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Health and work-life balance across types of work schedules: A latent class analysis

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ABSTRACT

This study explores how different aspects of working time demands (e.g., shift work) and working time control (e.g., beginning/end of workday) can be clustered into distinct types of work schedules and how they relate to health and work-life balance. Data from 13,540 full-time employees interviewed in the 2015 BAuA-Working Time Survey was used. By means of latent class analysis, we extracted six types of work schedules. Subjective health was highest in the flexible extended and flexible standard schedules, both featuring high working time control. Work-life balance was highest in the flexible standard and rigid standard schedules and lowest in schedules with high working time demands, namely the extended shift, rigid all-week, and rigid extended schedules. Employees with high working time demands and low control represent risk groups prone to impairments of well-being. Overall, this study offers an intuitive taxonomy for the design of sustainable work schedules.

1. Introduction

At the workplace, the duration and timing of work are crucial, as they not only determine how long employees are exposed to other working conditions but also how much time is available for recovery, leisure activities, or private obligations (Caruso et al., 2006; Costa et al., 2004). The relevance of various working time characteristics for employees' well-being has been highlighted by a wide array of research (e.g., Albrecht et al., 2017; Arlinghaus et al., 2019; Costa, 1996; Cygan-Rehm and Wunder, 2018; Moreno et al., 2019; Ng and Feldman, 2008; Nijp et al., 2012; van der Hulst, 2003).

However, research has primarily focused on studying single aspects of working time or interaction effects—mostly disregarding the fact that work schedules feature specific constellations of working time demands and resources (Tucker and Folkard, 2012; Van Aerden et al., 2014). Nevertheless, the consequences of working time design can be attributed to combinations of various working time characteristics rather than to one single factor (Costa et al., 2004). Thus, in order to better understand the impact of different types of work schedules on employees, it is crucial to consider patterns occurring in practice. Only recently, Fan et al. (2019) demonstrated that such holistic approaches can be promising by revealing which constellations of work resources and demands are found in a sample of IT and care workers and how these patterns relate to indicators of well-being.

Using data from the BAuA-Working Time Survey —a nationally representative survey of the German workforce—this study aims at extracting distinct types of work schedules and associated covariates by means of latent class analysis. Moreover, by linking the extracted types to employees' health and work-life balance, this study contributes to an understanding of the role of work schedules for employees' well-being.

1.1. Demand-control model

The demand-control model (DCM; Karasek, 1979; Karasek and Theorell, 1990) provides the theoretical foundation for the present study. In their model, Karasek and colleagues (Karasek, 1979; Karasek and Theorell, 1990) distinguish between the demands of a work situation (job demands) and the worker's decision latitude (job control) when facing these demands. More specifically, they place special emphasis on the interplay between these two aspects. The combination of high job demands and low job control is assumed to result in the highest level of strain, causing fatigue, physical illness, and job dissatisfaction, amongst others. In contrast, workers who have a high level of job control when facing high job demands are hypothesized to experience lower strain and, beyond that, job satisfaction as well as personal development. In addition, the combination of low job demands and high job control is predicted to be linked to relaxation and low levels of strain, and the combination of low job demands and low job control is

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predicted to result in average strain but a loss of productivity and work motivation (Karasek and Theorell, 1990). Working time represents a specific facet of working conditions. Thus, in the present paper, we apply the dimensions of demands and control to working time characteristics.

1.2. Working time characteristics

In accordance with Demerouti et al. (2001), we define working time demands as those aspects of working time that entail physical or mental exertion. Working time is characterized by duration, timing, and flexibility. In terms of duration of working hours, researchers have considered overlong working hours and overtime hours to be demanding (McNamara et al., 2011; Moen et al., 2013; Näswall et al., 2015; O'Driscoll et al., 1992; Voydanoff, 2005). With regard to the timing of working time, non-standard working hours such as weekend work, rotating shift work, and night work have been identified as working time demands (Barnes-Farrell et al., 2008; Presser, 2003). With respect to flexibility, research suggests that depending on whether working time is controlled by employees or employers, flexible working time arrangements may act as a resource or as additional strain for employees (e.g., Butler et al., 2009; Byron, 2005; Costa et al., 2004; Costa et al., 2006; Martens et al., 1999; McNamara et al., 2011; Thomas and Ganster, 1995). Thus, in the present paper we will examine company-oriented flexibility such as frequent changes in working hours due to organizational requirements as another aspect of working time demands.

On the other hand, working time control refers to an individual's autonomy over the duration and timing of work (Thomas and Ganster, 1995; Valcour, 2007). As an important work resource, working time control may help employees manage work and personal demands, thereby promoting health and work-life balance (Bakker and Demerouti, 2007; Bohle et al., 2011; Xanthopoulou et al., 2007; Takahashi et al., 2011). In line with this, Valcour (2007) argues that employees who report higher levels of working time control have more capacity to respond to life demands and may experience work demands, such as longer work hours, as less aversive. Hence, working time control may act as a buffer, modulating the detrimental effects of working time demands. To capture employees control over daily working hours, we focus on employees' control over the beginning and end of their workday as well as their control over taking a few hours off.

The diversification and individualization of work schedules (Lee et al., 2007) allows for sheer endless combinations of working time demands and working time control. Yet, because previous research has focused mostly on one- or two-dimensional approaches and specific occupational groups, little is known about the actual structure and prevalence of modern working time arrangements in the working population. Thus, the first purpose of this study is to identify types of work schedules with a distinct profile of working time demands and working time control. To our best knowledge, the present study is the first to use latent class analysis in exploring these questions by asking Research Question 1 (RQ1): Are there distinct types (latent classes) of work schedules?

1.3. Work schedules and employees' well-being

An extensive body of research highlights the relevance of work schedules for health and work-life balance (Tucker and Folkard, 2012). In line with the DCM (Karasek, 1979; Karasek and Theorell, 1990), we would expect the highest strain in jobs with high working time demands and low working time control. Specific to work schedules, several mechanisms have been proposed that account for relationships with employees' well-being.

