American Psychological Association
International Journal of Stress Management

ISSN: 1072-5245

2021, Vol. 28, No. 2, 105–116
https://doi.org/10.1037/str0000224

Don't Leave Your Heart at Work: Profiles of Work–Life Interference and Cardiometabolic Risk

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The present study adopts an exploratory, person-oriented approach to investigate possible patterns of work–life interference. We examine work–life interference from a cognitive (i.e., thinking about work), behavioral (i.e., engaging in work-related behavior), and performance perspective (i.e., reduced functionality in private life, or work–life conflict) in order to identify profiles of employees that could potentially remain uncovered with variable-oriented research. Furthermore, as work–life interference relates to well-being and health, we were interested in exploring possible differences between profiles in emotional exhaustion, cardiometabolic risk, and health-related behavior. Self-report data on work–life interference and well-being, as well as objective health data, were collected from a heterogeneous sample of 289 employees. Four profiles with different patterns of work–life interference were identified. Out of the four profiles, two profiles reported moderate and high work–life interference (the *Moderate Interference* and *High Interference* profiles). The other two profiles revealed distinct combinations of moderate and low performance and behavioral interference (the *Low Performance Interference* and *Low Behavioral Interference* profiles). The *High Interference* and *Low Behavioral Interference* profiles were identified as risk groups in terms of cardiometabolic health, while the *Low Performance Interference* and *Moderate Interference* profiles showed low to no risk. Regarding work-related well-being, the *High Interference* profile showed the highest risk of emotional exhaustion.

Keywords: work–life interference, person-oriented approach, latent profile analysis, well-being, cardiometabolic risk

An extensive body of literature on work–life interference (WLI) suggests that work may intrude private life in many different ways. Large representative studies come to similar conclusions, observing a deterioration in work–life balance in European employees (Eurofound, 2017a), and finding that work–life imbalance represents a significant stressor in many countries (Eurofound, 2017b). With WLI identified as a psychosocial risk factor, negatively associated with well-being (Eurofound, 2017b), Eurofound states that "reconciling demands from the workplace and the private sphere is a goal towards which both employees and employers should strive" (Wilkens et al., 2018, p. 57).

When it comes to work interfering with private life, a considerable amount of literature has been published on work–family or work–life conflict (WLC; see Amstad et al., 2011; Macewen & Barling, 1994; Major et al., 2002). According to Greenhaus and Beutell (1985), WLC occurs when performance in the private

This article was published Online First March 11, 2021.
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The authors would like to thank Takuya Yanagida for his helpful advice on data analysis and Marina Horvat for critical comments on one of the first versions of the manuscript. Results of this study were presented at the 13th Conference of the European Academy of Occupational Health Psychology, Lisbon, Portugal, and at the European Association of Work and Organizational Psychology Small Group Meeting "Working Anywhere, Anytime: Work Flexibility from a Management and an Occupational Health Perspective," Leuven, Belgium.

The raw data related to the variables included in the manuscript are available to any qualified researcher upon request.

The study procedures were carried out in accordance with the Declaration of Helsinki and national ethics regulations. This study protocol was approved by the ethics board of the Faculty of Arts, University of Maribor (date of approval: August 9, 2017) and ethical committee of the health care center (ruling number: 02/010/03-015-01/17). The participants were fully informed about the aim of the study and provided their written informed consent.

KK, ST, and CK developed the research ideas and designed the study. KK and ST managed the data collection. KK performed the data analysis and interpreted the results. KK and ST drafted the manuscript; CK provided critical comments and revised the manuscript. All three authors provided substantial intellectual input at all stages of the research process and approved the final version to be published.

This research was supported by the Center for Psychological Research and Practice (University of Maribor), Slovenian Research Agency—ARRS (Grant number: J5-9449), and the Uni:docs Fellowship Programme for Doctoral Candidates (University of Vienna).

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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domain is hampered due to the demands arising from the work domain. As WLC poses a risk for the health and well-being of employees (Greenhaus & Beutell, 1985), it is not surprising that a sizeable portion of the literature has focused on this relationship (Gisler et al., 2018). Such an endeavor is relevant, as there is clear and abundant evidence of the link between WLC and work-related, family-related, or general well-being outcomes (Allen et al., 2020; O'Donnell et al., 2019). Although work stress represents a risk factor for cardiovascular disease (Schnall et al., 2016), comparatively little is known of the associations between WLC and cardiovascular health. More precisely, a recent review by Gisler et al. (2018) found that most studies only consider psychological well-being and far less physical health, and mainly rely on self-report measures. Furthermore, in comparison to other well-being and health outcomes reported in the review, not many focus on cardiometabolic health. Most importantly, the studies give inconsistent and varying results, some finding a direct link between WLC and cardiovascular health, some none, and others finding an indirect link (Gisler et al., 2018).

