treated as separate indicators meaning that no composite scales were formed. All items were rated on a 4-point response scale with alternatives labeled “yes, often”, “yes, sometimes”, “no, seldom”, and “no, hardly ever.” Answers of “yes, often” were coded as 1, while all other responses were coded as 0. This coding strategy was more likely to capture stable characteristics of the work environment rather than short-term fluctuations. In the analyses, a single binary indicator represented each item. Table 2.1 presents the prevalence of “yes, often” responses (coded “1”).

Ill-being, in terms of emotional exhaustion, was measured with a two-year time lag. Five items were used in 2010 and 2012, while four items were used in 2014. Items used in 2010 and 2012 were excerpted from the Swedish version of the Maslach Burnout Inventory (Hallberg & Sverke, 2004), while the items used in 2014 were excerpted from the Shirom-Melamed Burnout Questionnaire (Grossi, Perski, Evengård, Blomkvist, & Orth-Gomér, 2003). These items (e.g., “My job makes me feel emotionally drained”) were rated on a 6-point response format ranging from 1 “few times a year or never” to 6 “every day” (a 7-point scale was used in 2014). The scale yielded high internal consistency ($\alpha = .87$ on average across time points) and moderate stability ($r = .66$ from 2010 to 2012, and $r = .53$ from 2012 to 2014). The mean index score from the scale was low ($M = 2.22$ [2010], 2.24 [2012], and 2.33 [2014], respectively). To simplify comparisons between groups, the index scores were standardized into a scale with $M = 0$ and $SD = 1$.

Well-being, in terms of job satisfaction, was also measured with a two-year time lag. A single-item indicator was used (“Roughly, how satisfied are you with your work?”). The response format ranged from 1 “very dissatisfied” to 8 “very satisfied.” The stability of the score was moderate ($r = .45$ from 2010 to 2012 and $r = .48$ from 2012 to 2014). The mean score was high ($M = 6.00$ [2010], 6.09 [2012], and 6.04 [2014], respectively). Again, the scores were standardized into a scale with $M = 0$ and $SD = 1$ to simplify comparisons between groups.

Occupational position was coded according to the SSYK classification, and reflects the skill level of a worker based on the complexity of work tasks and the length of the formal education that is typical for the particular occupation (SSYK; Statistics Sweden SCB, 2012). When comparing jobs, the jobs of technicians and associate professionals (e.g., dental hygienists) are considered less complex than are the jobs of professionals (e.g., dentists) and managers (e.g., managers in health care) within the same sector of work. Across the different time points, professionals formed the largest of the occupational groups (2008: 47.8%; 2010: 45.6%; 2012: 44.3%), followed by the group of technicians and associate professions (2008: 40.5%; 2010: 42.4%; 2012: 41.6%), while the minority group included managers and executives (2008: 11.8%; 2010: 11.9%; 2012: 14.1%). In the analysis, dummy variables were created for managers (1 = manager, 0 = not a manager) and technicians (1=technician, 0=not a technician), while professionals constituted the reference group.

Table 2.1 Study variables and correlations within time points (N = 1744)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Gender (1=female, 0=male)	-.12	.01	-.32	.23	.20	.07	.03	.00	-.01	.07	.05	.05	.12	.01
Age	.02	-.07	-.14	.07	.07	-.10	.02	.07	.11	-.01	.04	.06	-.01	.04
<i>Time 1 (2008)</i>														
1. Managers	.12													
2. Technicians	-.30	.40												
3. Engineers	-.07	.05	.19											
4. Healthcare professionals	-.10	.04	-.24	.20										
5. Education professionals	-.07	-.09	-.24	-.25	.20									
6. Learning opportunities	.04	-.07	.03	.02	-.07	.52								
7. Creativity requirement	-.03	-.08	-.02	-.08	.27	.18	.67							
8. Freedom how to work	.10	-.11	-.01	-.10	.14	.07	.14	.61						
9. Freedom what to do	.10	-.04	-.07	-.09	.11	.09	.15	.46	.29					
10. Working fast	.06	-.02	-.09	.07	-.06	.07	.05	-.11	-.06	.24				
11. Working intensively	.08	-.12	-.08	.02	.02	.08	.09	-.04	-.03	.52	.21			
12. Working with too much effort	.08	-.08	-.10	.01	.11	.03	.14	-.04	-.04	.31	.45	.22		
<i>Time 2 (2010)</i>														
1. Managers	.12													
2. Technicians	-.32	.42												
3. Engineers	-.05	.02	.19											
4. Healthcare professionals	-.07	.09	-.24	.20										
5. Education professionals	-.07	-.12	-.24	-.25	.20									
6. Learning opportunities	.00	-.08	.00	.00	-.03	.50								
7. Creativity requirement	.00	-.08	-.03	-.07	.23	.21	.67							
8. Freedom how to work	.08	-.13	.00	-.09	.10	.12	.16	.56						
9. Freedom what to do	.08	-.05	-.07	-.04	.08	.04	.14	.49	.28					
10. Working fast	.03	-.03	-.05	.07	-.02	.08	.07	-.04	-.02	.17				
11. Working intensively	.07	-.07	-.06	.02	.05	.09	.08	-.04	-.02	.49	.14			
12. Working with too much effort	.07	-.08	-.08	.00	.14	.04	.09	-.01	.00	.32	.43	.15		
13. Emotional exhaustion	-.05	-.06	-.09	.03	.15	-.04	.07	-.14	-.14	.23	.24	.27	2.2	
14. Job satisfaction	.12	-.03	-.01	.02	-.07	.14	-.01	.19	.16	-.06	-.07	-.14	-.43	6.0
<i>Time 3 (2012)</i>														
1. Managers	.14													
2. Technicians	-.34	.42												
3. Engineers	-.09	.07	.19											
4. Healthcare professionals	-.05	.07	-.24	.20										
5. Education professionals	-.09	-.09	-.24	-.25	.19									
6. Learning opportunities	.01	-.08	.03	.00	.01	.41								
7. Creativity requirement	-.03	-.07	-.03	-.07	.25	.22	.65							
8. Freedom how to work	.09	-.13	-.04	-.08	.09	.13	.14	.54						
9. Freedom what to do	.07	-.04	-.06	-.05	.02	.12	.12	.48	.27					
10. Working fast	.03	-.02	-.08	.07	-.02	-.01	.07	-.08	-.05	.16				
11. Working intensively	.08	-.09	-.07	.03	.03	.06	.08	-.03	.01	.49	.11			
12. Working with too much effort	.06	-.09	-.09	-.02	.17	.05	.13	-.06	-.05	.35	.45	.15		
13. Emotional exhaustion	-.02	-.07	-.06	.03	.15	-.02	.11	-.17	-.15	.22	.21	.31	2.2	
14. Job satisfaction	.08	-.04	-.03	.04	-.09	.16	-.01	.23	.19	-.09	-.08	-.15	-.48	6.1

Note. Psychological working conditions are coded 1= “yes, often” and 0= “yes, sometimes”, “no, seldom” or “no, hardly ever”. Prevalence in percentage of the response coded as “1” is presented in italics in the diagonal. Means are presented in italics in diagonal. For the occupational position comparisons, professionals are the reference group. For the sector of work comparisons, other professionals are the reference group. Significant correlations marked with bold, $p < .05$.

The sector of work was coded according to the SSYK classification, and reflects the skill specialization of a worker based on the similarity of the required knowledge, tools, equipment, and product or service being typical for the occupation (SSYK; Statistics Sweden SCB, 2012). The sample consisted of engineers and technical sciences professionals such as architects, analytical chemists, and statisticians (2008: 18.8%; 2010: 18.8%; 2012: 19.1%); healthcare professionals such as medical doctors, biologists, and pharmacologists (2008: 20.1%; 2010: 20.0%; 2012: 20.0%); education professionals such as teachers, lectures, and special education professionals (2008: 19.8%; 2010: 19.8%; 2012: 19.4%); and other professionals including business, art, and legal professionals (2008: 41.3%; 2010: 41.3%; 2012: 41.5%). In the analysis, dummy variables were created for engineers (1 = engineer, 0 = not an engineer), healthcare professionals (1 = healthcare professional, 0 = not a healthcare professional), and education professionals (1 = educational professional, 0 = not an educational professional), while other professionals constituted the reference group. The reference group included business professionals, legal professionals, archivists, librarians and related information professionals, social science and linguistics professionals, writers and creative or performing artists, religious professionals, and administrative professionals.

2.2.3 Analytic strategy

In this study, data were analyzed using latent class models, and their extensions, latent transition models, to estimate changes over time. Within this analytical approach, categorical latent variables are modeled to identify clusters of individuals who share a similar pattern of categorical indicators (for review see e.g., Collins & Lanza, 2010; Nylund, 2007). The analysis was divided into two main parts, following a classify-analyze strategy. First, we estimated the latent classes' measurement model (answering research question #1). Second, we validated the established latent classes by investigating the role of predictors of class membership (research question #2), testing differences between classes in terms of distal outcomes (research question #3), and estimating the longitudinal stability of classes and exploring transitions between classes over time (research question #4). The main advantage of the Latent Class Analysis (LCA) over traditional clustering methods (e.g., k means cluster analysis) is that the LCA estimates the uncertainty of a person's class membership, which can be referred to as measurement error (Wang & Hanges, 2011). To account for measurement error in class assignment, a three-step approach was implemented when estimating the effects of covariates and distal outcomes (Asparouhov & Muthén, 2014; Vermunt, 2010). First, we established an unconditional mixture model. Second, we classified participants according to their most probable latent class and estimated the measurement error of this assignment. Third, the latent classes were fixed at the values established for the time-invariant measurement model while taking into account the measurement error. This model was used to validate the latent classes by investigating their relationships with covariates and distal outcomes (i.e., auxiliary variables). Thus, the latent classes measurement model was treated as independent from its statistical relationship with both covariates and outcomes, which is a recommended solution in mixture modeling (Asparouhov & Muthén, 2014; Lanza, Tan, & Bray, 2013; Nylund-Gibson et al., 2014). Previous simulation analyses have confirmed that when classes are sufficiently well separated

(i.e. entropy above 0.6), the three-step approach works as efficiently as the traditional one-step approach (Asparouhov & Muthén, 2014).

All the analyses were performed using Mplus 7.2. Missing data were handled by the full information maximum likelihood estimation (FIML) with standard errors and a chi-square test statistic robust to non-normality (MLR, see Muthén & Muthén, 2012). The annotated Mplus code used to estimate all models is provided in the Appendix. All models were estimated with 700 random sets of start values to avoid the chance selection of a suboptimal solution (i.e., the local maxima problem; Hipp & Bauer, 2006). Model fit indicators included the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the sample-adjusted Bayesian information criterion (SABIC), with lower values indicating a better model fit for all indicators. BIC was used as the primary indicator, as previous simulation studies have identified BIC as the most accurate information criterion for determining the number of classes in mixture modeling (Nylund, Asparouhov, & Muthén, 2007). The entropy of the models was reported to describe the quality of the overall classification (Celeux & Soromenho, 1996). For model comparisons, the BIC difference was used with values higher than 10, providing strong evidence against the model with the higher BIC value (Kass & Raftery, 1995). Nested models were also compared with a chi-square difference test: the loglikelihood ratio test (LRT).

Table 2.2 Comparison of measurement models in Latent Transition Analyses

k	LL	SCF	#fp	AIC	BIC	SABIC	Entropy
2	-19683.34	1.04	45.00	39456.67	39702.55	39559.59	0.82
3	-18964.46	1.04	69.00	38066.91	38443.92	38224.72	0.73
4	-18816.31	1.09	93.00	37818.63	38326.78	38031.33	0.75
5	-18738.37	1.11	117.00	37710.73	38350.01	37978.32	0.75
6	-18697.33	1.05	141.00	37676.66	38447.08	37999.13	0.75
Final measurement model invariant across time points							
4	-18860.21	1.21	37.00	37794.43	37996.59	37879.05	0.73

Note: k = number of latent classes in the model; LL = model log likelihood; SCF = scaling correction factor of the robust maximum likelihood estimator (MLR); #fp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-adjusted BIC.

2.3 Results

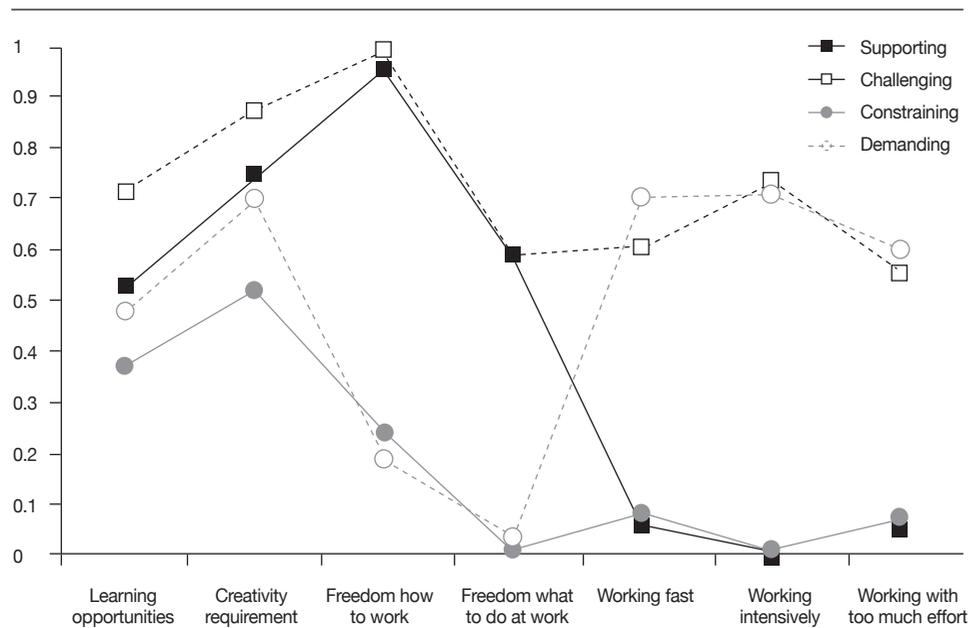
2.3.1 Structure of the patterns

The number of classes was first determined in separate analyses within each point in time. Results of these cross-sectional latent class analyses are provided in the Appendix. Models with two to seven classes were tested. At all three points in time, the BIC increased significantly for the six-class solution, suggesting the five-class option fit the best. However, the drop of the BIC value from the four- to the five-class solution was minimal. An examination of item response probabilities revealed that the four-class solution was almost identical at each time point, while the five-class model varied significant-

ly. A simultaneous analysis of the three points in time (see Table 2.2) confirmed that the four-class solution fit better than the five-class model ($\Delta BIC = 23.2$). Thus, we decided to retain the more parsimonious four-class model, as it was supported both theoretically and empirically.

Next, we tested the stability of the latent class structure over time, i.e., the longitudinal measurement invariance. The invariant model assumes that the same number of classes is identified over time, and it constrains the thresholds (i.e., item-response probabilities) to equality for each indicator within each pattern over time. The same structure of classes over time is not a necessary requirement for LTA. Yet, in practice, holding the measurement invariant facilitates meaningful comparisons over time (Nylund, 2007). The nested models comparison suggested that the time-invariant measurement model was significantly different from the free model (LRT $p = 0.005$). However, the BIC value dropped significantly when reducing the number of parameters ($\Delta BIC = 330.2$), indicating a better model fit of the time-invariant model. Also, the cross-sectional latent class analyses showed that the four classes were in fact very similar. Since an invariance of the measurement model would significantly simplify the overall model interpretation, we again decided to retain a more parsimonious model and held the measurement model as longitudinally invariant in subsequent analyses.

Figure 2.1 Patterns of item response probabilities for the four classes



2.3.2 Characteristics of the patterns

Research Question 1: describing the patterns of psychosocial working conditions.

Figure 2.1 shows the final item response probabilities for the four classes. A high probability of endorsing an item may be interpreted as high prevalence of a given characteristic of a work environment in a class. The working condition pattern characterized by a very low workload, a very low time pressure, medium learning opportunities, high creativity requirements, and a very high autonomy was labeled the “Supporting” class. On average, 38% of the sample was classified into this class and its prevalence was relatively stable over time. The working condition pattern involving a very low workload and a very low time pressure, but also low learning opportunities, medium creativity requirements, and a very low autonomy, was labeled the “Constraining” class. On average, 41% of the sample was classified into this class, and its prevalence increased over time. The working condition pattern with a high workload, a high time pressure, medium learning opportunities, high creativity requirements, but very low autonomy was labeled as the “Demanding” class. On average, 12% of the sample was classified into this class, and its prevalence was relatively stable over time. The working condition pattern with a high workload, a high time pressure, and very high learning opportunities, very high creativity requirements, and a very high autonomy was labeled the “Challenging” class. On average, 8% of the sample was classified into this class, and its prevalence was decreasing. Table 2.3 presents class membership as percentages of the sample.

Table 2.3 Class membership and transition probabilities

	Supporting (1)	Constraining (2)	Demanding (3)	Challenging (4)
Class membership based on the most likely latent pattern				
Time 1	0.37	0.34	0.16	0.12
Time 2	0.39	0.42	0.10	0.08
Time 3	0.37	0.48	0.10	0.05
Transition probabilities from Time 1 classes (rows) to Time 2 classes (columns)				
Supporting (1)	0.84	0.11	0.01	0.04
Constraining (2)	0.05	0.92	0.03	0.01
Demanding (3)	0.07	0.39	0.47	0.07
Challenging (4)	0.40	0.07	0.11	0.41
Transition probabilities from Time 2 classes (rows) to Time 3 classes (columns)				
Supporting (1)	0.82	0.13	0.02	0.04
Constraining (2)	0.04	0.92	0.04	0.00
Demanding (3)	0.05	0.32	0.58	0.05
Challenging (4)	0.37	0.08	0.18	0.37

Note. Probabilities of staying in the same class are marked in bold.

Research Question 2: relating the patterns to worker characteristics. Covariates were added to the model to understand whether any particular group was more likely to have any specific psychosocial working conditions. First, we tested whether time-invariant covariates (gender, being older than 50 years of age at the baseline) and time varying covariates (occupational position, sector of work) had time-invariant effects. In other words, all covariates were expected to influence class membership in the same way at each point in time. A comparison between the

models with all the covariates that had time-varying vs. time-invariant effects confirmed that the latter and the more parsimonious model fit the data equally well (LRT $p = 0.29$; $\Delta BIC = 150.7$).

Table 2.4 Predictors of class membership

	Supporting (1)		Constraining (2)		Demanding (3)	
	logit	OR	logit	OR	logit	OR
Gender	-0.15	0.86	-0.09	0.91	0.39	1.48
Age	0.10	1.10	-0.21	0.81	-0.10	0.90
Technicians	0.84***	2.31	1.09***	2.97	0.81***	2.26
Managers	-0.16	0.85	-0.76***	0.46	-0.18	0.84
Engineers	0.12	1.12	0.35	1.42	-0.22	0.80
Healthcare professionals	0.20	1.22	0.38	1.47	0.56*	1.75
Education professionals	-0.06	0.94	-0.85***	0.43	-0.45*	0.64

Note. OR = Odds Ratio. Gender is coded 1 = female and 0 = male. Age is coded 1 = older than 50 years and 0 = younger than 50 years. Challenging (4) class was selected as the reference. For the occupational position comparisons, professionals are the reference group. For the sector of work comparisons, other professionals are the reference group * $p < .05$; ** $p < .01$; *** $p < .001$

Next, we compared the effects of each of the four covariates (see Table 2.4). The null hypothesis was that the covariate of interest was not to contribute significantly to the classification (Collins & Lanza, 2010). In other words, when the null hypothesis is not rejected, workers are equally likely to be members of a certain class regardless of their gender, age, occupational position, and sector of work. Two covariates contributed to the classification above and beyond the other covariates: technician as occupational position ($\Delta BIC = 22$) and education professional as sector of work ($\Delta BIC = 13$). In comparison to the professionals, the technicians were significantly less likely to be members of the Challenging class than all other classes. In comparison with other professions, education professionals were significantly more likely to be members of the Challenging class rather than the Constraining class or the Demanding class. Even though being a healthcare professional did not contribute significantly to the classification above and beyond other variables, the results suggest that healthcare professionals may be significantly more likely to be members of the Demanding class than of the Challenging class. Also, women were more likely to be members of the Demanding class rather than the Challenging class, but this result was not statistically significant ($p = .52$).

Research Question 3: relating the patterns to worker well-being. The patterns were also validated with two-year lagged outcomes (distal outcomes). Class membership at one time point (in 2008, 2010, and 2012) was used to estimate the level of work-related ill-being and well-being in terms of exhaustion and job satisfaction at the subsequent time point (in 2010, 2012, and 2014, respectively; see Table 2.5). Importantly, the comparison was conducted within a certain time point, namely two years after an individual was assigned to a pattern and regardless of possible transitions between patterns, which means regardless of any current classification.