First and foremost, the length of working hours determines how long employees are exposed to demands and hazards in the workplace, such as adverse or exhausting working conditions or even toxic substances. Moreover, long working hours or overtime may lead to shortened recovery time (Caruso et al., 2006; Wirtz and Nachreiner, 2010). If employees cannot recharge their mental and physical batteries, this may result in impairments of psychological and physical health (Geurts and Sonnentag, 2006). Furthermore, shift work or night work may lead to a disruption of circadian rhythms, which are linked to biological functions such as hormone levels and sleep (Bøggild and Knutsson, 1999; Dorrian et al., 2011; Presser, 2003; Riethmeister et al., 2019; Spurgeon et al., 1997). Thereby, shift work or night work may have short- and long-term effects on health (Tucker and Folkard, 2012). In addition, role theory (Kahn et al., 1964; Pleck, 1977) states that employees possess limited resources for role fulfillment such as time or energy. Accordingly, working overlong hours or overtime leaves employees with reduced time and energy needed in other life domains such as family life. Furthermore, weekend work and shift work result in less time during hours classically reserved for private life. Moreover, if employers frequently change working hours, this involves a lack of predictability for employees. This may entail difficulties in organizing one's daily life (Martens et al., 1999), but also to biological and social desynchronization (Tucker and Folkard, 2012).

With regard to working time control, Nijp et al. (2012) proposed two regulatory mechanisms that may explain its potentially beneficial effects. First, the possibility of influencing one's working hours allows individuals to align working times with private obligations, meaning that conflicts between work and private life can be reduced (Nijp et al., 2012). Second, workers who have control over their working time are better able to adjust their working hours to their current state of well-being such as their fatigue or need for recovery (Nijp et al., 2012) and hence may be less likely to experience a state of exhaustion. Ala-Mursula et al. (2005) further suggested that working time control allows individuals to choose their working times according to certain conditions, such as the presence of valued colleagues or the lack of traffic jams. More generally speaking, working time control fulfills the basic psychological need for autonomy (Deci and Ryan, 2000).

Based on these theoretical considerations, another central aim of the present study is to examine the effects of the interplay between working time demands and working time control on health and work-life balance. Therefore, we ask Research Question 2 (RQ2): Are there differences in satisfaction with work-life balance and subjective health between types of work schedules?

2. Method

2.1. Sample

The present study uses data from the 2015 BAuA-Working Time Survey of the Federal Institute for Occupational Safety and Health (BAuA) in Germany. The BAuA-Working Time Survey is a nationally representative survey of 20,030 individuals aged 15 years and older who pursue paid employment of at least 10 h per week. The target population excludes occupations that are part of any operational or educational training, voluntary services, or occupations that were discontinued for more than three months at interview time. The survey was conducted from May 2015 to October 2015 by means of computer-assisted telephone interviews (CATI) using randomly generated landline and cell phone numbers. The aim of the survey was to measure and describe the organization of working time and working conditions in Germany as well as their associations with employees' well-being (Häring et al., 2016).

All dependent full-time (35 h or more per week) employees aged 15 to 65 were included in the present study. We excluded employees aged over 65 because this was the regular statutory retirement age in Germany in 2015 (Fehr et al., 2012). Self-employed and family workers

were not included because all non-employees have missing values on the overtime indicator since their working time is not fixed by contract. Our focus was on full-time employees because recent studies demonstrated that the effects of working time characteristics such as overtime and shift work significantly differed for full-time and part-time workers (Beckers et al., 2007; Tanner et al., 2017). The final subsample consisted of $n = 13{,}540$ employees with a share of 61.9% male participants. Employees in the subsample had a mean age of 45.80 years ($SD = 10.81$). Half of the respondents (50.3%) had a high educational level, 47.8% had a medium educational level, and 1.9% had a low educational level according to ISCED 2011 (UNESCO Institute for Statistics, 2012). About one third (31.6%) of the employees worked in small organizations with fewer than 50 employees, 27.8% worked in medium-sized organizations with fewer than 250 employees, and 40.6% worked in large organizations with 250 or more employees. Moreover, the majority of the sample (69.7%) worked in organizations that had some kind of employee representation. About three out of ten (31.1%) employees worked in the public sector, 26.9% worked in industry, 9.5% worked in crafts, 26.3% worked in services, and 6.2% worked in other not specified sectors. Since the subsample is representative of a large part of full-time employees in Germany, it features a great variety of economic branches and occupations. For instance, employees from all sections of the German Classification of Economic Activities, Edition 2008 (Federal Statistical Office Germany, 2008) and all sub-major groups of the International Standard Classification of Occupations 2008 (International Labour Office, 2012) were part of the subsample.

2.2. Measures

The seven indicator variables for working time demands and working time control were dichotomized to facilitate a parsimonious latent class model and a classification that is more easily interpretable (Quirk et al., 2013; Stapinski et al., 2016). We considered employees to do *shift work* if they worked in rotating shifts or if they worked exclusively at night. Employees who stated that they worked at least occasionally on Saturdays, Sundays, or holidays were considered to be doing *weekend work*. Employees were considered to work *overtime* if their actual working hours exceeded the number of contractual hours by more than 2 h per week. Employees whose actual working hours were 48 h or more per week were considered to work *overlong hours,* which is in accordance with the Working Time Directive (Council Directive, 1993). *Frequent changes in working hours* were measured with the item "How often do your working hours happen to be modified due to operational demands?" on a four-point Likert scale ranging from 1 (*frequently*) to 4 (*almost never*). Employees who reported frequent modifications were considered to experience frequent changes in working hours. *Control over beginning and end of workdays* was measured with the item "How much control do you have over when you begin and end each workday?," which was adapted from the Control Over Work Time Scale by Valcour (2007) based on Thomas and Ganster (1995). Responses could be given on a five-point Likert scale from 1 (*very little*) to 5 (*very much*). Employees choosing categories 4 or 5 were considered to have control over the beginning and end of their workday. *Control over a few hours off* was similarly measured with another item adapted from the Control Over Work Time Scale. Employees were asked, "How much control do you have over when you take a few hours off?" with responses ranging from 1 (*very little*) to 5 (*very much*) on a five-point Likert scale. Employees choosing categories 4 or 5 were considered to have control over a few hours off.