In the present study, we attempt to provide new insights into the relationship between WLI and cardiometabolic health, by responding to the call to distinguish between different types of interference in order to explore patterns of the relationship between WLI and health (Gisler et al., 2018). The notion that work can enter private lives in several ways is not new. Carlson and Frone (2003) proposed the distinction between internal (or psychological) involvement and external (or behavioral) involvement, highlighting the importance of differentiation between different forms of work entering private life when examining WLI.

Building on the call made by Gisler et al. (2018), and the distinction between internal and external interference proposed by Carlson and Frone (2003), we aim to explore patterns of WLI by broadening the scope of work interfering with life beyond WLC, by including the internal (psychological or cognitive) and external (behavioral) aspect as well. Moreover, we take a person-oriented approach (POA) to analysis, which offers a holistic approach to experiences of WLI, enabling us to explore possible patterns of WLI. Although internal (psychological) and external (behavioral) interference are most often considered as predictors of performance interference (WLC) in the variable-oriented approach, it has been previously argued that this approach "... may obscure the entirety of an individual's work life balance" (Rantanen et al., 2011, p. 32). Hence, considering the experience of WLC simultaneously with internal (psychological) and external (behavioral) WLI while using a POA may contribute to meaningful identification of risk groups. Furthermore, we argue that possible subgroups of employees experiencing WLI may, to some extent, contribute to the inconsistencies found by Gisler et al. (2018) regarding WLI and health. Such subgroups often remain uncovered in a variable-oriented approach, due to its assumption that the drawn sample belongs to the same population (no subpopulations exist) or that the found relationship is true for all individuals in the sample (ignoring outliers; Masyn, 2013; von Eye & Bergman, 2003; von Eye et al., 2015).

The present study contributes to the literature on WLI and cardiometabolic health in several ways. First, we add to the existing body of literature on work entering private life by using the POA while broadening the experiences of WLI beyond the interference with performance in private life (WLC), including internal (psychological; e.g., thinking about work) and external (behavioral; e.g., bringing work home) interference as well. In addition to exploring WLI in its entirety, this enables us to uncover potential patterns of WLI and risk groups that may be overlooked when using the variable-oriented approach. Second, we aim to offer new evidence on whether profiles or patterns of WLI are differently associated with subjective well-being and objective indicators of cardiometabolic risk. As cardiovascular diseases have become a global pandemic, responsible for approximately 30% of deaths (Schnall et al., 2016), it is critical to extend the list of potential risk factors as well as address the methodological shortcomings of previous studies. However, not all experiences of WLI are inevitably detrimental to health and well-being. Behavioral interference, for instance, may help to (at least) temporarily alleviate certain job demands (Matthews et al., 2014). Thus, to date, it is not clear which patterns of WLI may be especially problematic for long-term health and well-being. From a practical point of view, our findings may additionally inform tailored stress management activities and interventions (Gisler et al., 2018; Tetrick & Winslow, 2015), which can be mainly offered to employees with high WLI and at high risk for cardiometabolic diseases.

Theoretical Background

A Person-Oriented Approach to Work–Life Interference

From the perspective of role stress theory (Kahn et al., 1964), WLI occurs when pressures from one role (e.g., employee) make participation in other roles (e.g., partner, parent, friend) more difficult (Greenhaus & Beutell, 1985). The most frequently examined form of WLI is work–family conflict, defined as "the extent to which experiences in work (family) role result in diminished performance in the family (work) role" (Greenhaus et al., 2006, p. 65). In other words, participation or performance in the private domain is made difficult due to participation in the work domain (Carlson et al., 2000). Most definitions and operationalizations focus on the functionality or performance in private life, such as missing a family event (Amstad & Semmer, 2009), or the inability to contribute to private life due to work (Carlson et al., 2000). Therefore, we will refer to work-life conflict (WLC) as *performance interference (performance WLI)* from this point onward. However, WLI can be broader than the interference of work with performance in the private domain. Carlson and Frone (2003) differentiated between internally and externally generated interference or conflict, stating the importance of explicitly distinguishing between psychological and behavioral role involvement. Psychological role involvement is internally generated and described as the inability to stop thinking about work when the employee is at home. Albeit under slightly different definitions and operationalizations, previous literature comprehensively examined psychological involvement with work in private time, providing thorough evidence of WLI on a cognitive level (e.g., internally generated role involvement). In the literature, this is most commonly described as work-related problem solving about future aversive events and repetitive thoughts related to work issues (worry; Cropley & Zijlstra, 2011; Flaxman et al., 2012, 2018; Frone, 2015), or the inability to mentally "switch off" and detach from work (detachment; Sonnentag, 2018; Sonnentag et al., 2014; Sonnentag & Bayer, 2005; Sonnentag & Kruel, 2006). As most previous research stated above, as well as the description provided by Carlson and Frone (2003), focuses on work-related cognitions, we refer to it as *cognitive WLI* hereafter. Behavioral role involvement is, on the contrary, described as engagement in work-related behaviors while in the private domain, due to externally generated demands from the work domain. Previous research provides evidence of behavioral role involvement, clearly showing that work can enter private life behaviorally, such as bringing work home and engaging in work-related communications in private time (e.g., answering emails or phone calls; Allen et al., 2014; Kossek et al., 2012; Matthews & Barnes-Farrell, 2010). Although, again, different labels have been ascribed to similar constructs, such as cross-role interruptions and family-to-work transitions, all stress the aspect of actual work-related activities and not only work-related cognitions in private time (e.g., *behavioral WLI*). Taken together, both the proposed distinction by Carlson and Frone (2003) and the vast literature on WLI suggest that work interference with private life is broader than mere diminished functionality in private life.