As expected, membership in the Supporting class resulted in the lowest level of exhaustion two years later (lower than the sample mean), while membership in the Demanding class resulted in the highest level of exhaustion two years later (higher than the sample mean). Membership in the Constraining and the Challenging classes resulted in moderate levels of exhaustion (similar to the sample mean). Levels of job satisfaction were equally

high for members of the Supporting and the Challenging classes (higher than the sample mean), moderate for members of the Constraining class (similar to the sample mean), and the lowest among members of the Demanding class (lower than the sample mean).

Research Question 4: describing longitudinal changes. Table 2.3 presents the probabilities of change between classes from time 1 to time 2 and from time 2 to time 3. The two sets of estimates were shown to be similar; the model assuming stationary transition probabilities fit the data equally well as did the free model (LRT $p = 0.43$; $\Delta BIC = 59.6$). Thus, workers seem to have systematically changed class membership over time. Membership in the Constraining and Supporting classes were fairly stable (82% to 92% of workers stayed in these classes over time), while membership in the Demanding and Challenging classes was rather unstable (37% to 58% of workers stayed in these classes over time). Typically, workers were moving out from the classes with a high workload, time pressure, and work intensity into classes with the lower levels of these demands; 32% to 39% moved from the Demanding to the Constraining class, and 37% to 40% moved from the Challenging to the Supporting class. One exception involved the transition between high demand classes, i.e., from the Challenging into the Demanding class for 11% to 18% of workers, which represents quite a substantial loss of decision autonomy and a moderate loss of learning opportunities and creativity requirements. Similarly, a transition between low demand classes - i.e., from the Supporting class into the Constraining class for 11% to 13% of workers - represented a sharp decrease in decision autonomy and a moderate loss in learning opportunities and creativity requirements. All transitions resulted in an increasing prevalence of the Constraining class, which at time 3 included almost half of the sample, and a decreasing prevalence of the Challenging class, which, at time 3, included only 5% of the sample.

Table 2.5 Lagged effects of class membership on well-being

	Supporting (1)	Constraining (2)	Demanding (3)	Challenging (4)
<i>Time 1 classes > Time 2 outcomes</i>				
Exhaustion	-0.77	0.04 ^a	0.97	0.28 ^a
Job satisfaction	0.47 ^a	-0.27	-0.67	0.41 ^a
<i>Time 2 classes > Time 3 outcomes</i>				
Exhaustion	-0.67	0.10 ^a	1.11	0.47 ^a
Job satisfaction	0.48 ^a	-0.28	-0.76	0.46 ^a
<i>Time 3 classes > Time 4 outcomes</i>				
Exhaustion	-0.67	0.18	0.71 ^a	0.68 ^a
Job satisfaction	0.47 ^a	-0.24	-0.61	0.22 ^a

Note. Values above zero represent scores higher than the sample mean; values below zero represent scores lower than the sample mean. Values marked with the same superscript letter are similar within each row. All other values are significantly different from one another ($p < .05$).

2.4 Discussion

The results of this study provide a better understanding of what typical combinations of working conditions may look like, how prevalent they are among high-skilled workers, and what the different patterns mean for worker ill-being and well-being.

The findings of this study may broaden existing knowledge about psychosocial working conditions in at least three ways. First, the findings revealed differences within a group of high-skilled workers, who previous studies have usually treated as a homogeneous group. Second, this study applied a person-centered approach, and thus modeled relationships between more complex patterns of working conditions than is possible within the prevailing interaction frameworks based on a variable-oriented approach. Third, the results provided evidence regarding the stability of working conditions patterns, as well as the likelihood of transitions between patterns over time.

The four patterns identified in this study were shown to be relatively stable over time, meaning that the same types of psychosocial working conditions were found across three time points. Specifically, the patterns showed configural (same number of the patterns), structural (invariant measurement of the patterns), predictive (time-invariant effects of the predictors), and explanatory (replicated relations between pattern membership and well-being outcomes) similarity (Morin, Meyer, Creusier, & Biétry, 2015). Yet, the prevalence of the patterns changed throughout the six-year study period. Over time, more workers reported lower creativity requirements, learning opportunities, and decision autonomy, as well as a lower workload and less time pressure at work. Psychosocial working conditions typically changed from patterns with a high workload and time pressure to patterns with low levels of such demands. However, workers also transferred from patterns with higher decision autonomy, learning opportunities, and creativity requirements to patterns with lower levels of these resources. Finding out that these two types of transitions are the most common opens up a new line of research. For instance, the transition from patterns with a high time pressure and a high workload to those with low levels may represent individual job crafting or career development. On the other hand, the transition into patterns with low decision autonomy may relate to organizational changes or fluctuations between different stages of various projects. Future studies are needed to specify and systematically test such transferring conditions, and to examine whether there are any differences between specific groups of workers (e.g., women, older workers).

The present study findings complement those of previous research, in particular studies explaining the characteristics of any interplay between variables (or indicators). Similar to the variable-centered approach, which is typically represented by regression methods, a person-centered analysis aims at capturing the interrelatedness among variables (Wang & Hanges, 2011). However, there are key differences between these approaches. Such differences correspond with the type of research questions asked. The identification of latent classes through response patterns assumes that the phenomenon in question is inherently categorical (e.g., a pattern of resources available at work), while regression analysis assumes that the phenomenon is continuous (e.g., the amount of resources available at work). The two methods may seem contradictory, but are in fact complementary and can also be used in the same analysis (e.g., growth mixture modeling; Muthén & Muthén, 2000). However, the person-centered approaches allow for complex multivariate interactions to be simply and implicitly modeled (Morin, Morizot, Boudrias, & Madore, 2011). Thus, the person-centered approaches seem to more adequately describe the complex reality of modern work, where ill-being and well-being outcomes are predicted by a set of patterned indicators rather than by a single factor.

Finally, the findings of this study bring a new perspective to existing theories of psychosocial working conditions. Current theoretical approaches focus largely on labeling certain job characteristics as supportive, for example job control (Häusser et al., 2010) and job resources (Bakker et al., 2014), or as detrimental to well-being, for example job demands or hindrance stressors (Crawford, Lepine, & Rich, 2010; Tuckey, Searle, Boyd, Winefield, & Winefield, 2015). Even though most theories assume that interactions between different psychosocial factors play a key role, such hypotheses usually specify a priori the factors that will act as demands and those that are to be considered resources. However, several studies have shown that a particular work environment characteristic may be positively or negatively related to well-being indicators depending on the specific context of a given work environment. For example, autonomy has been shown to have a curvilinear relationship to employee engagement (Kubicek, Korunka, & Tement, 2014), which suggests that an optimal level of autonomy may vary depending on the availability of other resources at work. Moreover, creativity requirements have been shown to be positively related to worker well-being when complemented by other matching work environment characteristics such as job complexity and autonomy (Shalley et al., 2000). Thus, we argue that integrating such variability into a theoretical framework explaining the role of different work environment characteristics requires a more complex and broader approach. Taken together, the findings of the present study suggest that a stable set of patterns may be a more adequate way of describing a work environment in its entirety. Using such patterns as predictors of worker well-being may further the knowledge regarding the complex interactions between work characteristics, and allow moving beyond the labeling of control and demands.

2.4.1 Limitations

Obviously, the present results are limited to the study group and setting, which includes highly skilled workers in Sweden. Overall, workers in Sweden have good working conditions, and the majority of establishments have developed sufficient procedures for how to deal with psychosocial risks at work (Eurofound and EU-OSHA, 2014). When it comes to worker characteristics, the employment rate of older workers in Sweden is very high compared to other European countries (OECD, 2013). Thus, the sample analyzed in this study was fairly old. For methodological reasons, only workers in gainful employment were included in the analytic sample. With long parental leaves (over 12 months) being common in Sweden, and particularly so among younger women, this selection strategy may have excluded some younger workers. Moreover, Sweden has a very protective employment law; thus, a vast majority of workers enjoy secure working contracts and permanent employment (e.g., Virtanen et al., 2011). Finally, attrition patterns typical for longitudinal panel studies may have affected the representativeness of the sample, especially in the later data collection occasions. (Table A.2 in the Appendix presents detailed information about the representativeness of the selected subsample.) These limitations mean that further validation studies are needed for a meaningful generalization of the study findings across diverse populations of high-skilled workers, but also to occupational groups in other cultural settings.

We decided to use mixture modeling to allow for a contextual and comprehensive analysis of psychosocial working conditions (Härenstam, 2009; Wang & Hanges, 2011). Yet, we did not account for qualitative differences within the group of highly skilled workers, such as job demands and job resources particularly salient for any specific occupation (e.g., Lone et al., 2014). While some job characteristics may be detrimental for worker well-being in one occupation, this may not be the case for another occupation (Sparks & Cooper, 1999). However, instead of splitting the sample into smaller occupational groups, we focused on the highly prevalent and rather general indicators of psychosocial working conditions that correspond well with the cognitively demanding characteristic of high-skilled work. A contextualized at an organizational level or arbitrarily defined sets of indicators used in previous person-centered studies (Berntson et al., 2012; Härenstam et al., 2003; Vanroelen et al., 2010) have hindered us to generalize and replicate their results. This means that we believe that the restricted and theory-guided set of indicators used in this study, which are available in many datasets, will enable confirmatory analyses of the patterns. Moreover, this will enable the testing of whether the patterns replicate in other samples of high-skilled workers and other occupational groups in other cultural contexts (Morin et al., 2015).

Additionally, we dichotomized the items included in the analyses to further simplify interpretation of the results. These methodological decisions may be regarded as limitations, since they may be considered as resulting in a restricted response range. This means that it may be argued that the four-point response scale, which participants used to rate the prevalence of indicators representing psychosocial working conditions, could be treated as continuous and thereby enable the use of latent profile analyses (LPA) instead of latent class analyses (LCA) (e.g., Collins & Lanza, 2010). However, treating a variable with a skewed distribution and only four categories as continuous raises concerns regarding the possible interpretation of a mean score (e.g., Speelman & McGann, 2013). In contrast, recoding one response alternative (in this study, “yes, often”) as a zero-one indicator of the occurrence of an event simplifies the interpretation of the latent patterns. Moreover, given that a number of indicators and response scales used to measure the job demands-control dimensions tend to vary across different studies and languages (Fransson et al., 2012), compared to a mean score in LPA, a threshold estimate obtained in LCA may be easier to replicate meaningfully in another sample when performing future confirmatory analyses. However, it should be acknowledged that the impact of such preliminary measurement decisions on later pattern structures remains unknown and has been acknowledged as difficult to estimate (Morin, Gagné, & Bujacz, 2016).

2.4.2 Practical implications and future directions

Modeling the complexity of psychosocial working conditions into four patterns may greatly simplify any diagnostic process. It can also help practitioners to quickly identify and distinguish between any healthy and risky patterns. Furthermore, our findings can be linked to previous research by using the label job resources for positive aspects of work environment and while denoting challenging working conditions as job demands. Applying this to the present findings, the description of the

four patterns may be further simplified as follows: 1) the low demands-high resources pattern (Supporting), 2) the low demands-low resources pattern (Constraining), 3) the high demands-low resources pattern (Demanding), and 4) the high demands-high resources pattern (Challenging). Our study shows that these patterns are not equally prevalent in the sample of high-skilled workers. For example, the Challenging pattern that represents workers who deal with high demands at work seems to be quite rare (only 12% of the sample and decreasing over time). Thus, the strategy of balancing high demands with high resources (e.g., Bakker et al., 2010) only seems applicable in a limited number of situations.

The patterns and the typical directions of transitions may be used to plan targeted interventions. Instead of analyzing only the amount of positive and negative factors as experienced by workers within any work environment, the pattern approach focuses on the balance between different characteristics of the psychosocial work environment. Thus, the pattern-approach makes it easier to understand what any interrelations among work characteristics mean on an individual level. For example, the levels of exhaustion for the Constraining and Challenging patterns were shown to be similar, yet the reasons for their occurrence are different. In the Constraining pattern, workers may have limited decision autonomy and too few learning opportunities, while in the Challenging pattern they may experience an extensive workload and high time pressure. In view of this, different interventions - targeting different aspects of the psychosocial work environment and specifically focusing on different groups of individuals exhibiting different patterns - are likely to be needed for the two groups to decrease their ill-being and improve their well-being. Furthermore, some workers from the Challenging pattern may be at risk of losing decision autonomy, as they are likely to make a transition into the Demanding profile. Yet, a targeted intervention may prevent such a negative change.

Further studies are needed to explain why transitions in certain directions are more common than others. A further understanding of why changes occur would perhaps require an analysis including detailed information, not available here, on whether and how individuals craft their ways through their occupational careers. Also, the impact of societal and organizational changes should be included to determine the extent to which the transitions found are voluntary or involuntary and perhaps required because of societal change. Ideally, such research would also investigate whether transitions are related to life outside work (e.g., starting a family, parental leave, sickness absence) that may bring about changes in psychosocial working conditions among high-skilled workers. Such a holistic approach combining work and non-work factors would provide an in-depth understanding of how high-skilled workers adapt to change throughout their lives.

Chapter 3: Work engagement of self- employed high-skilled workers

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Abstract

Self-employed workers typically report higher well-being levels than employees. This study examines the mechanisms that lead to differences in work engagement between self-employed and organizationally employed high-skilled workers. Self-employed and organizationally employed high-skilled workers (N=167) were compared using a multigroup multilevel analysis. Participants assessed their job control (general level) and reported their work engagement during work tasks (task level) by means of the Day Reconstruction Method. Aspects of job control (autonomy, creativity, and learning opportunities) and task characteristics (social tasks and core work tasks) were contrasted for the two groups as predictors of work engagement. Self-employed workers reported higher levels of job control and work engagement than organizationally employed workers. In both groups, job control predicted work engagement. Employees with more opportunities to be creative and autonomous were more engaged at work. Self-employed workers were more engaged when they had more learning opportunities. On the task level, self-employed workers were more engaged during core work tasks and social tasks. The findings suggest that self-employment is an effective way for high-skilled workers to increase the amount of job control available to them, and to improve their work engagement. From an intervention perspective, self-employed workers may benefit most from more learning opportunities, more social tasks, and more core work tasks. Organizationally employed workers may appreciate more autonomy and opportunities for creativity. This study contributes to a better understanding of the role that job control and task characteristics play in predicting the work engagement of high-skilled self-employed and organizationally employed workers.

3.1 Introduction

Self-employed workers are healthier, happier, and more satisfied with their jobs than employees (Andersson, 2008; Baron, Franklin, & Hmieleski, 2016; Benz & Frey, 2008a, 2008b; Hundley, 2001; Schneck, 2014; Stephan & Roesler, 2010). More than one in seven workers in Europe is self-employed (European Commission, 2010) and many of the organizationally employed declare that they would prefer to be self-employed (Benz & Frey, 2004, 2008b). Specifically, individual contracting has become increasingly popular or even preferred among high-skilled workers, who typically are defined as individuals having a highly specialized education and working with complex and non-routine tasks (Barley & Kunda, 2006; Eurofound, 2014a; Wilkin, 2013).

However, still little is known about the potential differences in working conditions between self-employed and organizationally employed high-skilled workers. This relates to the fact that the vast majority of studies are based on employees, and typically neglect freelancers and entrepreneurs (Guest, 2004; Power, 2011). Particularly, predictors of work engagement, such as aspects of job control, have rarely been studied in workers with non-traditional employment forms. Moreover, no studies have yet managed to investigate work engagement while taking into account both multilevel (i.e., differenc-

es between persons as well as fluctuations from task to task) and group variation (i.e., differences between self-employed and organizationally employed workers). Thus, a comprehensive analysis is needed, taking both these sources of variability into account, to determine what explains higher levels of well-being among self-employed workers. This study provides a systematic and multilevel comparison between high-skilled self-employed and organizationally employed workers. Specifically, we aim to test whether differences in the work task arrangement drive work engagement in different ways, depending on the form of employment. Thus, we investigate whether self-employed workers, due to their higher job control and wider variety of tasks, find their tasks more engaging than employees. This means that the present study furthers the understanding of the differences between flexible and traditional forms of employment by determining which particular aspects of the work environment differ between self-employed and employees, and by testing how these differences affect their work engagement. Specifically, the main theoretical contribution of this study lies in explaining the mechanisms due to which self-employed and employees differ in their levels of well-being.

A multilevel study design allows for investigating differences in the work environment on both general and task-specific levels. Due to the affective character of work engagement, its dynamic and temporal aspects have recently gained much attention (Bledow et al., 2011; Breevaart et al., 2014; Oerlemans, Bakker, & Demerouti, 2014). Current reviews on the topic recommend studying work engagement as a variable that fluctuates not only between persons, but also within a day and between different work tasks (Bakker et al., 2011b; Sonnentag, 2017). The multigroup multilevel model, which allows for combining the advantage of the dynamic measurement of well-being across several different tasks while simultaneously investigating group differences between self-employed and organizationally employed high-skilled workers, constitutes an important methodological contribution of this study.

3.1.1 Job control of self-employed workers

Job control refers to the amount of decision authority and the level of skill discretion available to a worker (Karasek & Theorell, 1990). In practice, this means the extent to which a worker can decide how to work and what to do at work, and the extent to which opportunities to learn and be creative at work are available to a worker (Fransson et al., 2012). Thus, job control describes to what extent workers have control over organizing their individual tasks at work during a typical workday. When compared to groups with less education, high-skilled workers typically enjoy more job control due to good training opportunities and high work autonomy (Eurofound, 2014a). Yet the level of job control depends greatly on the sector of work and the form of employment. The self-employed – as compared to the organizationally employed – typically enjoy more autonomy, entrepreneurial creativity, and learning opportunities (Benz & Frey, 2008b; Schneck, 2014). Importantly, the majority of the self-employed individuals work in retail or agriculture, and only 10 per cent have their enterprise operating in the area of professional, scientific, and technical activities (European Commission, 2010). This means that a typical self-employed retail worker may indeed report much higher job control than a typical employee, despite them working within the same sector.

However, in the professional and technical sectors, where the most high-skilled workers operate, the advantage of self-employment is less clear. Nowadays, many organizationally employed specialists have the benefit of high autonomy and flexible work arrangements, including for instance remote work (Kelliher & Anderson, 2010), and enjoy more freedom to work creatively due to the managerial control focusing on goals rather than tasks (Grabner & Speckbacher, 2016). This may be particularly common for organizations in the creative sector (Florida, 2002; Penaluna & Penaluna, 2011). For instance, one study showed that self-employed managers and professionals have a smaller advantage over employees in autonomy and no advantage in skill utilization, as compared to workers in middle or low-skilled occupations (Hundley, 2001). However, results from other studies which have accounted for an occupational group or business sector in the statistical analyses suggest that self-employed workers still enjoy more autonomy and more decision authority than employees (Parslow et al., 2004; Prottas, 2008).

Taken together, it seems that the advantage of the self-employment in terms of the level of available job control needs to be investigated in a more controlled way i.e., taking into account any potential heterogeneity among self-employed workers (Johansson Sevä, Vinberg, Nordenmark, & Strandh, 2016). Thus, in this study we focus on a selected group of high-skilled workers, operating in the same creative sector, in order to investigate whether self-employment may bring an advantage in terms of the job control available to this group.

Hypothesis 1: Self-employed high-skilled workers report more job control (i.e., autonomy, learning, and creativity opportunities) than organizationally employed high-skilled workers.

3.1.2 Job control as a predictor of work engagement among the self-employed

Work engagement is a measure of work-related well-being that focuses on emotional experiences. This means that it refers to a psychological state, rather than a behavioral (Parker & Griffin, 2011). Bakker, Albrecht, and Leiter (2011) identified a “growing consensus that engagement can be defined in terms of high levels of energy and high levels of involvement in work” (p. 22). Thus, engaged workers experience positive feelings about their work situation and are motivated to expend energy on a task (Inceoglu & Warr, 2011). Work engagement may therefore vary significantly from task to task, particularly due to its momentary and affective character (Sonnentag, 2017).

Differences in work engagement between the self-employed and employees have seldom been investigated. So far, findings suggest that the self-employed may be more engaged than employees are (Gorgievski, Bakker, & Schaufeli, 2010). It is likely that a higher level of work engagement will result from the self-employed having a higher level of job control. Job control, together with other resources at work, have repeatedly been shown to be the most important predictors of work engagement for organizationally employed workers (Bakker et al., 2007; Crawford et al., 2010). Previous studies have found that this relationship also holds for self-employed workers, particularly with respect to

job autonomy. Specifically, workers benefitted from job autonomy regardless of whether they worked for themselves or for someone else (Dijkhuizen, Gorgievski, van Veldhoven, & Schalk, 2016; Prottas, 2008). In this study, we test whether higher job control may boost work engagement among self-employed workers in the same way as it does for employees.

Hypothesis 2a: Job control relates positively to work engagement for both organizationally employed and self-employed high-skilled workers.

Even though job control is likely to improve work engagement regardless of the employment form, the power of such a prediction might differ between the self-employed and the organizationally employed workers. One reason for this relates to differences in values and priorities between the two groups. For instance, many self-employed contractors name their preference for job variety as one of the important reasons for choosing this form of employment (Åstebro & Thompson, 2011; Peel & Inkson, 2004). Moreover, opportunities to be creative and express oneself are also key for the success of self-employed individuals (Eikhof & Haunschild, 2006). Thus, the self-employed clearly expect high levels of task variety, autonomy, and opportunities to be creative in their jobs.