Health and work-life balance were examined as continuous outcomes. *Subjective health* was assessed with the item "How would you describe your general health status?" Participants could respond on a five-point Likert scale ranging from 1 (*very bad*) to 5 (*very good*). *Satisfaction with work-life balance* was measured with the item "How satisfied are you with the fit between your work and private life?" Participants could answer on a four-point Likert scale from 1 (*not satisfied*) to 4 (*very satisfied*).

2.3. Analytical strategy

IBM SPSS Statistics (Version 24.0) was used for data preprocessing; Mplus version 7.4 (Muthén and Muthén, 1998–2015) was used for analyses concerning the research questions. Unless otherwise stated, an alpha level of 0.01 was used for statistical tests to account for the large sample size.

To address the first research question (RQ1), a latent class analysis (LCA; Goodman, 1974; Lazarsfeld and Henry, 1968) was conducted. LCA is a methodological approach that classifies individuals into homogeneous, unobserved subgroups (latent classes) based on their observed response-patterns on a number of indicator variables (Collins and Lanza, 2010; Vermunt and Magidson, 2002). Each of the latent classes is characterized by a distinctive profile of values on the indicator variables that is constant for all members of that class (McCutcheon, 1987). Maximum likelihood estimation with robust standard errors was used to estimate the model parameters. The exact number of latent classes representing different types of work schedules is unknown and cannot be estimated directly by the model. Therefore, an exploratory approach was used, with the appropriate number of classes being determined by comparing several models with an increasing number of classes (Geiser et al., 2006).

To describe the final class solution more precisely in terms of occupations, occupational groups according to the International Standard Classification of Occupations (ISCO-08; ILO, 2012) were considered. These were calculated for each latent class based on individuals' most likely class membership obtained from the posterior probabilities using IBM SPSS Statistics (Version 24.0). To gain further insights into the composition of the classes and the characteristics of the class members, covariates (gender, age, educational level, size of organization, employee representation, and time or performance pressure) were integrated into the model. We added covariates simultaneously by means of multinomial logistic regression. Individuals' most likely class memberships were regressed on the covariates while taking into account any misclassification in modal assignment (Vermunt, 2010). Resulting logit parameter estimates from the univariate multinomial logistic regression analyses were converted into odds ratios.

To address RQ2, weighted multiple group analyses were performed for the dependent variable. This approach is known as the BCH approach and is based on the work of Bolck et al. (2004). It involves performing separate weighted ANOVAs for every outcome variable, in which the groups correspond to the latent classes and the weights reflect the measurement error in the modal assignment (Bakk et al., 2013; Vermunt, 2010). We tested the equality of class-specific means by means of Wald tests (Bakk and Vermunt, 2016) using Bonferroni adjusted alpha levels of 0.0007 (0.01/15). Fig. 1 provides a diagram of the measurement model. Further methodological details of the LCA are given in the appendix.

3. Results

Table 1 presents descriptive statistics of the indicator variables and outcomes.

3.1. Types of work schedules (RQ1)

Statistical support and interpretability were highest for a model with six classes. The exact process of class enumeration is described in the appendix. The estimated class-specific item-response probabilities

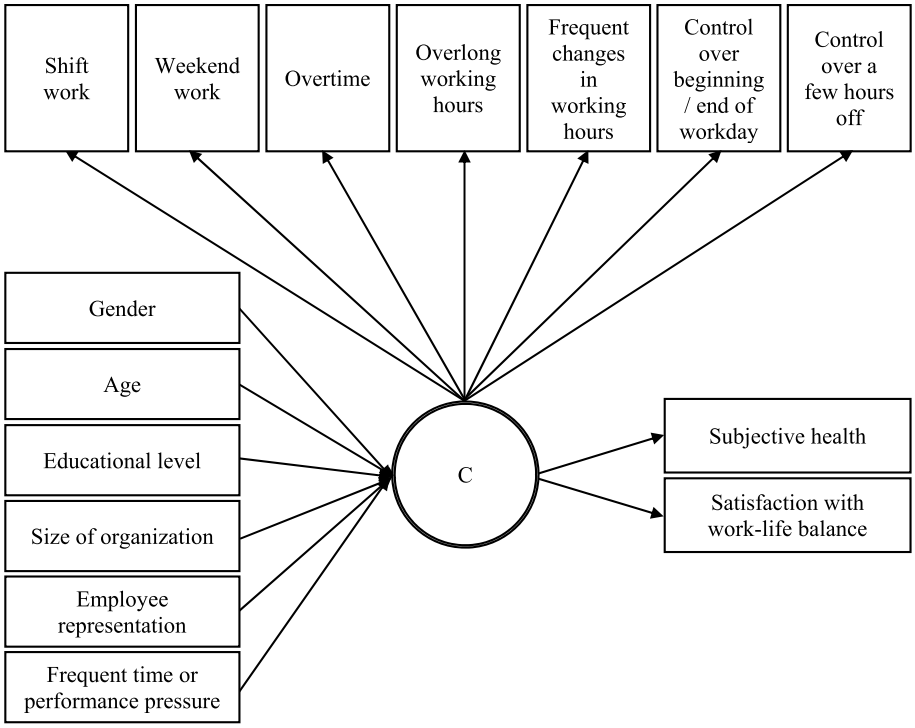

Fig. 1. Diagram of the latent class analysis model with indicators and outcomes. C = Latent class.

Table 1
Descriptive statistics of indicators and outcomes.