Although the variable-oriented approach is most commonly utilized in WLI research, there has been some research attesting that the identification of profiles provides additional information on cognitive, behavioral, and performance WLI (individually), and demonstrating that meaningful profiles can be identified. Specifically, previous research has identified profiles in terms of cognitive interference, such as work-related cognitions (Casper et al., 2019) or psychological detachment (Bennett et al., 2016), and behavioral interference in terms of cross-role behaviors (Kossek et al., 2012). The literature has also established that different patterns of diminished performance in private life can be identified (Moazami-Goodarzi et al., 2019; Rantanen et al., 2013). To the best of our knowledge, no prior study has taken a POA to simultaneously explore the experiences of cognitive, behavioral, and performance interference in their entirety. Despite the relative paucity of research considering different forms of WLI or using a POA, these studies suggest that findings from variable-oriented studies might not be uniform for all individuals. Thus, it can be concluded that the identification of profiles may offer unique insights into WLI and provide a new or complementary understanding of the interplay between work and private life. Drawing on this, we propose our first research question below. As no strong theory or previous evidence exists regarding the number and the nature of underlying latent profiles, we will take an exploratory approach to the analysis (see Finch & Bronk, 2011).

Research Question 1: Do distinct profiles of employees exist that vary qualitatively and quantitatively in their experiences of WLI (i.e., cognitive, behavioral, and performance WLI)?

Work–Life Interference, Well-Being, and Cardiometabolic Health

The adverse effects of WLI on the health and well-being of employees can be explained with the Effort–Recovery (E–R) model (Meijman & Mulder, 1998). In order to deal with work demands, effort is required, comprising all the responses on a physiological, behavioral, and subjective level (Fritz & Sonnentag, 2006). When the exposure to the demand ceases, the psychobiological systems will reverse to their baseline state within a certain period of time. Put differently, exposure to demands needs to be removed so that recovery can take place. However, if continued exposure to demands and insufficient recovery are present, negative effects may develop, which could persist over time and become irreversible (Meijman & Mulder, 1998). The E–R model highlights the importance of private time, in which the employee has the opportunity to recover from work demands (Sonnentag, 2001). When recovery is (chronically) unsuccessful, the negative effects could accumulate and lead to impaired well-being or physical health (de Jonge et al., 2012; Zijlstra et al., 2014; Zoupanou & Rydstedt, 2017, 2019). Previous research has suggested that work entering private life hampers the recovery process, as it reduces the opportunities to recover outside of work (Taris et al., 2006). Furthermore, a link to work-related well-being (e.g., exhaustion, burnout) and health has been established (Derks & Bakker, 2014; Geurts et al., 2003; Taris et al., 2006; Zoupanou et al., 2013).