When positive work characteristics, such as high job control, are experienced during almost every work task, the process of hedonic adaptation is likely to be triggered. Automatic adaptation to frequently occurring stimuli protects individuals from any excessive impact of external stimuli, but also allows individuals to react to novel stimuli when these occur in the environment (Frederick & Loewenstein, 1999; Thompson, 2009). This means that positive emotional reactions, such as an increase in work engagement, result from changes in circumstances regarding a valued goal rather than simply from the desirable characteristics of a situation, to which we tend to adapt (Carver & Scheier, 1990; Diener, Lucas, & Scollon, 2006). Moreover, this means that the characteristics of a favorable work environment do not increase workers well-being unless they change. When exposed to a series of events in which expectations are continuously met, worker well-being remains stable (de Jong, Rigotti, & Mulder, 2017). Due to the fact that people tend to shift attention toward novel stimuli, variety is crucial for maintaining high levels of happiness (Sheldon, Boehm, & Lyubomirsky, 2012; Sheldon & Lyubomirsky, 2012). What may be rare and unexpected for employees, such as being given an opportunity to work creatively, may be a part of the everyday experience of the self-employed. In this case, due to hedonic adaptation processes, the reaction of the self-employed to high job control may be weaker than the reaction of the employees, as seen in terms of an increase in work engagement.

Hypothesis 2b: Job control has a stronger relation to work engagement for the organizationally employed than for the self-employed high-skilled workers.

3.1.3 Task level variability of work engagement

Due to their particular work arrangements, the self-employed not only enjoy high job control, but also have to deal with a wide variety of tasks. As specified by the “jack-of-

all-trades” view of entrepreneurship, self-employed workers perform more diverse tasks than employees (Lechmann & Schnabel, 2014). Thus, their engagement can vary more from task to task. We hypothesize two specific types of tasks to be related to daily fluctuations in the work engagement of self-employed workers, namely social activities and core work tasks.

Social tasks, here defined as those tasks that are performed in interaction with other people, may be particularly beneficial for the well-being of self-employed individuals. Social support has been identified as one of the most important factors to reduce the negative effects of job demands on well-being (Bakker, Demerouti, & Euwema, 2005). Taking part in social activities may also support daily recovery (Sonnentag & Zijlstra, 2006). Thus, isolation can become a severe problem for self-employed individuals who lack the social opportunities of organizational employees (Baines & Robson, 2001). Since social tasks are less common among self-employed workers, they might be more important predictors of task level work engagement in this group. In other words, when the self-employed are given a chance to complete a task in interaction with other people, their work engagement is likely to rise.

The task level work engagement of the self-employed may also increase during core work tasks, which are here defined as tasks that are central for an individual’s professional identity. Non-core tasks refer to those tasks that are far from a worker’s area of expertise, and may thus be considered inappropriate or unnecessary (Sonnentag & Lischetzke, 2017). Due to illegitimate tasks threatening the personal work identity, such tasks may elicit stress reactions and decrease well-being (Madsen, Tripathi, Borritz, & Rugulies, 2014; Semmer, Jacobshagen, & Meier, 2015). Compared to employees, self-employed workers are known to perform a wider variety of tasks, which also include administrative and maintenance responsibilities (Lechmann & Schnabel, 2014). This may mean that they spend less time performing their core work tasks than the organizationally employed workers. Consequently, when the self-employed get a chance to work on tasks that are in line with their personal work identity, they are likely to react with higher work engagement.

Hypothesis 3a: Task level work engagement varies more for the self-employed than for organizationally employed high-skilled workers.

Hypothesis 3b: Task level work engagement is higher during social tasks and core-work tasks for self-employed workers.

3.2 Method

3.2.1 Participants and procedure

This study included high-skilled workers in Sweden. Participants were invited via professional social networks (e.g., LinkedIn, Swedish Association of Architects, Swedish Joint Committee for Artistic and Literary Professionals). Recruitment was based on the creative character of the participants’ job description. In the invitation message the tar-

get group was specified as follows: “In this study, we are interested in people whose work is essentially creative. This means that we are looking for people whose accomplishment, success, and income largely depend on their ability to invent new and original solutions. Typical occupations of such workers include e.g., architects, journalists, programmers, teachers, writers, entrepreneurs or executives in the creative sector.” Ethical approval was obtained from the Swedish Central Ethical Review Board (Ref. No. #2013/1929-31/5).

Table 3.1 Characteristics of the sample (N = 167)

	Self-employed (N=86)		Employees (N=81)	
	n	%	n	%
In relationship	75	87.2	69	85.2
With children living at home	44	51.2	43	53.1
Education				
University (more than 3 years)	41	47.7	38	46.9
University (up to 3 years)	29	33.7	33	40.7
Secondary	16	18.6	10	12.3
Occupation				
Senior officials and leaders	12	14.0	17	21.0
Engineers and designers	4	4.7	3	3.7
Teachers and researchers	2	2.3	15	18.5
Finance and business specialists	1	1.2	4	4.9
Art and culture specialists	23	26.7	5	6.2
Media and IT specialists	21	24.4	22	27.2
Administration and service	2	2.3	1	1.2
Other or unclassified	21	24.4	14	17.3
Managerial role	29	33.7	32	39.5
Employer				
Self-employed	84	100.0	-	-
Private	-	-	52	64.2
State	-	-	20	24.7
Other	-	-	9	11.1
Company size				
Working alone	61	70.9	-	-
Small (less than 50 people)	20	23.3	40	49.4
Large (more than 50 people)	5	5.8	41	50.6

The study was conducted online and participants got access via an anonymous link. Over 820 participants were invited (the precise number is impossible to specify since the anonymous link was also shared by participants in a “snowball” recruitment process), out of which 291 participants started a survey, which resulted in an approximate response rate of 35 per cent. Participants were given the right to withdraw at any point of the study, and 119 did so before completing the study (41%). Finally, data from 167 participants were included in the analysis, of which 86 had reported self-employment as their main employment type. The self-employed were generally older ($M = 44.32$, $SD = 10.71$) than the employed ($M = 39.51$, $SD = 9.11$; $t = 2.87$, $p = .005$), with the age ranging from 24 to 70. The sample had a balanced gender distribution, with 51% of women for self-employed and 56% of women for organizationally employed workers ($\chi^2 [1] = .29$, $p = .64$). Table 3.1 presents detailed sample characteristics.

Table 3.2 Descriptive statistics and correlations

	1	2	3	4	5	6	7	8
1. Creativity	-							
2. Learning	.52***	-						
3. Autonomy	.48***	.50***	-					
4. Engagement	.46***	.46***	.39***	-				
5. Age	.23**	.28***	.22**	.32***	-			
6. Gender	-.05	.06	.01	-.02	-.05	-		
7. Core work tasks	-	-	-	.13**	-	-	-	
8. Social tasks	-	-	-	.15***	-	-	-	-.06
M (SD) _{employees}	5.60 (1.19)	5.68 (1.04)	5.67 (1.27)	4.08 (1.04)	39.51 (9.11)	0.56	0.66	0.24
M (SD) _{self-employed}	6.42 (0.83)	5.98 (0.92)	6.27 (0.89)	4.59 (1.11)	44.32 (10.71)	0.52	0.57	0.18

Note. Gender is coded 1 (woman) and 0 (man). Main tasks and social tasks are coded 1 (yes) and 0 (no). Task level correlations are underlined. $N = 167$ individuals, $N = 536$ tasks. ** $p < .01$; *** $p < .001$.

The online questionnaire included three parts that were presented in the following order: demographics and personal characteristics, job control questionnaire, and the daily diary of work-related activities. Work tasks were reported by means of the Day Reconstruction Method (DRM; Kahneman et al., 2004). DRM is shown to facilitate access to momentary experiences stored in memory, providing reliable estimates of intensity and variations of affect during the day (Dockray et al., 2010). In DRM, participants are asked to recall their work tasks from the preceding working day, and to retrospectively assess their momentary engagement during each of these recalled work tasks. In total, 536 reports from work tasks were included in the analysis with an average of 3.2 recalled work tasks per participant (3.17 for employees and 3.24 for self-employed). Table 3.2 provides descriptive statistics and correlations between all the study variables.

3.2.2 Measures

All items included in the study were translated, and back-translated, from their English versions by two bilingual psychologists. We used a unified 7-point response format ranging from 1 = “not at all/never” through 4 = “moderately/sometimes” to 7 = “very much/all the time”.

Job control. Three items measured learning at work (“How often is the following true for you while you work: “I have the opportunity to take on difficult tasks”; “I have the opportunity to learn interesting things”; “I learn in order to keep myself updated”); two items measured autonomy at work (“I choose the way I work myself”; “I feel free to decide how I want to work”); and two items measured creativity at work (“I work creatively”; “I have a possibility to express myself creatively”). The entire scale had high internal consistency ($\alpha = .83$). The items were conceptually based on scales that have been used previously to measure job control (Fransson et al., 2012) and cognitive job resources (de Jonge et al., 2009; Sanne et al., 2005).

Work engagement. Four items measured state level work engagement during recalled work tasks (“To what extent during this activity did you feel: “engaged”, “inspired”, “happy”, “energetic”). The items were based on the Scale of Work Engagement and Burnout (Hultell & Gustavsson, 2010). In the DRM, the items are rated for each recalled work task. Thus, the work engagement scale needed to be short to limit boredom and fatigue among study participants. However, regardless of the small number of items, the scale had a high internal consistency ($\alpha = .90$).

Core work tasks were measured with reference to each recalled work task by a single binary item (“Were you working with key tasks for your job?”). A ‘yes’ was coded as 1, while ‘no’ was coded as 0. On average 61 per cent of the reported activities were coded as core work tasks (66% for employees, 57% for self-employed).

Social tasks were measured in reference to each recalled work task by a single binary item (“Were you interacting with other people?”). A ‘yes’ was coded as 1, while ‘no’ was coded as 0. On average 21 per cent of the reported activities were coded as social work tasks (24% for employees, 18% for self-employed).

3.2.3 Analytical strategy

This study aimed to test whether available job control played a similar role as a predictor of work engagement for both organizationally employed and self-employed high-skilled workers. We based our analytic strategy on the assumptions of measurement invariance in order to systematically test whether significant differences exist between model parameters. With few studies having compared organizationally employed and self-employed workers, it is still debated whether it is at all meaningful to contrast the two groups (Gorgievski et al., 2010; Parslow et al., 2004). Specifically, when comparing the mean levels of certain characteristics between groups, measurement bias can be a serious problem (Borsboom, 2006). Thus, we started our analysis by testing for the equivalence of measurement between self-employed and employees.

Due to the hierarchical structure of the data, with tasks nested in persons, we used hierarchical linear modeling. Task engagement data were analyzed using a multilevel factor analysis where a total covariance matrix is separated into within-person and between-person levels, and factor structure is estimated at each level (Hox, 2010; Muthén, 1994; Roesch et al., 2010). This approach takes into account both the state and trait variability of momentary affect i.e., the variability of general-level and task-level engagement of this study.

We first tested a confirmatory factor analysis (CFA) model for job control and a multilevel confirmatory factor analysis (MCFA) model for momentary engagement. Then, the measurement invariance of the CFA and the MCFA models for the self-employed and organizationally employed were investigated. Finally, a multilevel multi-group path analysis model was estimated separately for the self-employed and employees in order to systematically compare estimates between the groups. These models included task-level variables (social tasks, core work tasks) and general-level variables (job control) as predictors of task engagement.

All the analyses were performed with Mplus 7.2 (Muthén & Muthén, 2012), using the robust full information maximum likelihood estimation (MLR). For the evaluation of CFA models the following fit indices were used with the respective cut-off values: CFI, above .90 acceptable fit, above .95 good fit; RMSEA, below .08 acceptable fit, below .05 good fit; and SRMR, below .10 good fit (Kline, 2005; Williams, Vandenberg, & Edwards, 2009). The chi-square difference test was employed to compare the models using the adjusted Satorra-Bentler scaled chi-square.

3.3 Results

3.3.1 Measurement models

To test for invariance of job control measurement, the multigroup CFA model was specified on a person-level. First, we compared the one-factor and the three-factor structure. The three-factor model showed a significantly better fit to the data ($\Delta\chi^2_{adj} [3] = 226.75$, $p < .001$). Thus, we used this model to test the measurement invariance by constraining factor loadings and item intercepts to equality across groups, i.e. scalar invariance (Brown, 2006). The model fitted acceptably ($\chi^2 [30] = 45.38$, RMSEA = .08, CFI = .95, SRMR = .11), and was not worse than the configural model ($\Delta\chi^2_{adj} [8] = 9.17$, $p = .33$). All factor loadings were high and significant (varying from .56 to .96). Due to scalar measurement invariance, which confirms the full equality of measurements (Brown, 2006), factor parameters could be compared across groups. The factors labelled as creativity, learning opportunities, and autonomy were strongly correlated in the organizationally employed group (r between .60 and .71). In the self-employed group creativity and learning opportunities were strongly correlated ($r = .85$), while autonomy was moderately related to other factors ($r = .35$ and $r = .44$). Factor means were significantly higher in the group of self-employed ($\Delta = 0.36$, $p = .02$ for learning; $\Delta = 0.80$, $p < .001$ for creativity; $\Delta = 0.49$, $p < .001$ for autonomy). Thus, hypothesis 1 was confirmed. Interestingly, factor variances varied significantly less in the self-employed group ($\sigma^2 = .71$, $p = .01$ for learning; $\sigma^2 = .49$, $p = .04$ for creativity; $\sigma^2 = .50$, $p = .01$ for autonomy) in comparison to the organizationally employed group ($\sigma^2 = 1$).

To test for the invariance of the task engagement measurement, the multi-group MCFA model was established across the general and task levels. First, we examined the intra-class correlations (ICC) of the momentary engagement items. The ICCs varied from .37 to .57, suggesting that a large proportion of the total variability existed on the person-level (Hox, 2010). Similar values of ICCs have been found in other studies using MCFA (Bakker, Sanz-Vergel, Rodríguez-Muñoz, & Oerlemans, 2015; Dyer, Hanges, & Hall, 2005), which suggests that the multilevel structure was justified. Thus, the multi-group MCFA model was specified with the same one-factor structure (on each level) for the organizationally employed and self-employed. The configural model showed an excellent fit to the data ($\chi^2 [9] = 11.21$, RMSEA = .03, CFI = .99, SRMR_{within} = .02, SRMR_{between} = .01). Then, we proceeded to test the measurement invariance of the model parameters between groups. The scalar (full measurement invariance) model constrained to equality factor loadings (on both within and between levels) and item intercepts (on between level) across groups. The model fit remained excellent ($\chi^2 [18] = 18.96$, RMSEA = .01,

CFI = .99, SRMR_{within} = .03, SRMR_{between} = .02), and not worse than the fit of the configural model ($\Delta\chi^2_{adj}[9] = 7.57, p = .58$). All the factor loadings were high and significant on both levels of analysis (varied from .66 to .98). Thus, the measurement of task engagement was fully invariant across groups, indicating that the model parameters across groups could be meaningfully compared on both levels of analysis. On the task level, engagement varied more for the self-employed ($\sigma^2=1.14, p < .001$), therefore hypothesis 3a was confirmed. Yet on the general level, it varied less for the self-employed ($\sigma^2=0.88, p < .001$) in comparison to organizationally employed workers ($\sigma^2=1$). The mean level of engagement was significantly higher for the self-employed ($\Delta=0.42, p = .02$). In sum, the self-employed workers reported both higher levels of available job control (in terms of creativity, learning opportunities, and autonomy), and higher work engagement.

3.3.2 The differences between the self-employed and employees

Due to the full measurement invariance of the job control measurement across groups and the consistently high factor loadings for each latent factor representing creativity, learning, and autonomy, we concluded it was possible and meaningful to use a mean index score in the path analyses. For the same reasons, a mean index score of the four engagement items was used in the analyses.

Table 3.3 shows the results of the multilevel path analyses. On the general level, job control predicted engagement in both groups, but in a slightly different way. For the employees, all three components (creativity, learning, and autonomy) were positively related to person-level work engagement. The effect of learning, however, was the weakest and not significant. For the self-employed workers, learning opportunities had the strongest and a statistically significant positive relationship with work engagement. Thus, hypothesis 2a was confirmed, but only for specific aspects of job control in each group of workers. Further comparison of estimates revealed that autonomy was a significantly stronger predictor of task engagement for organizationally employed workers than for self-employed workers ($p = .01$). Similarly, creativity was a marginally stronger predictor for employees ($p = .06$). However, the effect of learning on task engagement seemed stronger for self-employed workers than for employees, but the difference was not statistically significant ($p = .09$). This confirmed hypothesis 2b for autonomy and creativity, but not for learning opportunities. In sum, job control predicted overall work engagement for both the self-employed and organizationally employed workers. However, depending on the specific aspect of job control, the strength of the prediction varied significantly between groups.

On the task level, core work tasks and social tasks were both significant predictors of the engagement of the self-employed workers. Thus, hypothesis 3b was supported. For the organizationally employed, these relationships were not statistically significant. Even though the relationships were somewhat stronger for the self-employed workers, the differences from the organizationally employed workers were not statistically significant ($p = .12$ and $p = .16$).

Table 3.3 Standardized model parameters of the multigroup multilevel model of predictors of work engagement among the self-employed and organizationally employed workers

	Organizationally employed	Self-employed	Between groups p value
<i>General level</i>			
Creativity	.31 *	-.10	.056
Learning	.13	.57 **	.090
Autonomy	.29 **	-.12	.012
Gender	-.15	.22	
Age	.01	.02	
R ²	.42	.26	
<i>Task level</i>			
Core work tasks	.12	.56 **	.123
Social tasks	.26	.70 **	.159
R ²	.01	.11	

Note. Gender is coded 1 (woman) and 0 (man). Main tasks and social tasks are coded 1 (yes) and 0 (no). * $p < .05$; ** $p < .01$.

3.4 Discussion

This study tested whether the relations between job control and work engagement differed between organizationally employed and self-employed high-skilled workers. Due to the full invariance of measurement across the two groups of workers, meaningful comparisons were possible. Our findings showed that employees with more opportunities to be creative and autonomous in their jobs also felt more engaged at work. Self-employed workers, however, were more engaged when having higher levels of learning opportunities. On the task level, self-employed workers were highly engaged during core work tasks and social tasks.

The findings suggest that job control is indeed an important predictor of worker well-being, regardless of the form of employment. Consistently with previous studies, high-skilled self-employed workers reported significantly higher levels of available job control as compared to organizationally employed workers (Protas & Thompson, 2006; Schneck, 2014). However, the specific function of different aspects of job control may vary between organizationally employed and self-employed workers. A possible explanation of these differences is that experiencing very high levels of job control frequently triggers an adaptation process known as the “hedonic treadmill” (Brickman & Campbell, 1971; Diener et al., 2006). This means that self-employed workers may have adapted to their almost unlimited autonomy and frequent opportunities to be creative, and so their work engagement seemed unaffected by these aspects of job control. However, the self-employed were likely to experience higher well-being when provided with learning opportunities, which are typically less available for this group. Specifically, self-employed workers typically participate in less training than employees, yet many declare a willingness to engage in education if they have the time and finances (European Commission, 2010). This suggests that

the self-employed, when compared to the organizationally employed, have more difficulties in attending formal training (Peel & Inkson, 2004).

Due to a higher level of available job control, self-employed workers also reported generally higher levels of work engagement than employees. This is consistent with previous studies showing that self-employment is beneficial for worker well-being (Benz & Frey, 2008b; Hundley, 2001; Schneck, 2014). Here, the self-employed group was more coherent in terms of work engagement on the general level. Organizationally employed workers varied more between each other, but their within-person engagement was similar from task to task. Yet, the self-employed reported more variability of task engagement. Such variability may also add to a higher level of challenges, and thus bring about more creativity and a higher need for learning among the self-employed.

3.4.1 Research limitations

Due to our focus on job control, the present study findings refer only to the positive side of the Job Demands Control model (Karasek & Theorell, 1990). However, a recent study among entrepreneurs found only positive aspects of work environment, not job demands, to be important predictors of work engagement (Dijkhuizen et al., 2016). Yet, some have suggested that increasing levels of the job control that are available to high-skilled workers add to an intensification of work and increasing job demands (Green, 2001; Kelliher & Anderson, 2010). This may be further complicated by, for instance, the distinctions between self-employed business owners and independent contractors. In comparison to organizational employment, the ownership of a small business seems to be associated with more job pressure, while independent contracting relates to lower demands (Prottas & Thompson, 2006). Thus, the role of high job demands for the work engagement of self-employed workers needs to be further investigated.