Measure	Descriptive statistics
Indicators	*n* (%)
Shift work	1,346 (9.94)
Weekend work	8,259 (61.00)
Overtime	7,362 (54.37)
Overlong working hours	2,966 (21.91)
Frequent changes in working hours	2,043 (15.09)
Control over beginning and end of workday	6,024 (44.49)
Control over a few hours off	6,500 (48.01)
Outcomes	Mean (*SD*)
Satisfaction with work-life balance	2.94 (0.81)
Subjective health	3.72 (0.99)

Note. $N = 13{,}540$. A correlation matrix can be obtained from the authors upon request.

for working time demands and working time control, as well as the class prevalence of the six-class model, are displayed in Fig. 2. We labeled each of the six classes based on the observed characteristics.

Class 1 (*"flexible extended"*) comprised employees who did not work shifts but had a high probability of working at least occasionally on weekends and working overtime. Moreover, members of this class showed the highest probability of overlong working hours and a low to medium probability of frequent changes in working hours. At the same time, this type was also characterized by having much control over beginning and end of workdays as well as over taking a few hours off. Overall, members of class 1 reported both high working time demands and high working time control. A look at the occupational groups assigned to this schedule revealed that business and administration (associate) professionals and production and specialized services managers represented the most frequent occupations in this schedule.

Members of class 2 (*"extended shift"*) showed the highest probabilities of shift work and working overtime as well as the second highest probability of weekend work. There was a medium probability that members worked overlong hours. Similar to the other classes, the probability of frequent changes in working hours was rather low but still higher compared to other classes. Employees in the extended shift schedule were also unlikely to have control over beginning and end of workdays or over taking a few hours off. Altogether, this type was characterized by high working time demands but low working time control. Most frequent occupations in this schedule were health associate professionals, metal, machinery, and related trade workers, as well as stationary plant and machine operators.

Class 3 (*"rigid standard"*) had the lowest probabilities of overlong working hours, frequent changes in working hours, and control over beginning and end of workdays. Moreover, employees assigned to this class had the second lowest probabilities of weekend work and overtime. Class members were also unlikely to work shifts and had little control over taking a few hours off. Thus, members of this class featured both low working time demands and low working time control. Business administration associate professionals, teaching professionals, and numerical and material recording clerks were most frequently represented in this schedule.

Members of the largest of the extracted subgroups, class 4 (*"flexible standard"*) did not work shifts or overlong hours and did not have frequent changes in working hours. Furthermore, members of this class showed the lowest probability of working on weekends and a medium probability of working overtime. On the other hand, they were very likely to have much control over beginning and end of workdays and over taking a few hours off. Thus, individuals assigned to this class had low working time demands but high working time control. The largest occupational groups assigned to this schedule were business administration (associate) professionals and science and engineering professionals.

Members of class 5 (*"rigid all-week"*) had a medium probability of working shifts but the highest probability of working on weekends. Other than that, they were unlikely to experience any of the examined working time demands. Furthermore, class members had a low probability of having control over beginning and end of workdays and over

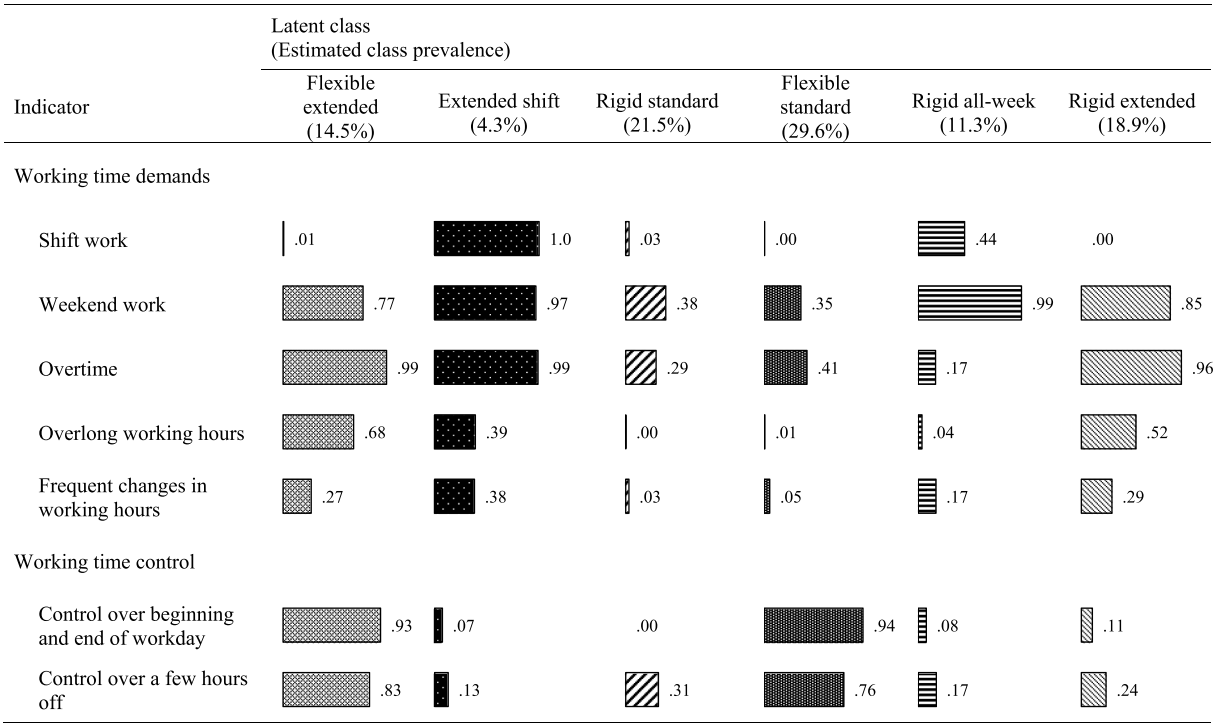

Fig. 2. Class-specific item-response probabilities and class prevalence of the six-class model.

taking a few hours off. Overall, this type showed high working time demands in terms of timing (but not duration) and low working time control. Occupational groups most frequently represented in this schedule were health associate professionals, stationary plant and machine operators, and metal, machinery, and related trade workers.