The Allostatic Load (AL) model provides a more thorough explanation of the physiological process of health impairment due to chronic stress and insufficient recovery. AL is the cost of adaptation, and it refers to the wear and tear the body experiences when adapting to environmental challenges, e.g., stressors (McEwen, 1998). AL develops in three phases. First, the primary mediators (mainly adrenal steroids and catecholamines, also cytokines) are activated and work to prepare the organism to cope with the threat to allostasis (Ganster & Rosen, 2013; McEwen & Seeman, 1999). Chronic activation of primary mediators may lead to secondary outcomes, where stress-related systems (e.g., cardiovascular, endocrine, immune) adjust their operating ranges in response to repeated activation of primary mediators. Secondary outcomes, such as blood pressure and high-density lipids, are mainly related to abnormal metabolism and cardiovascular risk, as well as insulin resistance (McEwen & Seeman, 1999). Although permanent damage is not necessarily yet inflicted, these dysregulations may lead to allostatic overload, characterized by disease endpoint (e.g., cardiovascular disease or diabetes; Ganster & Rosen, 2013). The cardiovascular and the metabolic system are the best-studied systems of allostatic load (McEwen, 1998). Activation of the hypothalamic–pituitary–adrenal axis due to stress is followed by the secretion of glucocorticoids and catecholamines, which prepares the body to tackle the stressor short term. However, repeated activation due to chronic stress exposure may lead to glyco-lipidic risk factors, such as increased body mass index (BMI), insulin resistance, and changes in blood lipids (increased total cholesterol, triglycerides, low-density lipoprotein, and decreased high-density lipoprotein; Li et al., 2007). Hence, glycol-lipidic indicators can serve as a measure of cardiometabolic health, indicative of allostatic load (Juster et al., 2010). Another common and established predictor of cardiovascular risk is the Framingham Risk Score, used to predict the 10-year risk of coronary heart disease. The risk score does not rely solely on physiological measures, as it comprises several risk factors beyond biochemical indicators, improving its predictive power (Levine & Crimmins, 2014).

Based on the E–R (Meijman & Mulder, 1998) as well as the AL model (McEwen, 1998), we propose our second and third research questions.

Research Question 2: Do identified profiles differ in work-related psychological well-being (emotional exhaustion)?

Research Question 3: Do identified profiles differ in composite cardiometabolic risk indicators (Framingham Risk Score; D'Agostino et al., 2008) and individual cardiometabolic risk indicators (cholesterol, high-density lipids, triglycerides, glucose)?

When studying cardiometabolic health, it is necessary to consider health-risk behaviors in addition to objective indicators of health, as they are closely related to the allostatic load and health (French et al., 2019; McEwen, 1998). Stressful situations not only lead to physiological responses, but behavioral responses as well, and can elicit behaviors that are harmful and costly to health (e.g., smoking or drinking; McEwen & Stellar, 1993). Health-risk behaviors are considered as individuals' coping strategies for stress and are a part of the overall allostasis (McEwen, 1998). Engaging in unhealthy behavior, such as nicotine or alcohol intake, was found to be related to work stress, as it has the potential to alleviate stress-related negative mood temporarily and reduce stress in the short term (Allen & Armstrong, 2006; Ng & Jeffery, 2003). Furthermore, stressors deplete cognitive and emotional energy, which is necessary for making healthy lifestyle choices (French et al., 2019). Such behaviors have the potential to alleviate stress temporarily but could contribute to adverse physical consequences long term, such as high blood pressure and type II diabetes (McEwen, 1998).

> *Research Question 4:* Do identified profiles differ in health-risk behaviors (smoking, alcohol intake)?

Method

Participants and Procedure

Study participants were recruited at an occupational health clinic in Slovenia. Employees coming for a routine health check with an occupational health physician were invited to take part in the study by a nurse. Individuals who agreed to participate were informed about the study, signed the informed consent (agreeing for their medical report to be transcribed for the study by the nurse), and were asked to fill out a work-related questionnaire. Nurses transferred the medical results to a dedicated section of the self-report questionnaire and received a small monetary incentive for their help with the study. The study procedures were carried out in accordance with the Declaration of Helsinki and national ethics regulations. The study protocol was approved by the university ethics board (date of approval: August 9, 2017) and the ethical committee of the health care center (ruling number: 02/010/03-015-01/17). The participants were fully informed about the aim of the study and provided their written informed consent.

Data were collected from 300 employees[1] coming for a medical examination. Thirteen individuals were excluded from the analysis due to a high nonresponse rate (>20% of items missing). The final sample thus consisted of 287 employees, of whom 42.6% were male, and the mean age of our sample was 42.8 years (SD = 10.15). The majority of the participants worked in the service sector (60.3%), of which 17.6% worked in education, 16% worked in sales and retail, and 12% worked in jobs relating to administration and organization. When it comes to the nonservice sector employees, the majority of the sample (43.6%) worked in production and assembly, followed by other manual laborers (e.g., cleaning and janitorial jobs; 21.8%). The highest proportion of employees finished a vocational college (28.2%), closely followed by employees with either a high school (22.1%) or university degree (22.1%). Employees in the sample had 11.9 years of organizational tenure (SD = 10.55) and worked 40.4 hr per week (SD = 11.83) on average. Employees in leadership positions amounted to 22.6% of the sample, with roughly equal distribution based on sex (51.5% of leadership positions are occupied by females), and 32.1% of our sample performed shift work. When it comes to private/family life, 82.6% of our sample consists of married individuals (or having partners), and 76.3% have children.