The results of this study are limited to the population of high-skilled workers of the creative sector. These workers reported extremely high levels of job control, with the variability being rather low. Thus, it can be argued that an unnecessarily restricted sample was selected for this study. However, the restriction in range problem refers broadly to the effects of sample selection processes that result in an observed sample which is not representative of the population of interest (Sackett & Yang, 2000). Since the self-employed high-skilled workers were in fact specified as the target population, a low variability of job control seems more likely to be a characteristic of this population rather than a side effect of a specific selection procedure. Also, the differences in variability were still interpretable, and the correlations between aspects of job control and engagement were similar to those reported in a meta-analysis (Halbesleben, 2010). Yet, due to the low variability of both job control and work engagement, the strength of the regression coefficient should be treated with caution for the group of the self-employed.

We decided to focus on the workers from the creative sector to avoid differences between employees and self-employed workers resulting merely from the sector of work rather than the form of employment. Self-employed freelancers, which comprise the

majority of our sample, are common among creative occupations in Sweden (Tinagli et al., 2007). Other high-skilled occupations, such as medical doctors or lawyers, are rather rare among the self-employed, and those organizationally employed probably have very different working conditions. Thus, we have tailored our sample of employees to match the sample of self-employed. Even though the sample seems heterogeneous in terms of job types, the common denominator of all these occupations is their categorization as creative workers (e.g., Florida, 2002). Within this group, self-employment is a valid career alternative that is considered by many. Thus, the differences between forms of employment can be estimated without running the risk of comparing pears to apples.

Due to the diary character of the present study, the items were shortened to reduce boredom and fatigue and increase the likelihood of participants completing the study. The items were also formulated rather generally to enable comparisons between the organizationally employed and self-employed workers. For these reasons, we decided against using any of the typical work engagement scales, which include wording that seems inappropriate for the measurement of task-to-task variability in work engagement (Bakker et al., 2011a). In future studies, the assessment may be further adjusted to capture a higher variability. For example, additional indicators could potentially be included to reflect more detailed aspects of the constructs of interest. Also, more objective measures of job characteristics might be an option for future research.

3.4.2 Practical implications

The main practical goal of our analyses was to determine whether the existing findings regarding predictors of work engagement including organizationally employed workers may be generalized to self-employed workers. We found no differences in the functioning of the measurement tool between the two groups, which suggests that the organizationally employed and self-employed workers interpreted self-report items in similar ways. In practice, this means that the same questionnaire items can be used to measure job control and work engagement for both the self-employed and organizationally employed workers.

From a career planning perspective, our research suggests that self-employment is an effective way for high-skilled workers to increase the amount of job control available to them and improve their work engagement. Even though employees may not always be able to just switch to self-employment, the advantage in terms of higher job control may be an important incentive that is likely to add to entrepreneurial intentions among high-skilled workers (Arshad, Farooq, Sultana, & Farooq, 2016; Pérez-López, González-López, & Rodríguez-Ariza, 2016). Moreover, this study detected significant differences between self-employed and organizationally employed in the role that different aspects of job control play in facilitating work engagement. The differences seem subtle, but may still be useful, for example when prioritizing between different interventions that target worker well-being in order to design sustainable careers. Specifically, our findings suggest that organizationally employed workers will benefit most from higher autonomy and more opportunities to be creative at work, while the self-employed benefit from being provided with more learning opportunities, encouraging team-work or other social activities, and limiting non-core work tasks.

Chapter 4: Creative tasks and positive emotions

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Abstract

Previous studies have linked positive emotions with creativity, but it remains unknown why creative activities may enhance positive emotions. This study tested how creative tasks influence autonomous self-expression and task absorption, and whether this in turn increases positive emotions. Data from 478 participants were divided into four language samples (English, German, Italian, and Polish) and analyzed in a series of multi-group structural equation models. The indirect effects were replicated in all samples. Creative tasks enhanced positive emotions through an increase in autonomy. However, participants who solved creative tasks also reported lower task absorption, and this has hindered their experience of positive emotions. In total, a small increase of positive emotions was recorded for creative tasks in comparison to non-creative ones. We suggest that creative activities may support autonomous functioning and enhance positive emotions, given that participants will stay sufficiently focused on the task.

4.1 Introduction

The power of positive emotions to unleash creativity has been repeatedly verified. Two meta-analyses confirmed that positive mood enhances creativity (Baas, De Dreu, & Nijstad, 2008; Davis, 2009). Interestingly, creative activities may further improve emotional well-being, forming a gain spiral (Amabile, Barsade, Mueller, & Staw, 2005; Bar, 2009; Richards, 2010). Even though an increase in positive emotions during creative activities has been previously hypothesized, circumstances when it occurs remain unknown. Thus, an investigation into whether and why creative tasks might enhance positive emotions forms the main theoretical contribution of this study. We argue that tasks requiring creativity may support autonomous self-expression, and this in turn enhances positive emotions. Our empirical strategy is based on randomized control trial methodology applied in multiple group setting. We investigate how creative tasks - in comparison to non-creative ones and across four diverse samples - influence feelings of autonomy, task absorption, and positive emotions. Such complex and robust empirical test gives our findings a chance to significantly contribute to the body of evidence connecting creativity with positive emotions.

4.1.1 Creativity and positive emotions

Creative activities have been widely used as a tool to improve mood. Clinicians have employed creative tasks during occupational therapies (Leckey, 2011), and mental health rehabilitation (Van Lith, Schofield, & Fenner, 2013). Creative activities were shown to alleviate depressive symptoms amongst cancer patients (Bar-Sela, Atid, Danos, Gabay, & Epelbaum, 2007), mental health patients (Caddy, Crawford, & Page, 2012), and prison inmates (Gussak, 2006). In an experimental setting, unstructured writing or drawing

improved the mood of participants who previously viewed a disturbing video (De Petrillo & Winner, 2005). Similar effects occurred in non-clinical samples (Bell & Robbins, 2007; Drake, Searight, & Olson-pupek, 2014). These findings suggest that creativity can reduce negative mood, but further changes from neutral to positive emotional state still await verification (Forgeard & Eichner, 2014).

Creativity is often considered a desirable feature due to its relationship with positive personality traits such as openness, curiosity, humor and flexibility (e.g., Cropley, 1990). Hence, creativity is listed as one of the character strengths (Park, Peterson, & Seligman, 2004). Previous findings suggest that strength-based interventions effectively increase positive emotions and life satisfaction (Proyer, Ruch, & Buschor, 2013). Using strengths in a novel and original way led to an increase in happiness in six months following the intervention (Seligman, Steen, Park, & Peterson, 2005). However, these studies investigated the role of several different character strengths, thus an isolated impact of creativity on emotional well-being remains unknown.

Only recently have researchers started to examine specific effects of creative activity on positive emotions. Silvia and colleagues (2014) have found that doing something creative at a given moment correlates with feeling happy and energetic at that moment. Moneta (2012b) has shown that having an opportunity to be creative at work triggers positive emotions. However, experimental studies on this topic brought unclear results: solving a divergent thinking task led to enhanced positive mood in one experiment (Akbari Chermahini & Hommel, 2012), but in the other study a creative task hindered positive emotions (Cseh, Phillips, & Pearson, 2015). Further research is needed to clarify these contradictory results. We aim at experimentally test whether an involvement in creative activities improves the level of experienced positive emotions.

Hypothesis 1: Creative tasks would enhance positive emotions.

4.1.2 Creativity and autonomy

Autonomy refers to an experience of ownership and volition of one's behavior (Ryan & Deci, 2006). Such sense of volition can be achieved for example by having an opportunity to make independent choices and express personal opinions (Van den Broeck, Vansteenkiste, De Witte, Soenens, & Lens, 2010). Offering choices supports autonomous expression of behavior, and is defined as one of the conditions for autonomy (Su & Reeve, 2011). Thus, a task instruction that encourages self-expression may enhance participants' autonomous motivation (e.g., Shalley & Perry-Smith, 2001). Creative activities may also promote autonomous self-expression due to their focus on originality and novelty. Creative tasks usually read as follows: compose a drawing of your own choice (Fink, Benedek, Grabner, Staudt, & Neubauer, 2007), write down your most interesting thoughts (Conti, Amabile, & Pollak, 1995), note your own original ideas (Bechtoldt, Choi, & Nijstad, 2012), and express your own opinions (Griskevicius, Cialdini, & Kenrick, 2006). Thus, autonomy may increase during creative activities as they encourage autonomous self-expression.

Furthermore, both theory and empirical evidence justify the existence of a link between autonomy and positive emotions. Proponents of the self-determination theory classify autonomy as one of the basic psychological needs (together with relatedness and competence; Ryan & Deci, 2000). They argue that the fulfillment of basic needs supports well-being, and mediates the effects of situational factors on well-being (Deci & Ryan, 2011; Sheldon & Gunz, 2009). Experiencing high levels of autonomy has been linked to positive emotions, including classroom engagement (Cheon, Reeve, & Moon, 2012), interest and enjoyment (Benita, Roth, & Deci, 2014), and psychological well-being across different cultures (Chen et al., 2015). We aim at testing whether creative tasks promote autonomy, and thus indirectly enhance positive emotions.

Hypothesis 2: Creative tasks would indirectly enhance positive emotions through an increase in autonomy.

4.1.3 Creativity and task absorption

Creative tasks are loosely formulated and can be solved in many different ways. No ultimate test exists for an assessment of validity or quality of their solutions (Coyne, 2005). Open formulation of the problem may present an exciting opportunity, but it also makes the results of a creative activity hard to predict. Such lack of a clear objective may decrease task absorption (e.g., Locke & Latham, 2002). Besides, performance in divergent thinking tasks requires effortful control, an executive cognitive function that helps staying focused on the task (Lin, Hsu, Chen, & Chang, 2013). Thus, it might be more difficult to resist distraction during a creative task in comparison to a non-creative, well-defined task.

Moreover, the creative process is characterized by a broad attention span (Kasof, 1997). Narrowing the field of attention has null or even negative effect on creativity (Baas, Nevecka, & Ten Velden, 2014; Colzato, Szapora, Lippelt, & Hommel, 2014), while allowing the mind to wander facilitates creative problem solving (Baird et al., 2012). Creative thinkers easily notice peripheral cues and connect previously unrelated ideas (Ansburg & Hill, 2003), possibly due to their impaired ability to suppress irrelevant cognitive activity (Takeuchi et al., 2011). Thus, a lower level of task absorption can be expected when solving a creative task due to both task characteristics (open formulation without a clear objective) and creative process characteristics (broad attention span).

At the same time, task absorption - staying fully focused on a task - facilitates the experience of positive emotions (e.g., feelings of flow, Csikszentmihalyi, 1990; work engagement, Bakker, Schaufeli, Leiter, & Taris, 2008). Activating positive emotions, such as engagement, relate strongly to being fully concentrated on one's work (e.g., Schaufeli, Salanova, González-romá, & Bakker, 2002). Moreover, practicing meditation that requires focused attention can increase positive affect (Colzato, Ozturk, & Hommel, 2012; Jain et al., 2007). Thus, we aim at testing whether creative tasks, in comparison to uncreative ones, may indirectly decrease positive emotions due to reduced task absorption.

Hypothesis 3: Creative tasks would indirectly decrease positive emotions through a decrease in task absorption.

4.2 Method

4.2.1 Participants

The study was conducted in Austria, Italy, Ireland, Poland, and in the UK. Ethical approvals were granted from local ethical committees in each of the countries. Adult participants were recruited via personal, social and university networks. All provided informed consent to complete the study in their free time.

A sample of 731 individuals participated in the online study across all countries. However, data from 253 participants (35%) were excluded from the analyses due to the following: 232 participants (32%) withdrew before the end of the study (30% registered for the study but withdrew prior to the task assignment, 2% withdrew without answering the post-task questions), and 21 participants spent less than twenty seconds or more than twenty minutes on a task (0.03%). The last exclusion criterion was based on the assumption that those who spent too little time on a task may have put insufficient effort in solving it, while those who spent too much time on a task may have been distracted by other activities. In total, data from 478 participants were analyzed (70% women; age range 18-65; for detailed demographic information see Table 4.1).

Table 4.1 Characteristics of the sample (N = 478)

	English (N = 159)	Italian (N = 106)	Polish (N = 123)	German (N = 90)	Total (N = 478)
Age (SD)	28.3 (9.8)	24.0 (2.9)	26.1 (6.3)	34.3 (13.7)	27.90 (9.5)
Education (SD) ^a	16.3 (3.2)	15.9 (1.9)	16.2 (2.9)	14.3 (3.6)	15.8 (3.1)
Women (%)	132 (83.0)	55 (51.9)	88 (71.5)	61 (67.8)	336 (70.3)
Nationality (%)					
Irish	37 (23.3)	-	-	-	37 (7.7)
English	52 (32.7)	-	-	-	52 (10.9)
Italian	-	105 (99.1)	-	-	105 (22.0)
Polish	-	-	123 (100)	-	123 (25.7)
Austrian	-	-	-	62 (68.9)	62 (13.0)
German	-	-	-	26 (28.9)	26 (5.4)
Other	70 (44.0)	1 (0.9)	-	2 (2.2)	73 (15.1)
Study area (%)					
Art & Humanities	26 (16.4)	26 (24.5)	16 (13.0)	5 (5.6)	73 (15.3)
Social Sciences	69 (43.4)	27 (25.5)	45 (36.6)	35 (38.9)	176 (36.8)
Business, Law	11 (6.9)	23 (21.7)	6 (4.9)	8 (8.9)	48 (10.0)
Engineering	34 (21.4)	17 (16.0)	50 (40.7)	2 (2.2)	103 (21.5)
Health	12 (7.5)	9 (8.5)	4 (3.3)	3 (3.3)	28 (5.9)
Not specified	7 (4.4)	4 (3.8)	2 (1.6)	37 (41.1)	50 (10.5)
Main activity (%)					
Paid work	42 (26.4)	18 (17.0)	32 (26.0)	43 (47.8)	135 (28.2)
Education	106 (66.7)	76 (71.7)	78 (63.4)	29 (32.2)	289 (60.5)
Other	11 (6.9)	12 (11.3)	13 (10.6)	18 (20.0)	54 (11.3)
Condition (%)					
Experimental	75 (47.2)	53 (50.0)	62 (50.4)	42 (46.7)	232 (48.5)
Control	84 (52.8)	53 (50.0)	61 (49.6)	48 (53.3)	246 (51.5)

Note. ^a Years of education starting from the first year of primary school.
SD = standard deviation.

Participants in the experimental group withdrew from the study more often, resulting in the control group being slightly larger ($\Delta N=14$). Mean age and gender distributions were similar in both conditions. Missing data occurred in 1.05% of cases and 0.10% of values.

4.2.2 Procedure

The study was conducted online and accessed via an anonymous link. Participants were informed that the topic under investigation was problem solving, and no links to creativity were given. The survey platform automatically and randomly assigned participants to solve a creative task (experimental) or a non-creative task (control). Within these groups participants were asked to choose a specific task based on short descriptions. Thus, participants could choose the task which best matched their preferred level of difficulty. Participants had unlimited time to solve the task (on average it took less than 5 minutes, see Table 2). Immediately after completion, participants' positive emotions, autonomy, and absorption were measured in reference to the task that they solved (i.e. "How did you feel while solving this task?"). Finally, participants reported the extent to which they experienced the task as creative, difficult, or dull (on a 7-point response scale where 1 = "not at all", 4 = "moderately", and 7 = "very much").

4.2.3 Experimental tasks

Participants in the experimental group solved one of the three creative tasks: 1) invent titles for a cartoon (Sternberg, 2006), 2) list different uses for a rubber band (Guilford, 1967), or 3) improve the design of a table for individuals with impaired vision (inspired by Torrance's product improvement task; Kim, 2006). The tasks were based on creativity tests, and therefore calibrated to trigger divergent thinking. Such tasks have many different solutions (triggering fluency), encourage switching between semantic categories (triggering flexibility), and enable individuals to approach a problem in a novel way (triggering originality).

In the control condition participants were given a choice between three non-creative tasks: 1) find the differences between two cartoons, 2) answer questions about a presented book excerpt (Sacks, 2008), or 3) write instructions on how to assemble a table based on given illustrations. The non-creative tasks were tailored so that the effort they required was similar to those of the creative tasks.

4.2.4 Manipulation check

Prior to the experiment, we conducted a validation study (Bujac et al., 2014). Competent judges (psychology and social sciences students or graduates; five in each lan-

guage group) were trained to rate tasks on the creativity criteria: fluency, flexibility and originality. The results revealed that the creative tasks had significantly higher potential to trigger divergent thinking than the non-creative tasks. These results were confirmed in the current study. Participants across all language groups considered the tasks to be more creative in the experimental condition ($F[1,475] = 100.06$, $p < .001$, $\eta^2 = .18$), and not particularly dull in either of the conditions ($F[1,475] = 0.03$, $p = .86$).

4.2.5 Analytical strategy

Multiple samples were analyzed separately, and were systematically compared to empirically test for the robustness of the results, following the assumptions of multivariate meta-analysis (Jackson, Riley, & White, 2011). Data were analyzed in a series of multi-group structural equation models (SEM). To test the plausibility of an indirect effect of creative tasks on positive emotions through autonomy and absorption, models with both direct and indirect paths were compared. Indirect effects were further tested using bootstrapping with 5,000 samples (e.g. Preacher & Hayes, 2008). Significant indirect effects are indicated by confidence intervals that do not include zero. Due to small numbers of indicators, an alternative definition and measurement of psychometric properties, appropriate for structural equation modelling, were applied (Bollen, 1989). Reliability could be defined as the magnitude of direct relations that a latent variable have with an item, and thus reliability coefficient would reflect the squared correlation between the item and the factor. Validity could be defined as the magnitude of direct structural relations between the factor and the item, and thus validity coefficient would reflect the standardized factor loadings.

All analyses were performed with Mplus 7.2 (Muthén & Muthén, 2012), using the robust full information maximum likelihood estimation (MLR). For the evaluation of a model the following fit indices were used with the respective cut-off values: CFI, above .90 acceptable fit, above .95 good fit; RMSEA, below .08 acceptable fit, below .05 good fit; and SRMR, below .10 good fit (Kline, 2005; Williams et al., 2009). Chi-square differences test was employed to compare models using the adjusted Satorra-Bentler scaled chi-square statistic (Muthén & Muthén, 2012).

Multigroup analyses. The invariance of the measurement model across language groups had to be tested first to secure a meaningful comparison of factor covariances. When a measurement tool is used across groups, its internal structure should follow at least two requirements: 1) the same number of factors should be found in all groups, i.e. configural invariance, and 2) the similar pattern of factor loadings should be observed across groups, i.e. metric invariance (e.g., Brown, 2006). Those requirements are met when a model that imposes them fits the data well, allowing the structural parameters across groups to be legitimately examined and compared (e.g., (Meredith & Teresi, 2006; Raykov, Marcoulides, & Li, 2012).

Table 4.2 Descriptive statistics and correlations among the study variables

English above German below	1	2	3	4	5	6	7	8	9	10	M English	SD English
1. Interested		.73	.49	.23	.16	.35	.32	-.11	.07	.24	4.55	1.48
2. Engaged	.67		.39	.28	.15	.36	.43	-.26	-.04	.32	4.89	1.45
3. Happy	.61	.56		.24	.16	.35	.31	-.03	.01	.23	3.98	1.86
4. Decide	.37	.40	.40		.52	.23	.27	.14	.05	.05	5.44	1.55
5. Express	.13	.19	.35	.60		.16	.17	.41	.12	-.06	4.90	1.95
6. Focused	.05	.18	.16	-.03	.00		.73	-.16	.07	.19	2.80	1.77
7. Absorbed	.21	.25	.24	.14	.18	.54		-.23	.00	.24	3.28	1.85
8. Task	-.15	-.20	.01	.12	.24	-.15	-.30		.29	-.36	-	-
9. Difficulty	-.07	-.10	-.07	-.11	-.03	.21	.10	-.03		.05	2.42	1.64
10. Time in minutes	.32	.25	.13	.03	-.10	.04	.18	-.40	.04		3.99	3.30
M German	4.82	4.89	3.86	5.42	4.82	2.46	2.98	-	2.33	4.51		
SD German	1.69	1.65	1.67	1.66	1.87	1.68	1.88	-	1.47	3.85		
Italian above Polish below	1	2	3	4	5	6	7	8	9	10	M Italian	SD Italian
1. Interested		.61	.51	.26	.31	.26	.37	.04	.02	.10	4.53	1.58
2. Engaged	.88		.41	.08	.16	.29	.34	-.24	.18	.33	4.63	1.37
3. Happy	.59	.55		.23	.28	.11	.16	-.05	-.06	-.02	3.31	1.42
4. Decide	.61	.54	.53		.69	.06	.19	.35	-.02	-.13	4.84	1.71
5. Express	.44	.37	.46	.61		.06	.10	.40	-.01	-.24	4.81	1.91
6. Focused	.47	.49	.28	.28	.22		.57	-.13	.05	.06	2.56	1.55
7. Absorbed	.57	.58	.34	.29	.15	.76		-.11	-.05	.16	3.06	1.68
8. Task	.15	.06	.27	.31	.59	-.07	-.10		-.01	-.51	-	-
9. Difficulty	.04	.02	.04	-.05	-.01	.01	.03	.06		.26	2.41	1.35
10. Time in minutes	.08	.07	.08	-.05	-.15	.14	.19	-.24	.25		4.51	3.76
M Polish	4.99	5.18	3.72	4.76	4.93	2.49	3.40	-	2.46	4.77		
SD Polish	1.50	1.52	1.57	1.93	2.09	1.91	2.06	-	1.49	3.81		

Note. Task is coded 0 (non-creative) and 1 (creative). Significant coefficients marked in bold, $p < .05$.