Class 6 (*"rigid extended"*) did not comprise shift workers, but members of this class were likely to work overtime and on weekends. Moreover, class members had a medium probability of working overlong hours and a low to medium probability of experiencing frequent changes in working hours. At the same time, there was a low probability that members of this class had control over beginning and end of workdays and over taking a few hours off. In summary, this type was characterized by high working time demands and low working time control. Teaching professionals, drivers and mobile plant operators, and health associate professionals were the occupational groups most frequently assigned to this schedule.

Table 2 presents the results of multinomial logistic regression examining the demographic and occupational covariates associated with types of work schedules. The flexible standard schedule was chosen as reference group because it had the highest prevalence. Compared to males, females had lower odds of working the flexible extended schedule, the rigid all-week schedule, or the rigid extended schedule than of working the flexible standard schedule. Older employees had lower odds of being assigned to the extended shift schedule or the rigid extended schedule as compared to the flexible standard schedule. Furthermore, respondents with a higher educational level had higher odds of working the flexible extended schedule but lower odds of working the extended shift schedule, the rigid standard schedule, or the rigid all-week schedule in comparison to working the flexible standard schedule. Employees who worked in large firms had lower odds of being assigned to the rigid standard schedule or the rigid extended schedule than to the flexible standard schedule. Respondents who stated that their organization had an employee representation or works council had lower odds of working the flexible extended schedule or the rigid standard schedule but increased odds of working the extended shift schedule as compared to the flexible standard schedule. Moreover, employees

Table 2
Relationship of Latent Class Solution with Covariates.

Covariate	Flexible extended		Extended shift		Rigid standard		Rigid all-week		Rigid extended	
	Logit (*SE*)	*OR*	Logit (*SE*)	*OR*	Logit (*SE*)	*OR*	Logit (*SE*)	*OR*	Logit (*SE*)	*OR*
Gender	−1.22** (0.10)	0.30	−0.16 (0.11)	0.85	0.07 (0.07)	1.08	−0.28* (0.10)	0.76	−0.18* (0.07)	0.83
Age	0.00 (0.00)	1.00	−0.02** (0.00)	0.98	0.00 (0.00)	1.00	0.00 (0.00)	1.00	−0.01* (0.00)	0.99
Educational level	1.00** (0.10)	2.71	−1.29** (0.10)	0.27	−0.59** (0.07)	0.56	−1.62** (0.10)	0.20	−0.14 (0.07)	0.87
Size of organization	−0.09 (0.06)	0.92	−0.11 (0.08)	0.90	−0.72** (0.05)	0.49	−0.01 (0.08)	0.99	−0.58** (0.05)	0.56
Employee representation	−0.82** (0.10)	0.44	0.49* (0.16)	1.63	−0.39** (0.08)	0.68	0.32 (0.16)	1.38	−0.21 (0.09)	0.81
Frequent time or performance pressure	1.42** (0.09)	4.12	1.23** (0.12)	3.41	0.08 (0.07)	1.08	0.50** (0.10)	1.65	1.19** (0.07)	3.28

Note. $N = 13{,}540$. Reference is flexible standard. *SE* = standard error; *OR* = odds ratio. Gender: male = 0, female = 1; age = continuous; educational level: low = 0, medium = 1, high = 2; size of organization: small (< 50 persons) = 0, medium-sized (< 250 persons) = 1, large (≥250 persons) = 2; employee representation: no = 0, yes = 1; frequent time or performance pressure: no = 0, yes = 1.
*p < .01. **p < .001.

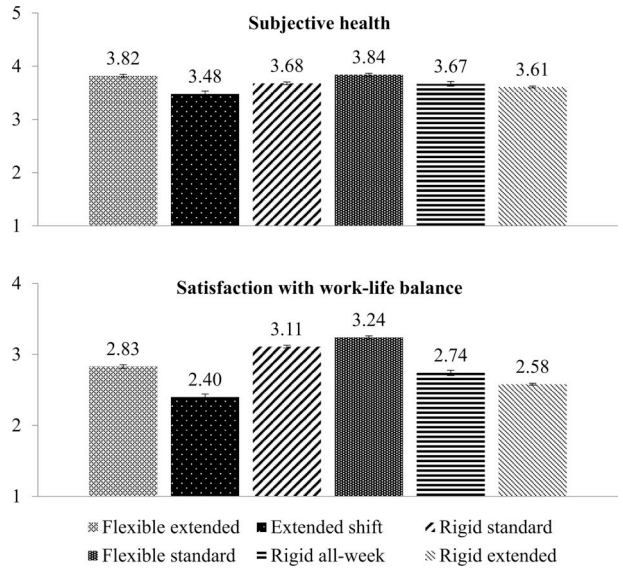

Fig. 3. Estimated class-specific means and standard errors on outcome variables. Error bars represent standard errors. Subjective health (n = 13,520); satisfaction with work-life balance (n = 13,531).

Table 3
Results of pairwise Wald tests (χ^2) between types of work schedules.

Pairwise tests	Subjective health (n = 13,520)	Satisfaction with work-life balance (n = 13,531)
FE vs. ES	32.64*	76.03*
FE vs. RS	15.47*	84.92*
FE vs. FS	0.08	187.76*
FE vs. RW	8.68	4.58
FE vs. RE	26.22*	52.53*
ES vs. RS	11.49	237.98*
ES vs. FS	41.65*	354.52*
ES vs. RW	6.28	31.30*
ES vs. RE	4.82	13.19*
RS vs. FS	26.37*	30.45*
RS vs. RW	0.01	63.03*
RS vs. RE	2.73	292.50*
FS vs. RW	11.88*	170.69*
FS vs. RE	52.51*	668.81*
RW vs. RE	1.26	14.44*

Note. df = 1. FE = flexible extended; ES = extended shift; RS = rigid standard; FS = flexible standard; RW = rigid all-week; RE = rigid extended. *p < .0007.

whose work was characterized by frequent time or performance pressure had higher odds of being assigned to any other schedule except the rigid standard type in comparison to the flexible standard schedule.