Self-Report Measures

Cognitive WLI was measured using 10 items, adapted or developed based on the definition of worry, which aligns with the characterization of the internal (psychological) aspect of interference proposed by Carlson and Frone (2003). Worry captures not only the physiological and cognitive effects of past and current stressors but also the effects of anticipated events. Therefore, worry may cognitively protract the effects of stressors and contribute to poor health (Brosschot et al., 2007; Ottaviani et al., 2017; Verkuil et al., 2010). Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) was used as a basis for items. Seven items from the PSWQ were fit to be adapted to reflect the future-oriented nature of perseverative cognition, as well as the work-related context (sample item: "My worries about upcoming work overwhelm me."). Three additional items were developed (sample item: "In my free time, I worry about upcoming work."), resulting in 10 items measuring worry (full item list available on request from the authors), which showed high reliability (α = .94). A five-point Likert scale was used (1 = *not at all typical of me*, 5 = *very typical of me*) to assess the items.

Behavioral WLI was measured using four items from the work interrupting nonwork behaviors subscale from the work–life indicator (sample item: "I allow work to interrupt me when I spend time with my family or friends."; Kossek et al., 2012) on a five-point agreement scale (1 = *Strongly disagree*, 5 = *Strongly agree*). Items showed adequate reliability (α = .85).

Performance WLI was measured using the strain-based work–family conflict subscale (Carlson et al., 2000; Tement et al., 2010). We used three items and adapted them to reflect a broader range of private activities (family, friends, leisure), using a five-point agreement scale (sample item: "When I get home from work, I am often too frazzled to participate in my private activities." α = .87).

Work-related well-being was measured using the five-item emotional exhaustion subscale from the Maslach Burnout Inventory—General Survey (Sample item: "I feel emotionally drained from my work."; Maslach et al., 1986). The scale uses a seven-point Likert scale, ranging from 0 (*Never*) to 6 (*Every day*), and shows adequate reliability (α = .86).

In order to test the construct validity of the study variables, a confirmatory factor analysis was carried out, showing an adequate model fit (χ^2 = 463.3, df = 203, RMSEA = .075, CFI = .94, AIC = 16,945). Furthermore, the model showed superior fit to the one-factor model (χ^2 = 1,610.99, df = 209, RMSEA = 0.15, CFI = .66, AIC = 18,080.7), demonstrating that the measures represent distinct constructs.

[1] Considering the sample size required for an adequate function of fit indices is at least 200–250 (Information Criterion and likelihood ratio test, see Nylund et al., 2007; Tein et al., 2013), and the availability of resources, the sample size of about 300 employees was determined to be adequate prior to data collection.

Measures of Health Risk Behavior

Participants reported on their average weekly alcohol consumption (how many units of alcohol, with one unit corresponding to 3 oz of wine or 8.5 oz of beer or 1 oz of spirits), and how many cigarettes they smoke per day (if a smoker).

Objective Cardiometabolic Health Measures

As part of the medical examination, anthropometric measurements were taken, such as the measurement of body weight in kilograms and height in centimeters. Fasting blood samples were taken from all participants, and the sample analyses were carried out at the health clinic.

Based on the biomarkers of allostatic load, identified in previous studies (Juster et al., 2010), and the availability of information, we included total serum cholesterol, high-density lipids, triglycerides (mmol/L), and blood glucose (mmol/L) as individual indicators of cardiometabolic risk.

To further assess the cardiometabolic risk of participants, two versions of the Framingham Risk Score (D'Agostino et al., 2008) were calculated. The provided algorithm uses sex-specific Cox proportional hazards regression to estimate 10-year absolute cardiometabolic disease risk. The model includes age, total cholesterol, high-density lipids cholesterol, systolic blood pressure, the use of antihypertensive medication, smoking, and diabetes status (D'Agostino et al., 2008). We also calculated a simplified model, which does not require laboratory testing, and replaces blood lipids with BMI (D'Agostino et al., 2008), as blood lipids analysis was not carried out for all employees in the sample.

Analytic Approach

After investigating descriptive statistics and intercorrelations (see Appendix) as well as the validity and reliability of the self-report scales, we computed the factor scores for each scale, using a nonarbitrary method for scaling latent variables (see Little et al., 2006). We continued with inferential statistics using a POA to analysis. Latent profile analysis (LPA) "... describes how the probabilities of a set of observed variables or indicators vary across groups of individuals where group membership is not observed" (Muthén & Muthén, 2000, p. 883). In other words, LPA aims to identify latent profiles that can describe the association among the observed variables. This is achieved by adding classes (or profiles) until the best model fit is reached, where model parameters are the probabilities of individuals being in each class or profile, as well as the probabilities of fulfilling each given profile membership. Posterior probabilities are provided for each individual, based on the profile model (Muthén & Muthén, 2000).