4.2.6 Measures

All items used in the study were translated from the English versions. We employed unified 7-point response format where 1 = “not at all”, 4 = “moderately”, and 7 = “very much”. See Table 4.2 for the correlations between all the variables used in the analyses.

Positive emotions. Three items measured positive emotions (“To what extent during the task have you felt: interested”, “happy”, and “engaged”). The items were based on the Basic Emotions State Test (BEST, Vittersø, Oelmann, & Wang, 2009), and the scale yielded high internal consistency (average across language groups $\alpha = .81$). Average estimated item reliability coefficient amounted .61 and average standardized validity coefficient reached .77 across items and language groups.

Autonomy. Two items measured autonomy (“I felt free to decide for myself.”, “I was free to express my ideas and opinions.”). The items were based on scales measuring the satisfaction of basic need for autonomy within the self-determination theory framework (Longo, Gunz, Curtis, & Farsides, 2014; Van den Broeck et al., 2010), and were moderately correlated (average across language groups $r = .60$). Average estimated item reliability coefficient amounted .62 and average standardized validity coefficient reached .78 across items and language groups.

Task absorption. Two items measured task absorption (“I was so focused that I forgot where I was.”, “I was so absorbed that I forgot about everything else.”). The items were based on scales measuring the experience of flow (Martin & Jackson, 2008), and were moderately correlated (average across language groups $r = .65$). Average estimated item reliability coefficient amounted .65 and average standardized validity coefficient reached .80 across items and language groups.

Control variables. Two task-related control variables were accounted for in the final analysis: difficulty of the task, and time spent on solving the task. Difficulty of the task was subjectively reported; participants assessed to what extent they considered the task to be difficult. Time spent on the task was measured automatically, and without participants’ knowledge, by calculating for how long task instructions were displayed in the browser. In general across groups, creative tasks were experienced as slightly more difficult ($F[1,475] = 4.24, p = .04, \eta^2 = .01$), yet participants spent less time solving them ($F[1,475] = 81.98, p < .001, \eta^2 = .15$).

Baseline pretest. Due to the randomization procedure, the comparison groups should be characterized by the same baseline distribution of the dependent variables. To test this assumption, an average daily level of these variables was estimated using the Day Reconstruction Method (Kahneman et al., 2004). In reference to the episodes from the preceding day, participants reported their perceived autonomy, task absorption and positive emotions during each of the activities. The multivariate ANOVA analysis found no differences in baseline measurement between experimental and control groups (for positive emotions $F[1,475] = .30, p = .59$; for autonomy $F[1,475] = .31, p = .58$; for task absorption $F[1,475] = .08, p = .78$). Therefore, pre-existing individual differences were omitted in the analyses.

4.3 Results

4.3.1 Measurement model

The confirmatory factor analysis model was specified with three correlated factors (autonomy, task absorption, and positive emotions). The three-factor structure fitted the data well across all language groups (RMSEA=.06, CFI=.98, SRMR=.04), securing the configural invariance (see Model 1 in Table 4.3). The metric model fitted the data as good as the configural model ($\Delta\chi^2 [12] = 14.55, p = .27$), suggesting the invariance of factor loadings (see Model 1a in Table 4.3). Further analyses were based on the established metric invariance of the measurement model (i.e. factor loadings were always fixed to be equal across language groups).

Table 4.3 Multigroup model fit and model fit comparison

	χ^2	df	RMSEA	CFI	SRMR	$\Delta\chi^2$ adj	Δ df	Δ p
<i>Measurement model^a</i>								
1. Configural	60.75	44	0.056	0.984	0.041	-	-	-
1a. Metric invariant across groups	75.48	56	0.054	0.981	0.055	14.55	12	0.267
<i>Structural model</i>								
2. Partial mediation	170.83	104	0.073	0.949	0.060	-	-	-
2a. Partial mediation invariant	191.69	119	0.071	0.944	0.078	21.15	15	0.132
3. Full mediation	180.41	108	0.075	0.945	0.060	9.21	4	0.056
3a. Full mediation invariant	198.57	120	0.074	0.940	0.080	18.26	12	0.108

Note. ^a Solution with three correlated factors: positive affect, absorption and autonomy.

4.3.2 Structural model

The indirect model was specified as follows: the task (creative or non-creative) predicted the extent to which participants felt autonomous and absorbed by the task. Both autonomy and task absorption predicted the variability of positive emotions (see Figure 4.1). The task effects on autonomy, absorption and positive emotions were adjusted for control variables (time spent of the task and self-reported difficulty of the task).

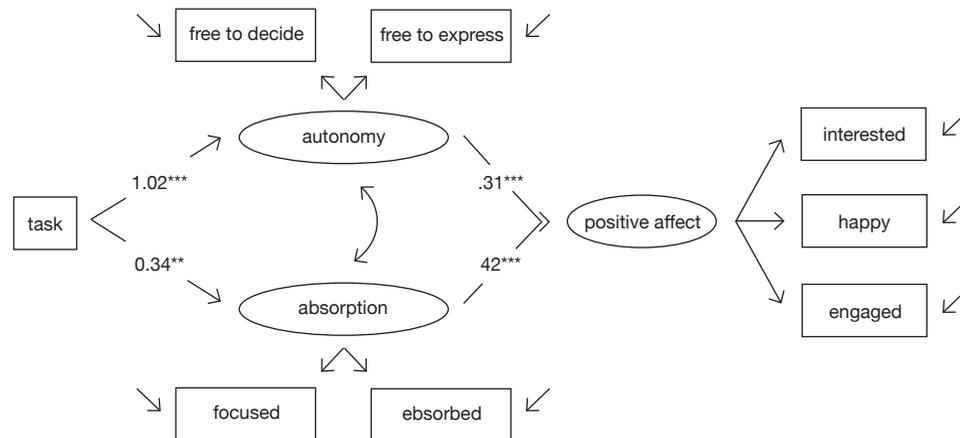
The analyses started with a partial mediational model where both direct and indirect paths were free to vary across groups (see Model 2 in Table 4.3). Revealing that direct paths were insignificant in all groups, we proceeded to test a full mediational model (see Model 3 in Table 4.3). The fit indices did not detect a significant worsening of this more parsimonious model ($\Delta\chi^2 [4] = 9.21, p = .06$), suggesting that the indirect paths can fully account for the effects of the task on positive emotions.

Finally, the structural paths were shown to be invariant across all language groups for both partial mediation model (see Model 2a in Table 4.3) and full mediation model (see Model 3a in Table 4.3). In the creative condition, autonomy was significantly higher, and task absorption was significantly lower across all language groups (see Figure 4.1). Creativity of the task was a more important predictor of autonomy (across groups average $R^2 = .20$) than it was of task absorption (across groups average $R^2 = .08$). Positive emotions increased for participants who felt autonomous and absorbed during the task. Higher perceived difficulty of the task reduced positive emotions, and longer time spent on the task enhanced them. Invariance of the effects of control variables was not tested; they were allowed to vary across language groups. In general, the model explained from one third to half of the variability of positive emotions (see Table 4.4).

Indirect effects. Following the constraints placed on the adjacent paths, indirect effects were also invariant across all language groups (see Table 4.4). Solving the creative task led to a higher level of positive emotions through an increase in autonomy. However,

during creative tasks absorption was lowered, which further decreased positive emotions. The opposite indirect effects of autonomy and task absorption summed up into a total small increase of positive emotions after solving the creative task.

Figure 4.1 The final model of indirect effects of creative tasks on positive emotions



Note. Task is coded 0 (non-creative) and 1 (creative). Structural paths constrained to equality across groups. Figure presents standardized estimates of the English language group. * $p < .05$; ** $p < .01$; *** $p < .001$

Table 4.4 Indirect effects of creative tasks on positive affect in standardized coefficients

	Indirect via Autonomy		Indirect via Absorption		Total		R ²
	β	95% CI	β	95% CI	β	95% CI	
English	.32	.20; .44	-.14	-.25; -.04	.18	.00; .35	.43
Italian	.36	.21; .50	-.16	-.28; -.04	.20	.01; .39	.40
Polish	.32	.20; .44	-.14	-.25; -.04	.18	.01; .35	.50
German	.29	.17; .41	-.13	-.23; -.03	.16	.00; .32	.36

Note. Task is coded 0 (non-creative) and 1 (creative). CI = confidence interval. Structural paths constrained to equality across groups.

4.4 Discussion

This study tested whether and why creative tasks may bring more positive emotions than non-creative ones. As expected, open-ended and imaginative tasks promoted autonomous self-expression and enhanced positive emotions. This effect was limited by the fact that participants spent less time solving the creative task, and thus decreased task absorption have limited their emotional experience.

In total, creative tasks brought more positive emotions than non-creative ones, yet the effect was weak.

In general, participants reacted positively to a freedom of self-expression that creative task provided, and their emotional well-being improved. Creative activities may support autonomous expression of behavior as they offer choices, have non-controlling language of instructions, and are often pursued as means of personal growth (Su & Reeve, 2011). Acting creatively enables perspective taking (Grant & Berry, 2011), provides a growth-based rationale for an activity (Ohly & Fritz, 2009), and serves as a socially accepted form of expressing frustration (Kim, Zeppenfeld, & Cohen, 2013). In a previous study, participants who solved a creative task reported an increased spontaneous interest in the subsequent activity (Conti et al., 1995). Hence, we suggest that creative activity may support autonomous functioning and increase emotional well-being, given that participants stay sufficiently focused on a task.

4.4.1 Generalizability of the results

The findings of this study are based on complex and robust methodology, combining the randomized control trials with multigroup analyses. Such strategy allows for simultaneous comparisons of effects across four samples, which is the main empirical contribution of this study. We replicated the results across four language samples, showing their relative robustness. A multigroup analysis offers three important advantages over traditional methods (e.g., ANOVA). First, it accounts for possible biases in measurement across groups, a crucial benefit for cross-cultural studies (Davidov, Schmidt, & Billiet, 2011). Second, it estimates several effects in one analysis, thus controlling for the within-study correlations that occur when multiple effects are calculated for the same participants (Jackson et al., 2011). Third, obtaining similar results from several samples strengthens the conclusions and secures their international generalizability. Meta-analytic and cross-cultural studies – like the present one – complement and extend single-sample study designs (Anderson et al., 2004).

Furthermore, a quality of our randomized controlled study results depended greatly on the appropriateness of the control condition. We aimed at designing control tasks that differed from the experimental tasks only by the lack of support for the creative process. Previous studies failed to compare the effects of creativity to such clear control, mainly because a placebo task was also somewhat creative (e.g., write down your early memories, Seligman et al., 2005; find a word association, Akbari Chermahini & Hommel, 2012). Therefore, the non-creative tasks employed in this study were designed to have all the features of creative tasks apart from the ability to trigger divergent thinking.

Our findings are in line with the results obtained by Akbari Chermahini and Hommel (2012) who recorded an increase in positive mood after solving a divergent thinking task. Tasks typical for creativity tests were previously used in studies on positive mood and creativity (Baas et al., 2008; Davis, 2009). They are also good predictors of creative achievement (Kim, 2008), even though divergent thinking is just one of

the cognitive skills underlying the creative process (Runco & Acar, 2012).

In order to avoid confounding influences identified in previous studies, our design did not involve negative mood induction (excluding the role of emotional regulation strategies e.g., De Petrillo & Winner, 2005) and clinical samples (excluding the role of therapeutic relationship e.g., Van Lith et al., 2013). The study design also accounted for the confounding effects of decreased task absorption. Our conclusions are similar to the results of Cseh and colleagues (2014) who found that flow (i.e. profound task absorption) moderated affect improvement during the creative task.

4.4.2 Limitations and future directions

This study found only a small effect of creative tasks on positive emotions. A long-term exposure may influence well-being more powerfully (Seligman et al., 2005), possibly due to a gain spiral of resources (Hobfoll, 1989). Future studies may investigate positive emotions experienced by participants who complete creative tasks regularly for a longer period of time.

A more absorbed participation in the creative condition would strengthen the effect of creative activity on well-being. Lower task absorption was expected in a creative condition, yet it could have been facilitated by the study design. For instance, the design could include procedures known to increase participants' epistemic motivation (i.e., their willingness to expend effort needed to reach an accurate understanding of a task; De Dreu, Nijstad, Bechtoldt, & Baas, 2011). Examples of such procedures include setting a minimum time limit that participants must spend solving a task (Kruglanski, Shah, Pierro, & Mannetti, 2002), and informing participants that after the task they will be asked to describe their thought process (Scholten, van Knippenberg, Nijstad, & De Dreu, 2007).

The assessment of this study was limited by a small number of indicators. We have prioritized the validity of item content over their range, a strategy previously used for building short personality measures (e.g., Gosling, Rentfrow, & Swann, 2003). Even though two items are certainly not enough to build a stand-alone scale with good psychometric qualities, choosing one or two best indicators is plausible in structural equation modeling (Hayduk & Littvay, 2012). Alternative measures of reliability and validity (Bollen, 1989) and the replication of the model across several samples provides some evidence regarding reliability and validity of our assessment, yet for further research we recommend the use of well-established measures whenever possible.

The fit of our final model was acceptable, yet with room for improvement. Apart from the impact of imperfect measurement (i.e., small number of indicators), the loss in a model fit could have resulted from the omission of important variables influencing the connection between creative activity and positive emotions. For example, individuals high in need for closure prefer order and predictability (Kruglanski & Webster, 1996), which creative tasks lack. This could make some individuals feel incompetent, and consequently decrease their positive emotions. Forthcoming studies should pay more attention to feelings of competence and self-efficacy, which are important predictors of involvement in creative behavior (Tierney & Farmer, 2011).

In conclusion, we hope that future research will unveil the potential of creative activities to form a gain spiral with positive emotions, as supported by the reciprocal relationship between creative behaviors and the basic need for autonomy (Devloo, Anseel, De Beuckelaer, & Salanova, 2014). Creativity may be exercised not only for the sake of developing a product or improving one's performance, but simply for the sake of gaining autonomy in expressing oneself.

Chapter 5: Discussion

This final chapter of the dissertation summarizes the findings of the three empirical studies, and reviews their contribution to theory and practice. The research questions presented in the first chapter are answered, and the ways in which these answers manage to advance existing theories are discussed. Methodological contributions, study limitations, and future directions are also reviewed. Finally, the results are translated into a set of practice-friendly suggestions. The chapter ends with a conclusion highlighting the importance of the thesis contributions in the context of the changing character of high-skilled work.

5.1 Main findings

The empirical studies presented in this dissertation aimed to answer three broad research questions. The answers to these questions are reviewed below.

1. How do different aspects of high-skilled workers' work environment contribute, separately or together, to the sustainable development of worker well-being?

All three studies found that aspects of job control were related to worker well-being. However, these relations were context dependent i.e., autonomy, learning, and creativity as predictors of worker well-being were related to each other. Thus, specific characteristics of high-skilled workers' work environments contributed to the development of worker well-being, both separately and in relation to one another.

The prospective study identified two general groups of high-skilled workers that were differentiated by patterns of working conditions: a group characterized by very high procedural and decision autonomy and medium to high creativity and learning opportunities, and a group characterized by very low procedural and decision autonomy and medium to low creativity and learning opportunities. In terms of the relation to the well-being indicator (job satisfaction in this study), workers belonging to the high autonomy group tended to have significantly higher well-being than the workers belonging to the low autonomy group, regardless of the levels of demands they experienced at work. However, when taking the ill-being perspective into account (measured by emotional exhaustion in this study), workers in the low autonomy group tended to have similar levels of exhaustion to workers in the high autonomy and high demands group. This result confirms that measuring work experience from both positive (well-being) and negative (ill-being) perspectives provides a more diverse picture of high-skilled workers' situation (Huber et al., 2011).

The comparative task level study found that each of the aspects of job control separately predicted task level work engagement. In the group of employees, creativity and autonomy were both significant predictors of work engagement, while learning was not. In the group of self-employed high-skilled workers well-being was higher for those with higher learning opportunities, but did not differ for those with higher creativity and autonomy at work. Moreover, when the strength of prediction was directly compared between the groups, autonomy - and to a smaller extent also creativity - were stronger predictors of

well-being for the employees than for the self-employed workers. Thus, the predictive role of autonomy and creativity seem to depend on the form of employment of a high-skilled worker. As suggested by previous research, the self-employed workers enjoyed higher creativity and autonomy levels than the organizationally employed workers (Benz & Frey, 2008b). Thus, it may be argued that workers tend to adapt to these aspects of job control that are constantly available to them, as suggested by the hedonic adaptation theory (Diener et al., 2006).

The comparative task level study also revealed that work engagement was higher for self-employed workers during tasks categorized as their core work activities, in comparison to non-core work tasks, and during tasks performed together with other people, in comparison to those performed individually. These results confirm that work engagement differences already occur on the task level (Sonnentag, 2017), and thus a change in the task structure may help with sustaining higher well-being levels among workers.

Therefore, the experimental study tested how aspects of job control affect well-being on the task level. It showed that well-being (measured as momentary positive emotions in this study) increased during creative tasks, in comparison to non-creative tasks. Moreover, during creative tasks participants reported much higher autonomy, as well as lower task absorption, than during non-creative tasks. The increase in positive emotions was fully mediated by an increase in autonomy and a decrease in absorption. At the same time, creative tasks were perceived as more difficult than non-creative tasks, thus providing higher learning opportunities. Altogether, tasks formulated in a way that encouraged creative thinking increased the perceived autonomy of a participant, and were considered more challenging. This result may explain which aspects of a work environment bring more well-being to high-skilled workers, compared to a less specialized workforce (Eurofound, 2014a). Specifically, an abundance of creative tasks at work is a probable cause of high worker well-being (Benz & Frey, 2008b).

In sum, this thesis investigates the interplay of autonomy, learning, and creativity as predictors of well-being within the group of high-skilled workers. Consistently with previous research (e.g., Daniels et al., 2013; Daniels, Beesley, Wimalasiri, & Cheyne, 2013; Nielsen et al., 2017), all the studies have found that job control predicts worker well-being, both on the person and the task levels. However, the studies also revealed the unique role of each of the aspects of job control. This implies that in the group of high-skilled workers, autonomy and opportunities to be creative and learn should be considered separate predictors of worker well-being, which may also relate to and influence one another.

2. What differences and similarities exist between subgroups of high-skilled workers in terms of working conditions and well-being at work?

The empirical studies included in this dissertation investigated the differences among high-skilled workers when divided into subgroups based on gender, age, patterns of job control and demands at work, occupational position, sector of work, form of employment, as well as language and nationality. Moreover, the studies investigated differences in the availability of job control aspects, well-being levels, and the predictive strength that job control had on well-being in each of the groups.

As for demographics, the prospective study did not find significant differences between men and women, nor between younger and older workers (when controlling for sector of work and occupational position). Similarly, the comparative task level study found no differences between women and men. Age was significantly related to all aspects of job control, as well as to levels of well-being, meaning that older workers had more favorable working conditions and higher levels of work engagement. However, when age was included as a predictor of well-being alongside autonomy, creativity and learning opportunities, its effect was insignificant. These results are not surprising given that seniority usually gives access protection rights and better working conditions (Eurofound, 2016). Also, the sector of work was expected to be a stronger predictor of working conditions than gender, due to the current labor markets being gender segregated to a significant extent (Eurofound, 2013).

In terms of available job control and experience of job demands, the prospective study has distinguished empirically between four clusters of high-skilled workers characterized by different patterns of working conditions. In general, classes of workers were defined by high vs. low procedural and decision autonomy as well as high vs. low quantitative demands at work (including workload and time pressure). Thus, the levels of autonomy and demands seem to differentiate between high-skilled workers better than opportunities to be creative and to learn. This means that creativity and learning opportunities are quite common for high-skilled workers, while perceived autonomy and experienced demands may be either rather high or rather low. These findings are consistent with recent results of the Sixth European Working Conditions Survey (Eurofound, 2016), which show that high-skilled workers typically have a profile of working conditions characterized by high skill discretion and manageable demands. However, it is not uncommon for managers, professionals and technicians to have surprisingly low decision latitude and high demands at work.

As regards occupation, the prospective study found significant differences among workers from diverse sectors and different occupational positions. Educational professionals were significantly more likely than other professionals to have high autonomy as well as high demands at work. Moreover, the findings suggest that health care professionals were more likely than other professionals to have high demands and low autonomy at work. In terms of occupational positions, technicians were significantly less likely than professionals to have high autonomy and high demands at work.