3.2. Associations with health status and work-life balance (RQ2)

Results from the weighted multiple-group analyses, including estimated class-specific means and standard errors on the outcome variables, are displayed in Fig. 3. The results of all pairwise Wald tests are provided in Table 3.

In terms of subjective health, we found significant differences between latent classes, Wald χ^2 (5, N = 13,520) = 116.11, p < .001. Members of the flexible standard class reported the highest subjective health, whereas members of the extended shift class reported the lowest subjective health. Pairwise tests showed that employees assigned either to the flexible extended class or the flexible standard class experienced significantly better subjective health than employees assigned to the extended shift class, the rigid standard class, and the rigid extended class. Employees with the flexible standard class further showed significantly higher values than employees in the rigid all-week class.

Types of work schedules also significantly differed in satisfaction with work-life balance, Wald χ^2 (5, N = 13,531) = 1,037.70, p < .001. Satisfaction with work-life balance was highest in the flexible standard class and lowest in the extended shift class. Results of the pairwise tests showed that employees assigned to the flexible standard class were significantly more satisfied with their work-life balance, whereas members of the extended shift class were significantly less satisfied than employees assigned to any other class. Moreover, satisfaction with work-life balance was significantly higher in the rigid standard class in comparison to the flexible extended class, the rigid all-week class, and the rigid extended class. Employees assigned to the flexible extended type or the rigid all-week type in turn had significantly higher values than those assigned to the rigid extended class.

4. Discussion

The aim of the present study was to extract distinct types of work schedules based on working time demands and working time control and to explore their associations with health and work-life balance in a representative sample of full-time employees in Germany. Thereby, the present paper contributes to our understanding of work schedules in our modern world of work in multiple ways.

First, latent class analysis pointed towards six types of work schedules. One work schedule (rigid standard) featured low working time demands and low working time control, another (flexible standard) featured low demands and high control, and another (flexible extended) featured high demands and high control. Most importantly, our analyses revealed three types of work schedules (extended shift, rigid all-week, rigid extended) that are characterized by a profile of high demands and low control. Overall, latent class analysis showed that work schedules can be categorized in accordance with the four quadrants of the DCM. Of the six identified work schedules, three (extended shift, rigid all-week, rigid extended) fall under the category of high-strain schedule within the framework of the DCM and can thus be considered risk groups.

Second, the latent class approach also allowed us to estimate the prevalence of the different work schedules within a representative sample of German full-time employees. Every fifth employee had a schedule characterized by a constellation of low working time demands and low control. Three out of ten employees worked in schedules consisting of a combination of low working time demands and high control. Another 13% worked in schedules with high working time demands and high control. More than one in three employees was allocated to one of the three constellations featuring high working time demands and low control. Most notably, rotating shifts or night work rarely occurred in combination with high working time control so no "flexible shift" schedule was extracted. This demonstrates that certain constellations of working time characteristics that are conceivable in theory are rarely found in practice. Such distributional characteristics are often overlooked in traditional regression and interaction analyses that examine main effects or moderation hypotheses. In contrast, the use of LCA enables us to examine which work characteristics co-occur or are mutually exclusive in our contemporary world of work. Such relationships between work demands and resources have been mostly neglected in previous research and deserve more attention (Bakker and Demerouti, 2017). After all, knowledge about distributional characteristics can be used to promote work design by highlighting which combinations of demands and resources are common practice and which require new concepts and interventions.

Third, the latent class approach allowed us to examine the

relationships between commonly occurring constellations of working time characteristics and employees' well-being. Thereby, the present study advances the knowledge about the role of work schedules for employees' health and work-life balance. More specifically, subjective health was highest for work schedules comprising high working time control. This refers both to control over the beginning and end of work day and over taking a few hours off—opportunities that are, for instance, often available in flextime schedules. The beneficial role of working time control for health is in line with both the DCM (Karasek, 1979; Karasek and Theorell, 1990) and previous research (e.g., Ala-Mursula et al., 2006; Tucker et al., 2015). Satisfaction with work-life balance was highest in constellations featuring low working time demands and lowest for types of work schedules including combinations of shift work, weekend work, long working hours, and overtime. It is notable that the risk groups (extended shift, rigid all-week, rigid extended), which can be identified on the basis of the DCM (Karasek, 1979; Karasek and Theorell, 1990), not only reported the worst health but also the lowest satisfaction with their work-life balance. Overall, this provides support for the applicability of the DCM also in the context of working hours and work-life balance.

Control over working time may often enable employees to better align working hours with their private obligations. However, in line with previous research (Jansen et al., 2004), our results indicate that working time control may not be a universal remedy in case of structural time conflicts. The high levels of control among employees in the flexible extended schedule did not fully alleviate the effect of overlong working hours, overtime, and weekend work on work-life balance: Employees who worked the flexible extended schedule were significantly less satisfied with their work-life balance than employees in the flexible standard schedule. Covariate analyses revealed that employees who frequently experienced time or performance pressure were more likely to be assigned to the flexible extended than the flexible standard schedule. This indicates that employees who face permanent time or performance pressure might not be able to tailor their working hours to their personal needs. What is more, working time control can potentially be used by employees to prolong their working hours or continue working on weekends to cope with a high workload. Interestingly, compared to all other schedules, employees in the flexible extended schedule least often reported the existence of an employee representation in their organization. Taken together, our results suggest that working time control can be an important resource in the hands of employees but might offer little protection if employees are left alone with an excessive workload.

Also for other schedules, our additional analyses on the composition of the work schedules showed differential patterns of socio-demographic, organizational, and professional characteristics. For instance, covariate analyses highlighted that employees in the extended shift, the rigid all-week, and the rigid-extended schedule also frequently worked under time and performance pressure. A glance at the occupations revealed that many employees in these three risk groups worked as health associate professionals, who are known to face high emotional and physical work demands (Clauss et al., 2016). Overall, this indicates that employees in these schedules are exposed to a number of demanding working conditions. Furthermore, together with employees in the rigid all-week schedule, employees in the extended shift schedule least often reported a high educational level. A high socio-economic status, however, can be a protective factor, especially when it comes to health (e.g., Adler et al., 1993; Sekine et al., 2009). Along with work at unfavorable hours, overtime, and low working time control, this could explain why employees in these risk groups reported the lowest health status and work-life balance. Overall, our analyses illustrate that adverse working time characteristics and work demands accumulate among certain potentially vulnerable groups of employees, pointing towards multicausal relationships.