We used the manual approach to LPA (Asparouhov & Muthén, 2014), wherein the first step, we enumerated profile models, going upward from the two-profile solution. Our decision on the best fitting model was made following the recommendations of Tein et al. (2013), using the information criterion (IC; Akaike's information criterion, Bayesian information criterion, and sample size adjusted Bayesian information criterion; with lower values indicating a better fit), bootstrap likelihood ratio test (BLRT, significant p value indicates that the K_0 class model provides a better fit than the K_{-1} model), and entropy (higher value indicating better discrimination between classes). After deciding on the most fitting solution, we continued the analysis with the profile probabilities. Next, we specified the latent profile model, using the logits for the classification probabilities for the most likely latent profile membership, which enabled us to add auxiliary variables to the model without affecting the profile enumeration and accounting for classification uncertainty (the Bose–Chaudhuri–Hocquenghem (BCH) method; Asparouhov & Muthén, 2014). To further explore our research questions, we tested whether profiles differ significantly on cardiometabolic risk and well-being outcomes. The relationship between the profiles and auxiliary variables (cardiometabolic, health risk, and well-being variables) was allowed to vary across profiles, and the full information maximum likelihood method (FIML) was applied to handle missing data on auxiliary variables. To calculate pairwise comparisons of profile means on auxiliary variables, model constraints were added to the model, and the overall χ^2 test was calculated. The analyses were carried out using Mplus Version 8 (Muthen & Muthen, 2017).

Results

To explore our first research question, we enumerated two- to six-profile solutions.[2] Considering that the IC values increased going from a five- to a six-profile solution, the BLRT p value reached 1, and the convergence issues with the five- and six-profile solutions, the profile enumeration was stopped with the six profiles. Looking at the values of IC in Table 1, a substantial drop was observed for one- to four-profile solutions, going from four- to five-profile solutions shows the smallest decrease, and going from five- to six-profile solution resulted in an increase of the IC values. The BLRT indicates that two- to four-profile solutions fit the data well, while five- and six-profile solutions yield a nonsignificant BLRT. Lastly, looking at the entropy, all solutions reached an acceptable value (above 0.80; Collins & Lanza, 2010; Tein et al., 2013). Thus, we conclude that the four-profile solution fits the data best, as indicated by the IC, as well as the BLRT. The four profiles are shown in Figure 1.

Based on the characteristics of profiles regarding cognitive, behavioral, and performance WLI (see Figure 1), the profiles were named the *Moderate Interference* profile, the *Low Performance Interference* profile, the *Low Behavioral Interference* profile, and the *High Interference* profile. Looking at the mean values of WLI (see Table 2), we can see that the *Moderate Interference* profile was the largest and had, as the name suggests, moderate mean values for all forms of WLI. Second in size was the *Low Behavioral Interference* profile, which had moderate cognitive and performance WLI and showed the lowest mean value of behavioral WLI. The *Low Performance Interference* profile was third in size and was characterized by low values of cognitive and behavioral WLI, as well as having the lowest experiences of performance WLI of all profiles. Last in size was the *High Interference* profile, reaching the highest mean values on all forms of WLI.

Descriptive statistics for demographic variables of the four profiles can be found in Table 3. The profiles were relatively equal based on sex, with the exception of the *High Interference* profile, which was mainly composed of females. The *High Interference* and the *Low Behavioral Interference* profiles attained a slightly higher average

[2] All enumerated solutions were run with 5,000 initial stage starts and 200 final stage optimizations; 1,000 initial iterations and 200 final iterations.

Table 1
Fit Statistics for Profile Structure

Profiles	LL	FP	AIC	BIC	SSA-BIC	BLRT-*p*	Entropy
1	−1227.81	6	2467.61	2489.57	2470.54	/	/
2	−1131.96	13	2289.92	2337.50	2296.27	<.001	.79
3	−1084.51	20	2209.02	2282.21	2218.79	<.001	.79
4	**−1055.63**	**27**	**2165.26**	**2264.07**	**2178.45**	<.001	**.77**
5	−1035.58	34	2139.16	2263.58	2155.76	.053†	.81
6	−1028.79	41	2139.57	2289.61	2159.59	1.00†	.83

Note. † = Convergence issues; LL = Log likelihood value, FP = Free parameters; AIC = Akaike's information criterion, BIC = Bayesian information criterion; SSA-BIC = Sample size adjusted Bayesian information criterion; BLRT-*p* = *p* value of the bootstrap likelihood ratio test. Except the BLRT test, other values in the model are not tested for significance, but interpreted by comparing different model solutions (IC) or in comparison to a rule of thumb (Entropy). Bolded is the model solutions that shows the best fit.

age than other profiles. The *Low Behavioral Interference* profile had the lowest educational level, and the *Moderate Interference* had the lowest average working hours, as well as the lowest tenure.