The differences in forms of employment were investigated in the comparative task level study. Similarly to the results of previous studies (Benz & Frey, 2004; Prottas, 2008; Schneck, 2014), self-employed workers had higher levels of all aspects of job control, and they reported higher work engagement during their tasks at work than organizationally employed high-skilled workers did. Interestingly, all the job control aspects were strongly related to each other in the group of employees, but in the group of self-employed workers only creativity and learning were strongly correlated, while autonomy related only moderately with the other two job control aspects. Moreover, the study also detected differences in the variability of job control aspects and well-being. Autonomy, creativity, and learning opportunities varied significantly less within the group of self-employed workers, in comparison to employees. Similarly, work engagement varied

less in the group of self-employed workers as compared to the organizationally employed workers on the person level. However, on the task level engagement varied more for the self-employed. In other words, employees in general had various well-being levels that did not differ much from one task to another. Self-employed workers in general had similar and high well-being levels, yet their work engagement varied significantly from task to task. Again, this result speaks in favor of differentiating between person and task levels when it comes to work engagement (Sonnentag, 2017).

Finally, the studies also investigated differences in the predictive strength that aspects of job control had on well-being. The experimental study was conducted in a multigroup setting to systematically test differences in the strength of prediction for four groups of respondents who spoke different languages (English, Polish, Italian, and German). The prediction model was shown to be invariant across all the four language groups. This means that creative tasks predicted increased autonomy levels, which in turn predicted higher positive emotions, in a similar way, regardless of the language group. Thus, the predictive role of creativity and autonomy on well-being may be generalized across workers from diverse European languages and national groups.

In sum, the studies of this thesis revealed many differences between subgroups of high-skilled workers. This suggests that the large group of high-skilled workers is internally quite diverse. Thus, to fully understand working conditions in high-skilled work, and their impact on workers' well-being, a more nuanced analysis is needed, which takes into account the differences between subgroups of workers. Moreover, existing differences - such as gender, language, nationality, employment form, sector of work - should be tested for their possible impact on the relations between job control and worker well-being, before the results can be generalized across diverse groups of workers (e.g., Borsboom, 2006).

3. Is there a way to improve the well-being of high-skilled workers, who as a group already have favorable working conditions?

The levels of job control aspects were generally high, confirming that high-skilled workers indeed had favorable working conditions. Nevertheless, some high-skilled workers enjoyed better well-being levels than the others, suggesting that further improvements are possible. The studies presented in this dissertation identified several possible ways to help building and sustaining the work-related well-being of high-skilled workers.

First, the results of the comparative task level study suggest that different interventions may improve the well-being of workers with diverse forms of employment. Specifically, it seems that organizationally employed workers would benefit from higher autonomy and more opportunities to be creative at work, since these were the strongest predictors of their work engagement. In contrast, self-employed high-skilled workers may benefit from increased learning opportunities, more social tasks and less administrative or other non-core work tasks. Similarly to previous results, self-employment was shown to be beneficial for worker well-being (Hundley, 2001; Schneck, 2014). Thus, organizationally employed high-skilled workers may even consider changing their form of employment in order to increase their job control levels.

Second, the prospective study revealed how the availability of job control varies within the group of high-skilled workers and over time. In this study, each worker was classified to one of the four classes characterized by different patterns of working conditions. The study estimated the amount of workers belonging to each of the classes i.e., the prevalence of each pattern of working conditions, and modeled transitions between classes over time. Interestingly, the prevalence of patterns with high autonomy levels was similar to the prevalence of patterns with low autonomy levels in the group of high-skilled workers. Moreover, the prevalence of low autonomy patterns tended to increase over time at the cost of a decreasing prevalence of the high autonomy patterns. These results reveal that high-skilled workers not only differ in autonomy levels, but also that they are prone to losing their autonomy over time. Combined with the fact that patterns of working conditions characterized by a low autonomy resulted in generally lower job satisfaction and higher emotional exhaustion of workers, this means that interventions aimed at increasing autonomy and preventing autonomy loss may help in sustaining the well-being levels of high-skilled workers. Such autonomy supportive interventions include, for example, providing greater choice at work and encouraging self-initiation (Gagne & Deci, 2005; Su & Reeve, 2011).

Third, the experimental study tested whether altering task instructions in a way that enables autonomous self-expression may yield more positive emotions. The results revealed that tasks formulated in a way that encourages creativity i.e., tasks that have many different solutions, encourage switching between semantic categories, and enable individuals to approach a problem in a novel way, increase autonomy, which in turn increases the positive emotions of participants. Thus, formulating or rephrasing work tasks in a way that will encourage creativity may serve as an intervention to improve the autonomy levels of high-skilled workers, and in turn boost their well-being. Moreover, as previous research has shown that positive emotions help people think creatively (Baas et al., 2008), more creative tasks at work may trigger a gain spiral: creative tasks lead to higher autonomy, higher autonomy leads to more positive emotions, and positive emotions bring even more creativity.

In sum, the results found several possible interventions to improve the well-being of high-skilled workers. For example, interventions focusing on increasing and sustaining high autonomy levels may prove to be particularly beneficial. Moreover, the findings suggest that interventions should be carefully targeted at specific groups of workers, such as the self-employed or organizationally employed, managers or technicians, education sector workers or health sector workers. Finally, the results of the empirical studies suggest that task level interventions may significantly improve worker well-being. For example, high-skilled workers may benefit from more creative tasks, more freedom to choose what to do and how to work, and more challenging tasks.

5.2 Thesis' contribution

5.2.1 Theoretical contribution

Arguably, the working conditions of high-skilled workers may always be characterized by certain levels of autonomy, creativity and learning opportunities. Consequently, these aspects of job control not only coexist but are also likely to influence one another. Thus, the main theoretical contribution of this thesis lies in investigating the interrelations between aspects of job control, as well as their distinct and joint effects on worker well-being.

The empirical studies included in this dissertation indicated that levels of autonomy, creativity and learning tend to vary somewhat independently from one another. Should the three aspects of job control represent one unanimous phenomenon, their levels will simultaneously be either high or low. However, the results presented in this dissertation suggest that this is not the case, which brings an important extension to the theoretical assumption that positive characteristics of work environments may be grouped into one umbrella category of job control or job resources (Bakker et al., 2014; Karasek & Theorell, 1990). At least in the group of high-skilled workers, aggregating all the aspects of job control into a single construct may lead to an oversimplified description of the reality. Thus, a more nuanced view of job control is needed to better understand the differences between high-skilled workers.

This dissertation presents a set of methodologies that allow for such a more detailed investigation of job control aspects, and consequently reveal a number of new relations that are still pending theoretical explanations. For example, person-centered approaches provide information about the prevalence, stability and transitions between groups of workers characterized by different patterns of working conditions. This way of analysis requires a new language to describe the findings, other than the one typically used in the field of working conditions research thus far. Instead of interpreting mean levels of each of the separate variables, the results reveal patterns of interrelating variables, as well as their prevalence in the population. In other words, instead of talking about high or low levels of job control, the findings provide details on the number of workers having favorable or unfavorable patterns of working conditions. Recently, such descriptions have become more popular, mainly because it is easily applicable to practice in terms of policy changes or intervention planning (Eurofound, 2014a, 2016). From the perspective of theory development, person-centered approaches allow for the investigation of complex interrelations among aspects of job control. Thus, they give a chance to formulate more specific hypotheses regarding several characteristics of work environments treated as separate variables, rather than aggregated constructs.

The aspects of job control not only vary independently, but are also likely to influence one another. Thus far, researchers have almost solely investigated the interactive effects of job control and job demands (e.g., Van de Ven, Vlerick, & de Jonge, 2008), or alternatively studied the three-way interactive effects between internal resources, job control and job demands (e.g., Meier, Semmer, Elfering, & Jacobshagen, 2008). Relationships within aspects of job control have been omitted, mainly due to the common practice of

aggregating them into one construct. However, the results presented in this dissertation suggest that investigating a dynamic interplay of autonomy, creativity and learning in the work environment may further our understanding of mechanisms that lead to increased worker well-being. For example, previous research revealed that job satisfaction increases when creativity requirements at work are complemented by sufficiently high autonomy (Shalley et al., 2000). The results of the experimental study included in this dissertation explored this result, showing that creative tasks may actually increase autonomy levels. Consequently, the relationship between creativity and autonomy at work may be causal and not only correlational. As suggested by conservation of resources theory (Hobfoll, 1989), current findings suggest that a possible gain spiral connects creativity, autonomy and positive emotions at work (Amabile et al., 2005). Moreover, such causal relationships may also connect other aspects of job control with well-being indicators, for example challenge, learning and engagement, as suggested by the “flow” theory (Cseh et al., 2015; Csikszentmihalyi & Lefevre, 1989; Moneta, 2012b). Thus, in order to further develop the theories of healthy work, a dynamic interplay of positive aspects of work environments should be investigated and explained.

Another important theoretical advancement brought by the findings presented in this dissertation lies in investigating the multilevel character of job control aspects. Due to the momentary character of emotional experiences, task-level measurement of well-being has become a recommended approach (Bakker et al., 2011b; Kahneman et al., 2004; Sonnentag, 2017). However, research has rarely investigated day level or task level variability in aspects of job control (e.g., Tadić et al., 2015). A momentary experience of autonomy, and opportunities to be creative and to learn at work, may vary significantly from a general evaluation of the extent to which these aspects of job control are available to a worker. In other words, one may experience high autonomy in many work tasks, but still evaluate the overall autonomy level at work as low. This is because what people remember may be quite different from what they actually experienced (Kahneman, 2000). Moreover, just as task or day level assessments may differ from person level judgments, the amount of available job control may further differ on the group level. Workers from the same organization, sharing similar work environments, may not necessarily fully agree on the levels of job control available in this environment (LeBreton & Senter, 2008). Thus, investigations of task level relations, group level profiles, and multilevel interactions are needed to further the understanding of the role aspects of job control play in sustaining worker well-being.

Finally, the group comparisons investigated in this dissertation define the extent to which job control theory can be generalized among different groups of workers. The Job Demands Control (JDC) model was originally specified based on differences between occupations i.e., distinguishing between the active jobs of for example engineers, teachers, or physicians, and the passive jobs of, for example, janitors or miners (Karasek & Theorell, 1990). Further applications of the model, as well as its extensions, including the Job Demands Resources (JDR) model, have applied its theoretical principles to the differences between individuals within (or regardless of) occupations. Even though the JDC and the JDR models have been widely tested across diverse groups of occupations (for review see e.g., Bakker et al., 2014; Häusser et al., 2010), systematic comparisons showing how the models apply for specific sectors of work or forms of employment are

rare. Some of the first attempts to understand the different meanings of work environment characteristics, such as work pressure or opportunities to be creative, for workers in different occupations, jobs, or workplaces suggest that the same aspect of the work environment may be considered challenging by one group and hindering by the other group of workers (Bakker & Sanz-Vergel, 2013; Shalley et al., 2000). The results presented in this dissertation provide an overview of the differences in the functioning of one of the basic principles of the JDC model, namely that job control predicts higher well-being, across diverse groups of workers. The existence of such differences raises yet another argument for a more nuanced view of job control and its functions in the group of high-skilled workers.

In sum, this dissertation indicated several ways in which the relationship between job control and well-being may be further investigated. Current theories of healthy work take a rather narrow angle when explaining predictors of worker well-being, focusing on aggregated variables measured on the person level, which are then assumed to predict well-being indicators in the same way for diverse groups of workers. This dissertation argues for a more nuanced view, which includes taking into account separate functions of different aspects of job control, their complex and possibly causal interactions, their changing multilevel character, and their unique roles in specific groups of workers.

5.2.2 Methodological contribution

Apart from abovementioned theoretical advances, this dissertation also contributes to the development of methods used in the area of research on working conditions. The empirical studies were designed in ways that allowed for applying novel modeling techniques. Table 5.1 presents a summary and comparison of the methodologies employed in the studies. Three main methodological advances offered by this dissertation are discussed below.

First, a form of a confirmatory strategy was used in all three studies. In general, confirmatory designs are recommended because they inspire significantly more confidence in the results (Finch & Bronk, 2011; Morin et al., 2015; Norton, Cosco, Doyle, Done, & Sacker, 2013; Schaufeli et al., 2002). In other words, the quality of evidence increases when similar results are obtained across groups or across time. Thus, the studies presented in this dissertation provide examples how to include confirmatory strategies into a single study design. The prospective study confirmed the existence of the same four classes of high-skilled workers, characterized by different patterns of working conditions, across three measurement occasions. This means that these four patterns of working conditions may be considered typical for high-skilled workers. The comparative task level study systematically contrasted two groups of workers, thus revealing which aspects of the predictive model may be considered similar and which differ between these groups. The experimental study also used a multi-group modelling strategy to confirm whether the results obtained in one language sample are replicated in the other three samples. Altogether, this dissertation presents a range of methods that help to test hypotheses systematically across groups and measurement occasions in order to increase the confidence in the obtained results.

Second, diverse methodologies applied across the empirical studies allowed for the triangulation of results. All three studies found that aspects of job control are significant predictors of well-being, and the fact that this result was confirmed on group, person, and task levels strengthens and diversifies its interpretation. Moreover, the application of both person-centered and variable-centered approaches also provides a wider perspective on the issue of working conditions (Collins & Lanza, 2010; Wang & Hanges, 2011). These two approaches may be considered complementary, with the former focusing on the prevalence of certain sets of characteristics in the population, and the latter investigating the strength of relationships these characteristics have with one another. Interestingly, the two models may even be statistically identical, yet conceptually they will have a very different interpretation (Borsboom, Mellenbergh, & van Heerden, 2003). Thus, the application of these two approaches encourages a more in-depth discussion of work environments in high-skilled work.

Third, the methodologies applied in this dissertation emphasize the importance of task level measurements of well-being. Current approaches acknowledge that work engagement has an affective and momentary character, and thus it emerges and varies already on the task level (Sonnentag, 2017). More and more scholars call for the application of daily diary studies in order to capture within person fluctuations of well-being (Bakker et al., 2011b; Breevaart et al., 2014; Mojza, Lorenz, Sonnentag, & Binnewies, 2010; Ohly, Sonnentag, Niessen, & Zapf, 2010; Van den Broeck, Schreurs, Guenter, & van Emmerik, 2015). Thus, this dissertation investigates and interprets the effects of available job control on worker well-being using work tasks as basic units of analysis whenever possible. The main advantage of such a strategy lies in introducing a possibility to describe dynamic mechanisms, such as for example habituation to task features (e.g., Thompson, 2009), shifting absorption levels (e.g., Lin, Hsu, Chen, & Chang, 2013), reaction to boring and unsuitable tasks (e.g., Semmer et al., 2015). Thinking of working conditions as characteristics of a task, which change and fluctuate, forms a bridge between cross-sectional studies and experimental tests. Thus, this dissertation provides an example how task level mechanisms may be applied to explain person and group level differences. It also shows that working conditions may actually be translated to the level of task instructions and be experimentally manipulated.

Table 5.1 Summary and comparison of the methodologies used in the three empirical studies

	Sample	Design	Model
<i>Chapter 2</i>	1744 high-skilled workers in Sweden of a representative sample of the working population, mainly close to their fifties at the baseline, the majority of them were women	prospective study over 6 years and 3 measurement occasions, with well-being and ill-being variables measured with a 2-year time lag after working conditions measurement	Latent Transitions Analysis model, a longitudinal extension of Latent Class Analysis (LCA) model
<i>Chapter 3</i>	167 high-skilled workers in Sweden, mainly in their forties, half of them women, working in the creative sector	536 reports from work tasks as a basis for a cross-sectional comparison between two groups (self-employed and employees) on two levels (person and task)	multilevel multi-group model, based on Multilevel Confirmatory Factor Analysis (MCFA) measurement model

	Sample	Design	Model
<i>Chapter 4</i>	478 participants, the majority of them were women and university level students, most close to their thirties, from four language groups: English, Italian, Polish, and German	online experiment on the effects of creative tasks (independent variable) on positive emotions (dependent variable) through a change in autonomy and absorption (mediators)	multi-group Structural Equation Model (SEM) estimating both direct and indirect effects

In sum, the studies presented in this dissertation apply several novel methodological approaches, and therefore each study brings a fresh perspective on the relationship between job control and well-being. Furthermore, a combination of such divergent perspectives forms a main methodological advantage of this dissertation. By looking at distinct levels of analysis, diverse model specifications, and different samples, this dissertation provides a systemic view of worker well-being and its predictors in the group of high-skilled workers (see Figure 1.1 in the Introduction chapter).

5.3 Limitations and suggestions for future research

This thesis focuses mainly on the importance and functionality of positive aspects of the work environment as defined by the job control concept. Moreover, the empirical studies reported in this dissertation were conducted on a sample of highly educated individuals from European countries. This narrow scope of investigation brings limitations to the results in several ways.

First, the analyses and discussion omit those positive aspects of the psychosocial work environment that do not relate to work organization, but instead refer to social interactions. The main reasons for this is the overall purpose of this dissertation i.e., to test the very basic assumptions of the healthy work environment theory in a group of high-skilled workers. The decision to exclude social aspects of the work environment was also supported by a recent review of studies showing that the Job Demands Control model received more empirical support than its extended version, the Job Demands-Control-Support model (Häusser et al., 2010). Thus, further research is needed to investigate the role of social interaction variables in predicting high-skilled workers' well-being.

Second, variables representing personal resources were not measured in the empirical studies included in this dissertation. Previous research found that individual factors - such as self-efficacy, optimism, emotional stability, conscientiousness, proactive personality and self-esteem - are significantly related to work engagement and were able to predict worker well-being above and beyond work environment features (Christian, Garza, & Slaughter, 2011; Mäkikangas, Taru, Kinnunen, & Mauno, 2013). This is because such personal characteristics are likely to influence the way in which working conditions are interpreted, and may thus modify the extent to which work environment features predict worker well-being (Bakker et al., 2014). A possible impact of personal resources, as well as the coping and emotional regulation processes they may trigger, should be further investigated in future studies.

Third, apart from personal resources, the role of other individual differences was also omitted in this dissertation. Specific competencies and qualifications that are characteristic for certain groups of workers may have modified the role different job control aspects have in predicting worker well-being. For example, high-skilled workers from creative occupations, such as musicians and architects, may have higher creative competence and be more used to open-ended tasks than others (Benedek, Borovnjak, Neubauer, & Kruse-Weber, 2014; Cohen, 2005; Fink & Woschnjak, 2011). In contrast, workers from non-creative occupations, such as lawyers and medical doctors, may prefer higher levels of order and predictability, and express higher need for closure (Webster & Kruglanski, 1994). Thus, further research is needed to reveal whether certain personal characteristics are indeed more common in particular groups of workers, and whether such personal characteristics may moderate the role of job control aspects in certain occupations.

Fourth, in this thesis little attention is given to demands and ill-being as these are experienced by high-skilled workers. The decision to limit the scope of this dissertation to only positive aspects of the psychosocial work environment is consistent with current theories stating that aspects of job control are important predictors of worker well-being, regardless of the existing demands. This relates to two separate processes: the energy depleting process connecting job demands with ill-being and the motivating process connecting job resources with well-being (Bakker et al., 2014). Moreover, relationships between demands and work engagement tend to differ depending on whether a demand is appraised as a challenge or a hindrance (Crawford et al., 2010; Podsakoff, LePine, & LePine, 2007). This further complicates the role of demands in the context of high-skilled work, where almost no straightforward (e.g., physical) demands exist, and nearly all aspects of the work environment may be interpreted both as a resource and as a stressor. This means that further work is needed on clarifying what defines job demands in the context of high-skilled work, and then what role they play in predicting workers' well-being.

Fifth, the results, as discussed in this dissertation, are also limited by the unclear status of job control measurement. It is difficult to specify exactly what self-reported measures of job control, such as those used in the empirical studies of this dissertation, actually measure. Control can be viewed as 1) an objective characteristic of the situation, 2) a subjective evaluation reflecting individual judgment of a particular situation, or 3) as a general belief of an individual regarding the extent to which situations at work are controllable (Parkes, 1989). Even though the measurements used in this dissertation are aimed at capturing the second of these possible operationalizations of job control, it remains to be ascertained how the participants understood the questions. Moreover, possible qualitative differences in the interpretation of job control items, which may come from a certain standard understanding of autonomy, creativity and learning in specific jobs or occupations, may have influenced the quality of measurement. To reduce any confounding impact of different operationalizations of job control, the measurements used in the empirical studies referred as much as possible to specific situations and tasks. However, future research should explore in more detail how aspects of job control are defined and understood by high-skilled workers from different sectors, occupations, and with different forms of employment.

Sixth, the empirical studies included in this dissertation are limited by several characteristics of their study design. These include sample limitations, such as the use of convenience samples, overtime attrition patterns, and the overrepresentation of women. The samples included only Swedish high-skilled workers, who may enjoy more favorable working conditions than workers in other European countries (Eurofound, 2016). This may in turn imply that the reported differences within the group of high-skilled workers could be even more pronounced in other countries. For the same reason, the results presented in this dissertation may be limited to the Swedish (or Nordic) cultural and political background. Moreover, even though this dissertation presents multilevel interpretation of the results - including task, person and group levels - it did not include all possible levels of analysis such as day level, organizational level, and societal or national level. All these limitations reflect possible ways in which future research may complement the findings presented here.