4.1. Limitations and future research

Several limitations of the current study have to be acknowledged that have relevant implications for the interpretation of the results. First, causal inferences based on the present study cannot be drawn for several reasons: The study relies on cross-sectional data, which limits causal interpretability. Closely linked to this is the risk of selection bias due to the healthy worker effect: individuals with very poor health conditions may not be part of the sample, as they might have already left the labor force (Li and Sung, 1999). Similarly, employees who suffer from work-home conflicts may not be part of the sample either, as they may have already switched to a part-time schedule (Jansen et al., 2004) or may have refused to participate in the interview due to lack of time. These selection effects might have led to an underestimation of the effect of the differences in terms of health and work-life balance between different work schedules. Furthermore, poor health or problems with the compatibility of work and private life might have made employees switch to another less demanding schedule among the identified work schedules. However, health problems resulting from decades in shift work may persist even if someone has switched to a daytime schedule. Similarly, employees with high personal demands such as taking care of elderly relatives or small children might continue to face difficulties in juggling work and private life even if they switched to a more family-friendly schedule to promote their work-life balance. Therefore, transitions of highly stressed employees from highly to less demanding work schedules might have also equated differences between the levels of health and work-life balance in different work schedules. While selection processes might have obscured the real effects of work schedules to some extent, in other cases our analyses might have overestimated the health differentials between work schedules. For instance, employees with a high socio-economic status might choose jobs or be selected into occupations with more favorable work schedules as indicated by our analyses of covariates. Despite the beneficial effects of well-designed work schedules, high socio-economic status itself is already a protecting factor against poor health. To account for these effects, longitudinal analyses that consider transitions between work schedules and phases of employment and non-employment are required.

A second limitation concerns our measurement. Owing to the data collection via telephone, indicators used in this study were mostly single-item measures. These are less differentiated and more prone to measurement error than indicators consisting of several items. The use of such general measures of working time characteristics also entails the risk of overlooking specific details that could be crucial to employees' well-being. For instance, apart from being a shift or day worker, the specific cycle of shift and rest periods could be relevant for employees' health and work-life balance. Although not feasible for a representative telephone survey, future studies could retrieve a more nuanced picture of employees' working time by collecting detailed records of work and shift schedules in the form of diaries or by using payroll data. Moreover, we relied entirely on self-reports which increases the risk of common method bias (Podsakoff et al., 2003). In our study, however, working time characteristics were mostly measured by concrete measures, which were found to be less susceptible to common method bias (Feldman and Lynch, 1988). Furthermore, self-reported health measures can be influenced by factors such as personality (Sparks et al., 1997). Thus, future studies could complement self-reports with other methods, including objective health measures. Nevertheless, subjective measures of well-being can be valuable as well: Not only do they reflect employees' own perceptions—which are relevant enough—they also strongly correlate with objective markers (Layard, 2010).

Third, the identified types of work schedules strongly depend on the decision about which working time characteristics to include in the model. Our selection process was based on the DCM and thus theory-driven. Nevertheless, a different choice of working time characteristics as well as other dichotomizations of the indicators would have

presumably led to a different taxonomy. Thus, future research could examine other facets of working time demands and resources or other closely related work characteristics such as extended work-related availability or telework.

A fourth and major limitation is that we did not make statistical adjustments for covariates when examining relationships between work schedules and health and work-life balance. Thus, we did not correct estimates of employees' well-being for the effects of covariates. Nevertheless, our covariate analyses may give at least some idea of which multicausal explanations may determine employees' well-being. They showed that work schedules are associated with a variety of occupational and socio-demographic characteristics. However, other factors which we did not address could have also influenced the effects: For instance, shift and night workers more often work under unfavorable physical and mental working conditions than day workers (e.g., Brauner et al., 2018). Similarly, permanent workers have been found to have more control over work time than workers in precarious employment (McNamara et al., 2011). Furthermore, socio-economic status is both related to the quality of work schedules and employees' health (e.g., Adler et al., 1993; Sekine et al., 2009). Summing up, these aspects and numerous others could have influenced the relationships between work schedules and well-being. Thus, future research could pay more attention to confounding variables, for instance by means of propensity score analyses.

Finally, our findings are based on a nationally representative sample of full-time employees in Germany and thus may not readily be generalized to other countries or other groups of employees. Similar analyses could be carried out for part-time workers or self-employed persons, as they account for a significant proportion of the workforce. Furthermore, we endorse replication studies especially from countries with different cultural and structural backgrounds.

4.2. Practical implications

The present findings highlight the fact that working time demands in general, and multiple working time demands in particular, are a risk factor for poor health and work-life balance. Therefore, to protect employees' well-being, they should be avoided or at least be reduced. While shift work and weekend work are required in some occupations, well-designed shift schedules may retain employees' well-being. Furthermore, an adequate staffing level can often prevent overtime and overlong working hours.

Moreover, the results suggest that working time control may provide employees with an effective resource. Consequently, practitioners should consider implementing some form of working time control in those types of work schedules that still lack this kind of autonomy, namely the extended shift schedule, the rigid standard schedule, the rigid all-week schedule, and the rigid extended schedule. Though it may indeed be more difficult to implement schedule flexibility in some work environments, there are ways to provide employees with working time control, such as the introduction of self-scheduled shifts (Bambra et al., 2008; Garde et al., 2011). A possible downside of working time control might be, however, that employees use their autonomy to permanently work overtime or on weekends to manage an excessive workload. To prevent such self-exploiting behavior and to ensure sustainable working conditions, organizations should take care that the volume of work is manageable in the agreed working hours.