When it comes to work, nonservice sector employees were more dominant in the *Low Behavioral Interference* profile. The *Low Behavioral Interference* profile had the highest percentage of people with limited or other forms of contract, and the lowest number of employees in a leadership position. Furthermore, the *Low Behavioral Interference* profile had the highest percentage of individuals in a relationship, and with children.

To address the second, third, and fourth research questions, we tested whether the identified profiles differ on emotional exhaustion (work-related well-being), cardiometabolic risk indicators, and health-related behavior, using the BCH method. The results of the χ^2 tests are displayed in Table 4, showing several significant differences between profiles. The results are interpreted both in terms of clinical guidelines and in terms of pairwise comparisons between profiles.

The results of pairwise comparisons displayed in Table 4 showed significant differences between profiles on emotional exhaustion. The highest average score was found for the *High Interference* profile, significantly different from all other profiles. In contrast, the *Low Performance Interference* profile reached the lowest value, significantly different from other profiles. In terms of composite cardiometabolic risk indicators, the results in Table 4 show that the *Low Behavioral Interference* profile reached the highest value on both versions of the Framingham risk score, indicative of intermediate 10-year risk for coronary heart disease (CHD; Bosomworth, 2011). Although several group comparisons were found to be statistically significant, the overall χ^2 test was nonsignificant for FRS-BMI and only marginally significant for FRS-L ($p = .07$). All other profiles showed lower risk, with the *Moderate Interference* profile showing the lowest risk on FRS-BMI and the *High Interference* profile showing the lowest risk on FRS-L. The results for individual indicators of cardiometabolic risk (see Table 4) show that all profiles have a borderline risk for CHD based on cholesterol

Figure 1
Latent Profiles of WLI

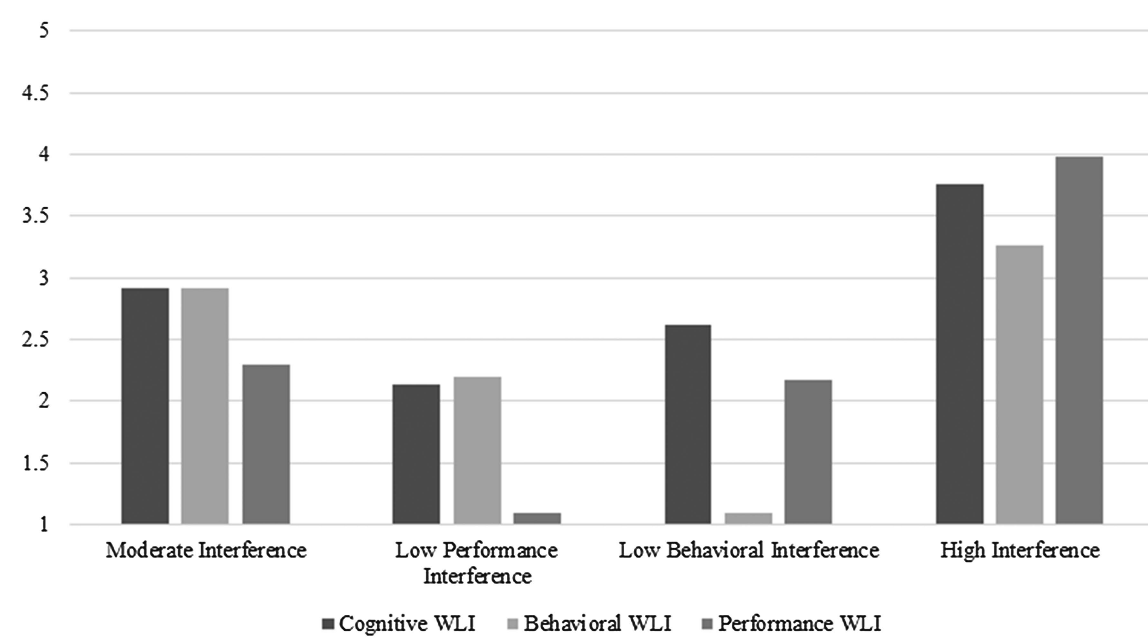

Table 2
Descriptive Information on Forms of WLI per Latent Profile

	% of sample	Cognitive WLI (*M*)	Behavioral WLI (*M*)	Performance WLI (*M*)
Moderate WLI	39.5	2.91	2.91	2.30
Low performance WLI	21.3	2.13	2.20	1.10
Low behavioral WLI	23.3	2.62	1.10	2.17
High WLI	15.8	3.76	3.26	3.98