Seventh, possible curvilinear relationships were not examined in this dissertation. The empirical studies investigated whether higher levels of autonomy, creativity, and learning may improve the well-being of high-skilled workers. However, neither of the studies has tested the possible curvilinearity of these relationships, even though previous research has suggested that very high levels of job control may actually be detrimental for well-being at work (Kubicek et al., 2014). The results presented in this dissertation confirmed that some high-skilled workers experience exceptionally high levels of autonomy, creativity and learning at their jobs. Thus, it may be hypothesized that such work environments trigger the “too-much-of-the-good-thing” effect. These effects have previously been found for example in relationships between leadership practices and organizational citizenship behavior of followers (Vergauwe, Wille, Hofmans, Kaiser, & De Fruyt, 2017), and between personality traits and job performance (Robbins, Le, Ilies, Holland, & Westrick, 2011). Thus, future studies may test whether, and in which circumstances, very high job control may decrease the well-being of high-skilled workers.

In sum, the generalizability of the findings presented in this dissertation is limited to linear relationships among aspects of job control and the well-being of high-skilled workers from developed countries. Thus, one should be cautious when applying these results to other groups of workers, other countries, other contexts, and other levels of analysis.

5.4 Implications for practice

The general lesson that should be learned from the results of this dissertation is that there is a call for a more nuanced approach to addressing high-skilled workers' needs. For practitioners willing to better understand the working conditions and well-being of high-skilled workers, this conclusion translates into the following set of suggestions.

Be specific when describing work environments. Aspects of job control, such as procedural and decision autonomy, the requirement to be creative, and learning opportunities, are each an important characteristic of a healthy work environment that should be considered separately to fully understand the complexity of high-skilled work. For example,

autonomy levels better differentiate high-skilled workers than creativity and learning opportunities. Even more specifically, high levels of procedural autonomy are more common than high levels of decision autonomy.

Take the perspective of the individual worker. Apart from describing work environments in terms of aggregated levels of each of the specific aspect of job control, aim to discover patterns of working conditions as experienced by an individual. A person-centered perspective gives a chance to understand the interrelations between different work environment characteristics, and thus plan more specific and better-targeted interventions. For example, workers may have similarly low levels of work-related well-being due to different causes. The majority may experience suboptimal well-being levels due to low autonomy, while a smaller group may suffer from high workload and time pressure.

Be aware of within group differences. Aspects of job control seem to have different functions in specific groups of workers. For example, for self-employed workers learning opportunities significantly increase work engagement, but for organizationally employed workers creativity and autonomy are more important.

Small task level interventions matter. Worker well-being arises through a series of affective and momentary experiences generated by each work task, and thus task characteristics play a significant role in shaping the general perception of work environments. Therefore, small changes in task instructions or context may bring a significant increase in worker well-being. For example, formulating task instructions in a way that enhances creativity (i.e., tasks that have many different solutions, encourage switching between semantic categories, and enable individuals to approach a problem in a novel way) will likely result in workers feeling more autonomous and experience more positive emotions.

Focus on building sustainable well-being. Apart from changes on a micro level, such as altering task instructions, be aware of long term changes in working conditions on the macro level. For example, autonomy loss is one of the most common indicators of workers moving from a healthy to a risky pattern of working conditions. Thus, interventions that help workers sustain high level of procedural and decision autonomy over longer periods of time will probably result in higher well-being levels and less ill-being symptoms.

5.5 Conclusion

The aim of this dissertation was to paint a more diverse picture of high-skilled work than has thus far been assumed in research on working conditions. In current knowledge-based economies, more and more workers reach the status of a professional or a manager. With over one third of the current workforce being involved in high-skilled work, it is not enough to simply state that high-skilled workers enjoy higher job control and well-being levels than their less educated colleagues. Thus, this dissertation analyzed differences and similarities within diverse subgroups of high-skilled workers, and therefore tested to what extent the basic assumptions of the healthy work theory may be applied to each of them. The findings presented in this dissertation suggest that high levels of well-being are not

equal across diverse types of high-skilled workers. Significant differences exist among groups representing diverse occupations, forms of employment, and most of all varying levels of available job control. A dynamic interplay of opportunities – to choose, to learn, and to be creative – seems to explain why some high-skilled workers are more engaged at work than others. Moreover, high well-being levels are also not permanent. The experience of being a high-skilled worker changes over time, and these changes start as early as in the momentary task-to-task fluctuations. Thus, this thesis concludes with a call for a more nuanced view of work environments, and consequently a more targeted approach to designing interventions aimed at improving the well-being of high-skilled workers.

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A.1 Survey items

Table A.1 Survey items comparison across studies

Chapter	Constructs measured	Example item
Autonomy		
Chapter 2	Decision autonomy	Do you have a choice in deciding what you do at work?
	Procedural autonomy	Do you have a choice in deciding how you do your work?
Chapter 3	Decision autonomy	I feel free to decide how I want to work.
	Procedural autonomy	I choose the way I work myself.
Chapter 4	Autonomy	During this task, I felt free to decide for myself.
Creativity		
Chapter 2	Opportunities to be creative at work	Does your work require creativity?
Chapter 3	Creativity at work	I have a possibility to express myself creatively.
Chapter 4	Solving a creative task	Invent titles for a cartoon.
Learning		
Chapter 2	Learning opportunities	Do you have the opportunity to learn new things through your work?
Chapter 3	Learning at work	I have a possibility to take on difficult tasks.
Chapter 4	Difficulty of a task	To what extent have you considered the task to be difficult?
Well-being		
Chapter 2	Job satisfaction	Roughly, how satisfied are you with your work?
	Emotional exhaustion	My job makes me feel emotionally drained.
Chapter 3	Positive emotions (engagement)	To what extent during this activity have you felt energetic?
Chapter 4	Positive emotions (engagement)	To what extent during the task have you felt engaged?

Appendix

A.2 Supplementary material and syntaxes for Chapter 2

A.2.1 Representativeness of the analytic sample

Table A.2 Comparison between analytic sample and full sample of high-skilled workers

2008	Analytic Sample (N = 1744)			Full Sample (N = 5955)			p
	Mean (SD)	n	% valid	Mean (SD)	n	% valid	
Age	47.36 (8.55)			49.27 (11.27)			<.01
Women		1060	60.8		3318	55.7	<.01
Managers		205	11.8		802	13.5	.06
Technicians		706	40.5		2591	43.5	.02
Born in Sweden		1635	93.9		5617	94.4	.33
University degree		1263	72.5		3718	62.5	<.01
Married or cohabitating		1061	60.8		3561	59.8	.44
Children living at home		1035	57.9		2825	47.9	<.01
Employed by government		967	57.7		2549	49.9	<.01
Employed by private		631	37.6		2092	41.0	.42
Small enterprises		731	43.5		2470	48.2	.74
Day job		1502	87.4		5012	85.6	.05
Shift work		121	7.0		386	6.6	.50
Non-regulated work hours		75	4.4		309	5.3	.13
Working conditions							
Learning opportunities	1.53 (0.59)	901	57.7	1.58 (.62)	2870	48.5	<.01
Creativity requirement	1.36 (0.56)	1174	67.4	1.40 (.58)	3836	64.9	.01
Freedom how to work	1.45 (0.61)	1054	60.6	1.47 (.64)	3550	60.1	.23
Freedom what to do	1.96 (0.77)	505	29.0	1.93 (.80)	1946	32.9	.16
Working fast	1.94 (0.68)	425	24.4	1.96 (.70)	1424	24.1	.28
Working intensively	2.14 (0.81)	371	21.4	2.12 (.80)	1260	21.4	.36
Working with too much effort	2.07 (0.74)	396	21.9	2.09 (.76)	1147	22.3	.32

Note: Sample selected for this study included high-skilled workers who were gainfully employed and completed the questionnaire at all the measurement occasions. Small enterprises were defined as those employing fewer than 50 individuals. Psychological working conditions were coded 1= "yes, often", 2= "yes, sometimes", 3="no, seldom" or 4="no, hardly ever". The figures present the prevalence in percentage of the response coded as "1".

A.2.2 Cross-sectional latent class analyses

The analysis of a latent mixture reveals diversity within a population. The number of possible subpopulations is finite, and some patterns will typically occur more often than others (Bergman, & Magnusson, 1997; Foti, Thompson, & Allgood, 2011). This unobserved heterogeneity can be identified and modeled through mixture models, such as Latent Class Analysis, LCA (e.g., McLachlan & Peel, 2000; Nylund-Gibson et al., 2014). LCA identifies subtypes of individuals who exhibit similar patterns of certain characteristics (Collins & Lanza, 2010; Wang & Hanges, 2011) meaning that individuals classified together have a similar pattern of responses to a set of questions representing individual characteristics.

The goal of cross-sectional analyses was twofold: 1) to examine how many groups with distinguished working conditions (classes) that emerge at each time point, and 2) to examine the similarity of the structure of the classes across time points. Thus, this preliminary analysis allowed us to test whether the class structure would replicate across

three time points.

All the analyses were performed with Mplus 7.11 using the same specification and model fit indices as in the main analyses (Latent Transition Analyses). The Bootstrapped Likelihood Ratio Test (BLRT) was only used in cross-sectional analyses as it is unavailable for models with more than one categorical latent variable (Muthén and Muthén, 1998-2012). The BLRT compares a k class model with a k-1 class model, with a significant p value indicating that a model with less latent classes should be rejected in favor of a model with more latent classes (Nylund, Asparouhov, & Muthén, 2007).

The Supplementary Table 2 present results of the cross-sectional latent class analyses. According to the BLRT, a six-class solution had the best fit at times 1 and 3, while a five-class solution had the best fit at time 2. However, the six-class solution suffered from estimation problems at time 2 and resulted in small classes (only 1.8% prevalence) at time 1. The drop in BIC value flattened out already around four classes. The change from the four to the five-class model resulted in a significant increase in BIC value at time 1 ($\Delta\text{BIC} = 23.4$), an insignificant increase at time 2 ($\Delta\text{BIC} = 1.5$), and an insignificant decrease at time 3 ($\Delta\text{BIC} = 3.6$). Thus, the BIC value provided strong support for the four-class model at time 1, and no evidence of the four-class model being worse than the five-class model at times 2 and 3.

The structure of the four-class solution at each point in time is presented in the Supplementary Figure 1. The estimated classes were very similar across time points. The same four-class structure was replicated in the longitudinal model reported in the main manuscript.

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

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

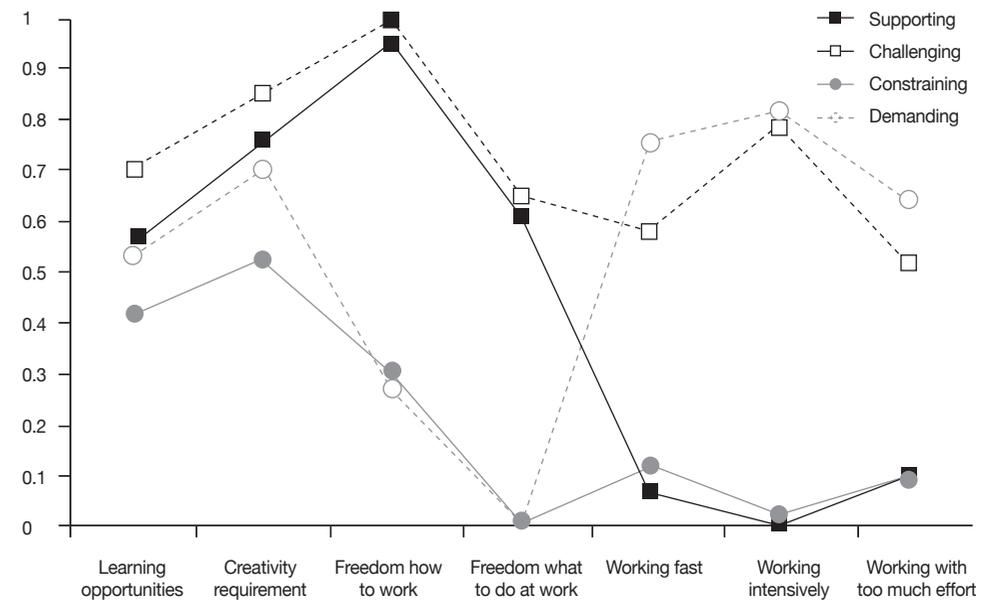
Muthén, L.K., & Muthén, B. (1998-2012). *Mplus User's Guide, 7th Edn.* Los Angeles, CA: Muthén and Muthén.

Table A.3 Model comparison in cross-sectional Latent Class Analyses

k	BLRT	LL	SCF	#fp	AIC	BIC	SABIC	Entropy
Time 1 (2008)								
2	<.000	-6885.59	1.03	15	13801.17	13883.12	13835.47	0.80
3	<.000	-6677.15	1.05	23	13400.29	13525.95	13452.88	0.71
4	<.000	-6607.68	1.03	31	13277.36	13446.73	13348.24	0.73
5	<.000	-6589.55	1.05	39	13257.09	13470.16	13346.26	0.75
6	<.000	-6575.80	1.08	47	13245.61	13502.38	13353.07	0.78
7	0.092	-6565.45	1.03	55	13240.90	13541.39	13366.66	0.80
Time 2 (2010)								
2	<.000	-6446.73	1.03	15	12923.46	13005.41	12957.76	0.81
3	<.000	-6194.42	1.03	23	12434.83	12560.49	12487.42	0.74
4	<.000	-6148.52	1.06	31	12359.05	12528.41	12429.93	0.77
5	<.000	-6119.40	1.01	39	12316.81	12529.88	12405.98	0.78
6	0.208	-6110.32	1.05	47	12314.65	12571.43	12422.11	0.74
7	0.999	-6105.00	1.04	55	12320.01	12620.49	12445.76	0.75
Time 3 (2012)								
2	<.000	-6341.11	1.05	15	12712.22	12794.17	12746.51	0.84
3	<.000	-6083.22	1.04	23	12212.45	12338.10	12265.03	0.73
4	<.000	-6050.48	1.19	31	12162.96	12332.33	12233.84	0.75
5	<.000	-6018.85	1.27	39	12115.70	12328.77	12204.87	0.71
6	<.000	-6000.55	1.04	47	12095.10	12351.88	12202.57	0.73
7	0.182	-5992.27	1.11	55	12094.54	12395.02	12220.29	0.74

Note: k = number of latent classes in the model; BLRT = p value of the parametric bootstrapped likelihood ratio test for k-1 vs. k classes; LL = model log likelihood; SCF = scaling correction factor of the robust maximum likelihood estimator. #fp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-adjusted BIC.

Figure A.1 Item-response probabilities for the four classes in the cross-sectional Latent Class Analyses 2008



2010

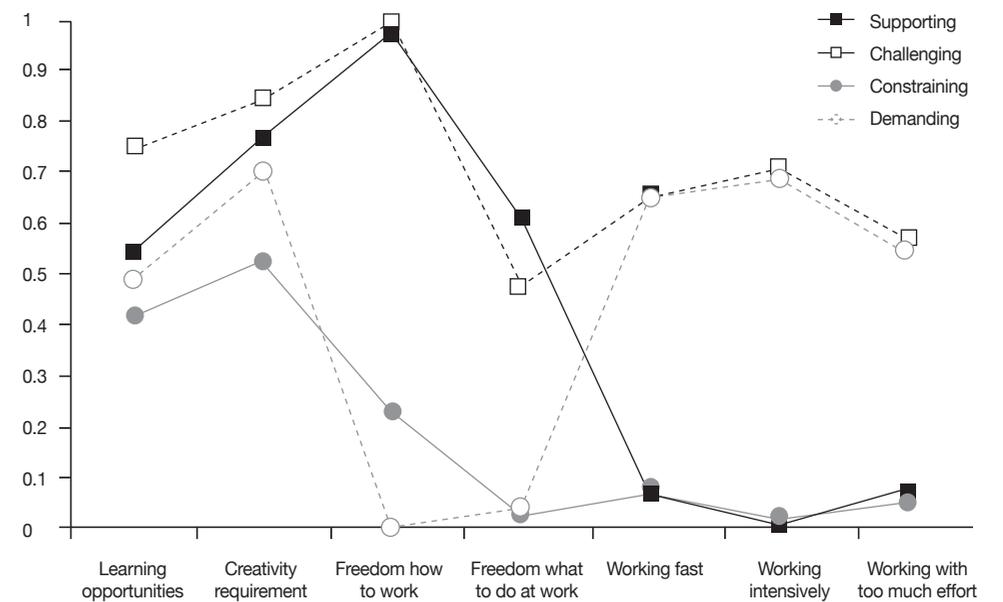
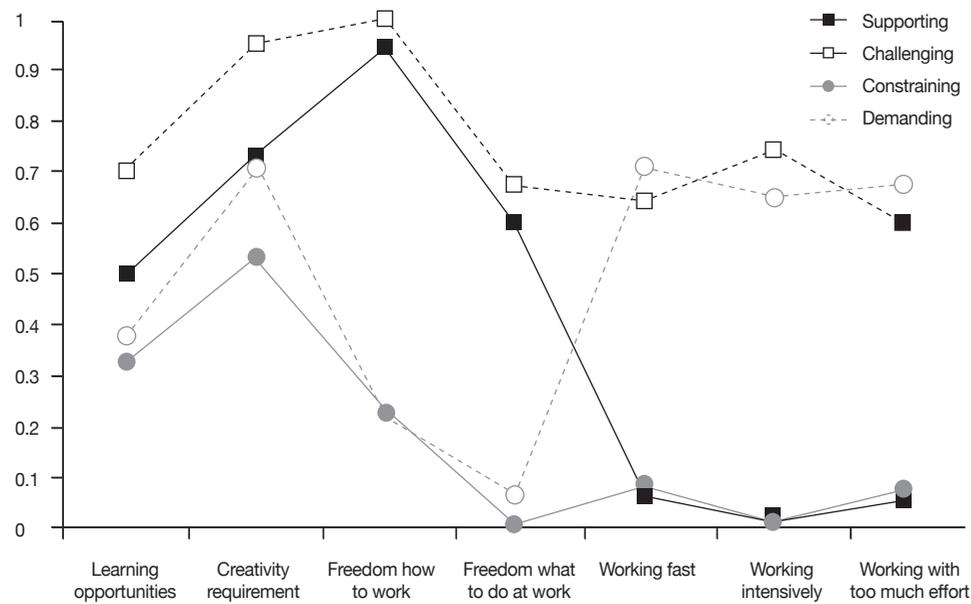


Figure A.1 Item-response probabilities for the four classes in the cross-sectional Latent Class Analyses 2012



A.2.3 Mplus input code to estimate the latent class analysis model

TITLE: Cross-sectional Latent Class Analyses

DATA: FILE = data.dat;

VARIABLE: NAMES =

!binary indicators of demands-resources at time 1

t1learn t1crdem t1how t1what t1fast t1hard t1effort

!binary indicators of demands-resources at time 2

t2learn t2crdem t2how t2what t2fast t2hard t2effort

!binary indicators of demands-resources at time 3

t3learn t3crdem t3how t3what t3fast t3hard t3effort

!covariates and outcomes were not be used at this stage of the analyses

t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech

t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;

MISSING are all (-9); *!defines missing values coding*

USEVARIABLES ARE *!list of variables for the analysis at time 1*

t1learn t1crdem t1how t1what t1fast t1hard t1effort;

CATEGORICAL = all; *!specifies all used variables as categorical*

CLASSES = c (4); *!defines a categorical latent variable c with 4 latent classes*

ANALYSIS:

TYPE = MIXTURE; *!defines mixture modelling*

PROCESSORS IS 4; *!defines nb of threads to speed up the analysis*

STARTS 700 100; *!increases the default nb of initial random starts to 700*

!and asks for 100 to be retained for final optimization

LRTSTARTS (0 0 100 40); *!defines a number of iterations for the BLRT*

PLOT:

type is plot2; *!request item probabilities plot to reveal a class structure*

series is t1learn (1) t1crdem (2) t1how (3)

t1what (4) t1fast (5) t1hard (6) t1effort (7);

OUTPUT:

tech14; *!request the results of the BLRT*

A.2.4 Mplus input code to estimate the latent transition analysis model

TITLE: Latent Transition Analysis

DATA: FILE = data.dat;

[VARIABLE command is specified in the same way as in the cross-sectional analyses; demands-resources indicators from all three data points are used]

CLASSES = c1 (4) c1 (4) c3 (4); *!defines three categorical latent variables*

!for three time points respectively with 4 classes each

[ANALYSIS command is specified in the same way as in the cross-sectional analyses]

MODEL:

%OVERALL%

MODEL C1: *!specifies the model at time 1*

%C1#1%

[t1learn\$1] ; [t1crdem\$1] ; [t1how\$1] ; [t1what\$1] ; [t1hard\$1] ; [t1fast\$1] ; [t1effort\$1];