5. Conclusion

Overall, the present study contributes to the human factors literature in multiple ways. First, we examine working time arrangements from a holistic point of view by focusing on the interplay between working time demands and working time control. Second, by identifying distinct types of work schedules, we provide an intuitive and tangible taxonomy that can aid researchers and practitioners alike. Third, our analyses revealed risk groups with unfavorable work schedules that are particularly prone to impairments of health and work-life balance. Taken together, our findings clearly point towards the reduction of adverse working time demands. Furthermore, they highlight the importance of granting employees some control over their working time, as this may promote health and may enable employees to better align their work demands with private obligations. However, our analyses also indicate that working time control may entail risks if employees use their autonomy to extend their working hours in case of deadline or performance pressure. Thus, our study is relevant to researchers but also to practitioners and organizations concerned with designing work schedules that retain and promote employees' well-being.

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Declarations of interest

None.

Appendix. Class enumeration in LCA

Decision on the number of classes is usually based on simultaneous consideration of multiple indices (Masyn, 2013) along with substantive criteria in terms of interpretability of the class solution (Collins and Lanza, 2010). In order to identify the optimal number of latent classes, the Bayesian information criterion (BIC; Schwarz, 1978), sample-size adjusted Bayesian information criterion (SSBIC; Sclove, 1987), adjusted Lo-Mendell-Rubin likelihood ratio test (aLMR; Lo et al., 2001), and bootstrap likelihood ratio test (BLRT; McLachlan and Peel, 2000) were employed in the present study. While BIC and SSBIC both are information-based criteria with lower values indicating a better fit of the model (Nylund et al., 2007), aLMR and BLRT are relative fit indices that compare the model fit of neighboring class models, precisely the k-1 and k class model with k denoting the number of classes (Masyn, 2013). A significant p-value indicates that the k class model fits statistically better than the k-1 class model. In addition, relative entropy (Ramaswamy et al., 1993) and average posterior class probability (AvePP) were considered in order to evaluate the quality of each latent class solution. Relative entropy is a measure of class separation with values ranging from 0 to 1, whereat larger values indicate better separation (Celeux and Soromenho, 1996). Asparouhov and Muthén (2014) consider an entropy level of 0.6 or higher as an indication of good latent class separation. The AvePP evaluates class-specific classification uncertainty. Values range from 0 to 1, while again larger values indicate higher classification precision (Masyn, 2013). Nagin (2005) suggests that all values be > 0.7 for adequate precision. To verify that the assumption of local independence holds, bivariate residuals were further inspected. Asparouhov and Muthén (2015) consider pairs with Pearson test statistic > 30 as severe violations of model fit. Missing values on the indicators were assumed to be missing at random with Little's MCAR-Test being significant, $\chi^2(104) = 536.03$, $p < .001$, and were handled by means of full information maximum likelihood (Graham, 2009).

The model selection criteria for the one- to seven-class solution are presented in Table A1. The eight-class model was not identified (condition number = 0.95E-09; Muthén and Muthén, 1998–2015) and is therefore not reported. The BIC values decreased until a five-class solution was found with the six-class solution having slightly higher values (ΔBIC = 9.00). The sample-size adjusted BIC was lowest for the six-class solution, yet values for the seven-class solution were only slightly higher (ΔSSBIC = 7.55). Both the aLMR test and the BLRT were significant for all models and thus did not contribute to the decision.

Table A1
Model Fit Information for LCA Model with 1–7 Classes

Model	LL	*n* par	BIC	SSBIC	aLMR	BLRT
1 Class	−53,850.88	7	107,768.35	107,746.10	N/A	N/A
2 Class	−51,383.53	15	102,909.76	102,862.09	4,870.70**	4,934.69**
3 Class	−49,704.80	23	99,628.40	99,555.31	3,313.92**	3,357.47**
4 Class	−49,113.03	31	98,520.98	98,422.46	1,168.18**	1,183.53**
5 Class	−48,855.80	39	98,082.61	97,958.67	507.80**	514.47**
6 Class	**−48,822.24**	**47**	**98,091.61**	**97,942.25**	**66.24****	**67.11****
7 Class	−48,800.67	55	98,124.58	97,949.80	42.58**	43.14**

Note. N = 13,540. LL = log-likelihood; *n* par = number of parameters; BIC = Bayesian information criterion; SSBIC = sample-size adjusted Bayesian information criterion; aLMR = adjusted Lo-Mendell-Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test. Bolded values indicate final model specification.
**$p < .001$.

Based on the results of fit indices, the five to seven class solutions were further examined in terms of classification diagnostics and interpretability (Masyn, 2013). Relative entropy was > .6 for all three models and thus suggested good class separation in each case (Asparouhov and Muthén, 2014), with values for the six- and seven-class solution (0.73 and 0.74, respectively) being slightly higher as compared to the five-class solution (0.69). The average posterior class probability showed adequate precision for the five- and six-class solution with all values > 0.7 (Nagin, 2005), but not for the seven-class solution (AvePP for class 4 = 0.60). Moreover, the seven-class model extracted a latent class that contained a very small proportion of the sample (< 2%), which is considered too small to be trusted as being generalizable to the broader population (Finch and Bolin, 2017). Thus, the five- and six-class models were further considered in terms of interpretation clarity. Three classes with low probabilities of shift work were consistently found in both the five- and six-class models. Further, in the five-class model the remaining employees were assigned to two classes with medium or high probabilities of working time demands including a medium probability of shift work. Instead, in the six-class solution, the remaining employees were assigned to three more clearly defined classes: (a) high working time demands including shift work, (b) high working time demands but no shift work, and (c) high working time demands concerning timing (shift work and weekend work) but not duration (overtime and overlong working hours). Given the statistical support and the substantive meaningfulness of the solution, the six-class model was selected as optimal and six types of work schedules were identified. All pairs of bivariate residuals were < 30 (Asparouhov and Muthén, 2015) and thus local independence was assumed to hold for the six-class solution.

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