%C1#2%

[t1learn\$1] ; [t1crdem\$1] ; [t1how\$1] ; [t1what\$1] ; [t1hard\$1] ; [t1fast\$1] ; [t1effort\$1];

%C1#3%

[t1learn\$1] ; [t1crdem\$1] ; [t1how\$1] ; [t1what\$1] ; [t1hard\$1] ; [t1fast\$1] ; [t1effort\$1];

%C1#4%

[t1learn\$1] ; [t1crdem\$1] ; [t1how\$1] ; [t1what\$1] ; [t1hard\$1] ; [t1fast\$1] ; [t1effort\$1];

MODEL C2: *!specifies the model at time 2*

%C2#1%

[t2learn\$1] ; [t2crdem\$1] ; [t2how\$1] ; [t2what\$1] ; [t2hard\$1] ; [t2fast\$1] ; [t2effort\$1];

%C2#2%

[t2learn\$1] ; [t2crdem\$1] ; [t2how\$1] ; [t2what\$1] ; [t2hard\$1] ; [t2fast\$1] ; [t2effort\$1];

%C2#3%

[t2learn\$1] ; [t2crdem\$1] ; [t2how\$1] ; [t2what\$1] ; [t2hard\$1] ; [t2fast\$1] ; [t2effort\$1];

```
%C2#4%
[t2learn$1] ; [t2crdem$1] ; [t2how$1] ; [t2what$1] ; [t2hard$1] ; [t2fast$1] ; [t2effort$1];
MODEL C3: !specifies the model at time 3
%C3#1%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1] ; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#2%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1] ; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#3%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1] ; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#4%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1] ; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
```

A.2.5 Mplus input code to estimate the latent transition analysis model with measurement invariance across time points

```
TITLE: Latent Transition Analysis
DATA: FILE = data.dat;
[VARIABLE and ANALYSIS commands are specified as before]
```

```
MODEL:
%OVERALL%
MODEL C1: !specifies the model at time 1 with constraints on thresholds
%C1#1%
[t1learn$1] (11) ; [t1crdem$1] (12); [t1how$1] (13); [t1what$1] (14); [t1hard$1] (15) ;
[t1fast$1] (16); [t1effort$1] (17);
%C1#2%
[t1learn$1] (21) ; [t1crdem$1] (22); [t1how$1] (23); [t1what$1] (24); [t1hard$1] (25) ;
[t1fast$1] (26); [t1effort$1] (27);
%C1#3%
[t1learn$1] (31) ; [t1crdem$1] (32); [t1how$1] (33); [t1what$1] (34); [t1hard$1] (35) ;
[t1fast$1] (36); [t1effort$1] (37);
%C1#4%
[t1learn$1] (41) ; [t1crdem$1] (42); [t1how$1] (43); [t1what$1] (44); [t1hard$1] (45) ;
[t1fast$1] (46); [t1effort$1] (47);
MODEL C2: !specifies the model at time 2 with constraints on thresholds
%C2#1%
[ t2learn$1] (11) ; [ t2crdem$1] (12); [ t2how$1] (13); [ t2what$1] (14); [ t2hard$1] (15) ; [
t2fast$1] (16); [ t2effort$1] (17);
%C2#2%
[ t2learn$1] (21) ; [ t2crdem$1] (22); [ t2how$1] (23); [ t2what$1] (24); [ t2hard$1] (25) ; [
t2fast$1] (26); [ t2effort$1] (27);
%C2#3%
[ t2learn$1] (31) ; [ t2crdem$1] (32); [ t2how$1] (33); [ t2what$1] (34); [ t2hard$1] (35) ; [
t2fast$1] (36); [ t2effort$1] (37);
```

```
%C2#4%
[ t2learn$1] (41) ; [ t2crdem$1] (42); [ t2how$1] (43); [ t2what$1] (44); [ t2hard$1] (45) ; [
t2fast$1] (46); [ t2effort$1] (47);
MODEL C3: !specifies the model at time 3 with constraints on thresholds
%C3#1%
[ t3learn$1] (11) ; [ t3crdem$1] (12); [ t3how$1] (13); [ t3what$1] (14); [ t3hard$1] (15) ; [
t3fast$1] (16); [ t3effort$1] (17);
%C3#2%
[ t3learn$1] (21) ; [ t3crdem$1] (22); [ t3how$1] (23); [ t3what$1] (24); [ t3hard$1] (25) ; [
t3fast$1] (26); [ t3effort$1] (27);
%C3#3%
[ t3learn$1] (31) ; [ t3crdem$1] (32); [ t3how$1] (33); [ t3what$1] (34); [ t3hard$1] (35) ; [
t3fast$1] (36); [ t3effort$1] (37);
%C3#4%
[ t3learn$1] (41) ; [ t3crdem$1] (42); [ t3how$1] (43); [ t3what$1] (44); [ t3hard$1] (45) ; [
t3fast$1] (46); [ t3effort$1] (47);
```

```
OUTPUT:
svalues; !requests model starting values
tech15; !requests estimated transition probabilities for the class variables
```

A.2.6 Mplus input code for the three-step procedure to account for measurement error using classify-analyze strategy

For information about the three step procedure please see:
Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, 0(July), 1–13. doi:10.1080/10705511.2014.915181

Nylund-Gibson, K., Grimm, R., Quirk, M., & Furlong, M. (2014). A latent transition mixture model using the three-step specification. *Structural Equation Modeling: A Multidisciplinary Journal*, (February 2015), 1–16. doi:10.1080/10705511.2014.915375

STEP 1

First, we saved the starting values of the latent transition analysis model with measurement invariance across time points using Mplus input presented in point 4 in this supplementary material.

STEP 2

Second, we saved the classification into participants' most probable latent class. We fixed the measurement model of latent classes using the starting values from step 1. This has to be done separately for each categorical latent variable.

Mplus input file for the time 1 categorical latent variable:

```

DATA: FILE = data.dat;
VARIABLE:
[NAMES specified as before]
MISSING are all (-9); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 1
t1learn t1crdem t1how t1what t1fast t1hard t1effort;
CATEGORICAL = all; !specifies all used variables as categorical
CLASSES = c1 (4); !defines categorical latent variable c1 at time 1 with 4 latent classes
AUXILIARY = !defines variables that will not be used in the analyses
! but will be included in the "savedata" command to enable further use
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;

```

ANALYSIS:

```

TYPE = MIXTURE; !defines mixture modelling
STARTS 0; !no initial random starting values are used since the measurement model is
fixed at !the values obtained for the longitudinal model with measurement invariance
MODEL:

```

```

%OVERALL% !symbol @ replaces * to fix the estimate at a specific value

```

```

[ c1#2@1.00655 ];
[ c1#1@1.08878 ];
[ c1#3@0.24792 ];
%C1#2%
[ t1learn$1@0.50589 ] (1);
[ t1crdem$1@-0.10454 ] (2);
[ t1how$1@1.15822 ] (3);
[ t1what$1@4.59868 ] (4);
[ t1fast$1@2.41916 ] (5);
[ t1hard$1@5.11668 ] (6);
[ t1effort$1@2.62016 ] (7);
%C2#1%
[ t1learn$1@-0.12372 ] (8);
[ t1crdem$1@-1.12088 ] (9);
[ t1how$1@-3.19092 ] (10);
[ t1what$1@-0.37944 ] (11);
[ t1fast$1@2.79368 ] (12);
[ t1hard$1@4.79094 ] (13);
[ t1effort$1@2.57148 ] (14);
%C2#3%
[ t1learn$1@0.07057 ] (15);

```

```

[ t1crdem$1@-0.87732 ] (16);
[ t1how$1@1.46090 ] (17);
[ t1what$1@3.37868 ] (18);
[ t1fast$1@-0.89747 ] (19);
[ t1hard$1@-0.92056 ] (20);
[ t1effort$1@-0.42118 ] (21);
%C2#4%
[ t1learn$1@-0.92792 ] (22);
[ t1crdem$1@-1.98470 ] (23);
[ t1how$1@-15 ] (24);
[ t1what$1@-0.37149 ] (25);
[ t1fast$1@-0.44296 ] (26);
[ t1hard$1@-1.03830 ] (27);
[ t1effort$1@-0.23139 ] (28);
!the following command saves the most probable classification at time 1
SAVEDATA: file=c1.dat; save=cprob; missflag = 999;

```

Mplus input file for the time 2 categorical latent variable:

```

DATA: FILE = c1.dat;
VARIABLE:      NAMES =
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
cprob1 cprob2 cprob3 cprob4 n1;
MISSING are all (999); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 2
t2learn t2crdem t2how t2what t2fast t2hard t2effort;
CATEGORICAL = all; !specifies all used variables as categoricalCLASSES = c2 (4);
!defines categorical latent variable c2 at time 2 with 4 latent classes

[AUXILIARY and ANALYSIS commands are specified in the same way as in time 1 input.
MODEL command is also specified in the same way due to the longitudinal measurement
invariance]
SAVEDATA: file=c2.dat; save=cprob; missflag = 999;

```

Mplus input file for the time 3 categorical latent variable:

```

DATA: FILE = c2.dat;
VARIABLE:      NAMES =
t2learn t2crdem t2how t2what t2fast t2hard t2effort

```

```
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
n1 cprob1 cprob2 cprob3 cprob4 n2;
MISSING are all (999); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 3
t3learn t3crdem t3how t3what t3fast t3hard t3effort;
CATEGORICAL = all; !specifies all used variables as categorical
CLASSES = c3 (4); !defines categorical latent variable c3 at time 3 with 4 latent classes
[AUXILIARY and ANALYSIS commands are specified in the same way as in time 1 input.
MODEL command is also specified in the same way due to the longitudinal measurement
invariance]
!the following command saves the most probable classification at time 1
SAVEDATA: file=c3.dat; save=cprob; missflag = 999;
```

STEP 3

Third, we fixed latent classes at the values established for the time-invariant measurement model while taking into account the measurement error. Please find a detailed description of the procedure in e.g., Nylund, Asparouhov, & Muthén, 2007.

```
DATA: FILE = c3.dat;
VARIABLE: NAMES =
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
n1 n2 cprob1 cprob2 cprob3 cprob4 n3;
MISSING are all (999); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 3
t3learn t3crdem t3how t3what t3fast t3hard t3effort;
usevar = n2 n3 n4; !modal classes assignment variables
nominal n2 n3 n4;

CLASSES = c1 (4) c2 (4) c3 (4);
ANALYSIS:
TYPE = MIXTURE;STARTS = 0;
MODEL:
%OVERALL%
c2 on c1; c3 on c2; !specifies an autoregressive structure
Model c1:
!Mixed model is specified to have just one indicator, a class assignment variable, and it
is fixed !at a value representing measurement error of the assignment. The values are ob-
```

```
tained from the !Step 2 output named "Logits for the Classification Probabilities for the
Most Likely Latent !Class Membership"
%C1#1%
[n1#1@4.427]; [n1#2@2.011]; [n1#3@-1.807];
%C1#2%
[n1#1@4.811]; [n1#2@6.417]; [n1#3@1.952];
%C1#3%
[n1#1@-1.035]; [n1#2@0.586]; [n1#3@2.043];
%C1#4%
[n1#1@-1.427]; [n1#2@-5.011]; [n1#3@-2.415];
Model c2:
%C2#1%
[n2#1@4.359]; [n2#2@1.803]; [n2#3@-2.071];
%C2#2%
[n2#1@4.799]; [n2#2@6.532]; [n2#3@2.200];
%C2#3%
[n2#1@-1.266]; [n2#2@0.354]; [n2#3@2.102];
%C2#4%
[n2#1@-1.431]; [n2#2@-5/296]; [n2#3@-2.840];
Model c3:
%C3#1%
[n3#1@4.713]; [n3#2@2.619]; [n3#3@-0.986];
%C3#2%
[n3#1@5.608]; [n3#2@7.536]; [n3#3@3.201];
%C3#3%
[n3#1@-0.593]; [n3#2@1.148]; [n3#3@2.789];
%C3#4%
[n3#1@-1.287]; [n3#2@-4.024]; [n3#3@-1.729];
OUTPUT:
tech15; !requests estimated transition probabilities for the class variables
```

A.2.7 Mplus input code to estimate the autoregressive latent transition analysis model with stationary transition probabilities

To specify stationary transition probabilities, the code used for defining an autoregressive structure was replaced with the following code:

```
c1#1 ON c1#1 (t11);
c2#1 ON c1#2 (t12);
c2#1 ON c1#3 (t13);
c2#2 ON c1#1 (t21);
c2#2 ON c1#2 (t22);
c2#2 ON c1#3 (t23);
c2#3 ON c1#1 (t31);
c2#3 ON c1#2 (t32);
```

```

c2#3 ON c1#3 (t33);
c3#1 ON c2#1 (t11);
c3#1 ON c2#2 (t12);
c3#1 ON c2#3 (t13);
c3#2 ON c2#1 (t21);
c3#2 ON c2#2 (t22);
c3#2 ON c2#3 (t23);
c3#3 ON c2#1 (t31);
c3#3 ON c2#2 (t32);
c3#3 ON c2#3 (t33);

```

A.2.8 Mplus input code to estimate the autoregressive latent transition analysis model with covariates

To include the covariates in the model and to specify their time-invariant effects, the following code was added under MODEL OVERALL command:

```

c1 on t1age t1gender (d1-d6);
c1 on t1exe t1tech (o1-o6);
c2 on t1age t1gender (d1-d6);
c2 on t2exe t2tech (o1-o6);
c3 on t1age t1gender (d1-d6);
c3 on t3exe t3tech (o1-o6);

```

A.2.9 Mplus input code to estimate the autoregressive latent transition analysis model with distal outcomes

To estimate means of the distal outcomes for each class, the following MODEL command was used (this is an example for job satisfaction, the same code was used for exhaustion):

```

Model c1:
%C1#1%
[n1#1@4.427]; [n1#2@2.011]; [n1#3@-1.807];
[t2ssat] (a1); t2ssat; !outcome means were labeled for each time point and each class
%C1#2%
[n1#1@4.811]; [n1#2@6.417]; [n1#3@1.952]; [t2ssat] (a2); t2ssat;
%C1#3%
[n1#1@-1.035]; [n1#2@0.586]; [n1#3@2.043];
[t2ssat] (a3); t2ssat;
%C1#4%
[n1#1@-1.427]; [n1#2@-5.011]; [n1#3@-2.415];
[t2ssat] (a4); t2ssat;

```

```

Model c2:
%C2#1%
[n2#1@4.359]; [n2#2@1.803]; [n2#3@-2.071];
[t3ssat] (b1); t3ssat;
%C2#2%
[n2#1@4.799]; [n2#2@6.532]; [n2#3@2.200];
[t3ssat] (b2); t3ssat;
%C2#3%
[n2#1@-1.266]; [n2#2@0.354]; [n2#3@2.102];
[t3ssat] (b3); t3ssat;
%C2#4%
[n2#1@-1.431]; [n2#2@-5/296]; [n2#3@-2.840];
[t3ssat] (b4); t3ssat;
Model c3:
%C3#1%
[n3#1@4.713]; [n3#2@2.619]; [n3#3@-0.986];
[t4ssat] (c1); t4ssat;
%C3#2%
[n3#1@5.608]; [n3#2@7.536]; [n3#3@3.201];
[t4ssat] (c1); t4ssat;
%C3#3%
[n3#1@-0.593]; [n3#2@1.148]; [n3#3@2.789];
[t4ssat] (c2); t4ssat;
%C3#4%
[n3#1@-1.287]; [n3#2@-4.024]; [n3#3@-1.729];
[t4ssat] (c3); t4ssat;
MODEL CONSTRAINT: !defines comparisons between classes
new (a12 a13 a14 a23 a24 a34 b12 b13 b14 b23 b24 b34
c12 c13 c14 c23 c24 c34 ab1 ab2 ab3 ab4
bc1 bc2 bc3 bc4 ac1 ac2 ac3 ac4);
!within-time comparisons
a12 = a1-a2; a13 = a1-a3; a14 = a1-a4; a23 = a2-a3;
a24 = a2-a4; a34 = a3-a4; b12 = b1-b2; b13 = b1-b3;
b14 = b1-b4; b23 = b2-b3; b24 = b2-b4; b34 = b3-b4;
c12 = c1-c2; c13 = c1-c3; c14 = c1-c4; c23 = c2-c3;
c24 = c2-c4; c34 = c3-c4;
!between time comparisons
ab1 = a1-b1; ab2 = a2-b2; ab3 = a3-b3; ab4 = a4-b4;
bc1 = b1-c1; bc2 = b2-c2; bc3 = b3-c3; bc4 = b4-c4;
ac1 = a1-c1; ac2 = a2-c2; ac3 = a3-c3; ac4 = a4-c4;

```

A.3 Supplementary material and syntaxes for Chapter 3

A.3.1 Mplus input code to estimate the measurement invariance model for aspects of job control

```
DATA: file is "data.dat";
VARIABLE:
names are ID filter selfempl gender age main crea1 crea2
choice1 choice2 learn1 learn2 learn3 engage inspire energy happy social;
usevariables are crea1 crea2
choice1 choice2 learn1 learn2 learn3;
useobservations are filter eq 1; missing are all (-9); grouping = selfempl (1=s 0=e);
ANALYSIS:
estimator is MLR; model is scalar;
MODEL:
mcog by learn1*; mcog by learn2; mcog by learn3;
mcre by crea1* ; mcre by crea2 ;
mau by choice1* ; mau by choice2 ;
mcog@1; mcre@1; mau@1;
output: stdyx; tech4;
```

A.3.2 Mplus input code to estimate the multilevel measurement invariance model for work engagement

```
DATA: file is "data.dat";
VARIABLE:
names are ID filter selfempl gender age main crea1 crea2
choice1 choice2 learn1 learn2 learn3 engage inspire energy happy social;
usevariables are engage inspire energy happy;
missing are all (-9); grouping = selfempl (1=s 0=e); cluster is ID;
ANALYSIS:
estimator is MLR; type is twolevel;
MODEL:
%within%
eng by engage* inspire energy happy (a1-a4);
eng@1;
%between%
beng by inspire* engage energy happy (b1-b4);
beng@1; [beng@0];
model s:
%within%
```

```
eng;
%between%
[beng]; beng;
OUTPUT: tech1 tech8 sampstat stdyx;
```

A.3.3 Mplus input code to estimate the multilevel multi-group path analysis model

```
DATA: file is "data.dat";
VARIABLE:
names are ID filter selfempl gender age main crea1 crea2
choice1 choice2 learn1 learn2 learn3 meng social;
usevariables are meng gender age main social mau mcog mcre ;
missing are all (-9); cluster is ID;
between are mau mcog mcre gender age;
within are main social;
grouping = selfempl (1=s 0=e);
DEFINE:
mau = mean (choice1 choice2);
mcre = mean (crea1 crea2);
mcog = mean (learn1 learn2 learn3);
center mau mcog mcre (grandmean);
ANALYSIS:
estimator is MLR; type is twolevel;
MODEL:
%within%
meng; meng on social main (a1-a2);
%between%
meng; [meng]; meng on mau mcog mcre (a4-a6);
meng on gender age;
model s:
%within%
meng; meng on social main (b1-b2);
%between%
meng; [meng]; meng ON mau mcog mcre(b4-b6);
MODEL CONSTRAINT:
NEW(dmai dsoc dau dcog dcre);
dmai = a2-b2;
dsoc = a1-b1;
dau = a4-b4;
dcog = a5-b5;
dcre = a6-b6;
OUTPUT: tech1 tech8 cinterval stdyx stdy std;
```

A.4 Supplementary material and syntaxes for Chapter 4

A.4.1 Mplus input code to estimate the final fully invariant mediation model

```

DATA: file is "four.dat";
VARIABLE:
names are lang gender age time ctask diff happy engage interest decide express focus
absorb ;
Usevariables are ctask interest happy engage decide express focus absorb time diff;
missing are all (-9);
grouping is lang (1=eng 3=it 4=pl 5=au);
ANALYSIS:
estimator is MLR; bootstrap is 5000;
MODEL:
Pas BY happy* interest engage; aut by decide* express; abs by focus* absorb;
abs, aut; pas; [ decide express happy interest engage focus absorb ];
[aut@0 pas@0 abs@0 ];
aut with abs;
aut abs on ctask (1-2) ; pas on aut abs (3-4);
pas abs aut on time diff;
model indirect:
pas ind ctask;
model it:
aut; pas; abs; [decide express happy interest engage focus absorb ];
[ aut@0 pas@0 abs@0];
model au:
aut@1; pas@1; abs@1; [decide express happy interest engage focus absorb ];
[aut@0 pas@0 abs@0];
model pl:
aut; pas; abs; [decide express happy interest engage focus absorb ];
[aut@0 pas@0 abs@0];
OUTPUT:
tech1; tech4; standardized; cinterval (bootstrap);

```

ERKLÄRUNG

gemäß § 6 Absatz 2 g) und gemäß § 6 Absatz 2 h) der Promotionsordnung der Fachbereiche 02, 05, 06, 07, 09 und 10 vom 04. April 2016

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