values (according to the National Cholesterol Education Program, 2001, NCEP), and no profile reached risk values for high-density lipids (HDL; NCEP, 2001). Furthermore, no significant differences between profiles were found for either. Results for triglycerides show that the *Low Performance Interference* profile reached the highest value, indicative of high risk (NCEP, 2001), and significantly different from all other profiles. Furthermore, the *High Interference* profile reached the second-highest value, significantly different from the *Moderate Interference* and *Low Performance Interference* profiles. Lastly, the glucose values indicate that the *Low Behavioral Interference* profile reached the highest value, indicative of diabetes (according to the International Diabetes Federation, 2017, IDF), and the *High Interference* profile reached the second-highest, indicative of prediabetes (IDF, 2017). Both profiles were significantly different from all other profiles. Last, we compared whether the profiles differ on health risk behavior variables (see Table 4). Differences were found for smoking, with employees in the *Low Behavioral Interference* profile on average smoking significantly more than members of other profiles. Considering alcohol intake, employees in the *High Interference* profile reported the highest average intake (11.8 units of alcohol weekly), significantly different from other profiles.

Discussion

In the present study, we aimed at examining patterns of work interfering with private life beyond WLC (interference with performance), including cognitive (psychological or internal; Carlson & Frone, 2003) and behavioral interference (internal; Carlson & Frone, 2003), with a POA to analysis. This enabled us to explore the experiences of WLI in its entirety and to identify subgroups of employees that may have remained uncovered with the variable oriented approach (Oberski, 2016). Furthermore, the study aimed at identifying possible risk groups by exploring the profiles in terms of well-being, cardiometabolic health, and health-related behavior.

Addressing the first research question, we identified four distinct profiles of employees in regard to cognitive, behavioral, and performance WLI on a heterogeneous sample of employees. The *Moderate Interference* and the *High Interference* profiles were characterized by moderate and high values (respectively) on cognitive, behavioral, and performance WLI. The *Low Behavioral Interference* profile showed moderate average values on cognitive and performance WLI, but the lowest value on behavioral WLI. Lastly, the *Low Performance Interference* profile was identified, showing moderate-to-low values on cognitive and behavioral WLI, and reaching the lowest value on performance WLI. Our results show that unique patterns of WLI can be identified, or in other words, there are groups of employees that differ qualitatively (relatively to

Table 3
Descriptive Statistics for the Four Profiles of WLI

		Moderate WLI		Low performance WLI		Low behavioral WLI		High WLI	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Age		41.99	9.62	41.84	11.29	43.59	11.00	44.64	8.05
Weekly working hours		39.29	9.32	40.10	7.33	41.03	18.07	42.47	9.59
Tenure (in months)		127.78	109.32	162.55	145.91	133.93	136.09	166.82	117.46
		Freq.	%	Freq.	%	Freq.	%	Freq.	%
Sex	Male	44	41.1	34	53.1	29	40.8	16	35.6
	Female	62	57.9	30	46.9	42	59.2	29	64.4
Level of education	Primary	1	1.0	2	3.3	4	5.9	1	2.3
	Secondary	53	51.0	33	54.1	45	66.2	19	44.2
	Tertiary	43	41.3	25	41.0	19	27.9	21	48.8
	Doctorate	7	6.7	1	1.6	0	0	2	4.7
Sector	Service	73	68.2	38	59.4	31	43.7	31	68.9
	Other	31	29.0	24	37.5	35	49.3	11	24.4
Contract	Temporary	8	7.5	11	17.2	11	15.5	5	11.1
	Permanent	98	91.6	48	75.0	57	80.3	39	86.7
	Other	0	0	4	6.3	3	4.2	1	2.2
Leadership position	Yes	31	29.0	12	18.8	7	9.9	15	33.3
	No	75	70.1	52	81.3	60	84.5	30	66.7
Shift work	Yes	25	23.4	24	37.5	26	36.6	17	37.8
	No	82	76.6	40	62.5	44	62	28	62.2
Marital status	Single	16	15.0	9	14.1	19	26.8	6	13.3
	In a relationship	91	85.1	55	86.0	50	70.4	38	84.4
Children	Yes	78	72.9	45	70.3	55	77.5	38	84.4
	No	29	27.1	18	28.1	14	19.7	7	15.6

Table 4
Three-Step Results for Well-Being and Cardiometabolic Risk Indicators

	Moderate interference (A)	Low performance interference (B)	Low behavioral interference (C)	High interference (D)
Emotional exhaustion	$1.91^{B,D}$	$1.00^{C,D}$	2.16^{D}	3.98
FRSB	7.08^{C}	7.52^{C}	10.38	7.41
FRSL	8.28^{C}	8.47^{C}	13.07^{D}	7.58
Cholesterol	5.50	5.67	5.41	5.38
HDL	1.40	1.33	1.41	1.50
Triglycerides	$1.11^{B,D}$	$6.11^{C,D}$	1.30	1.32
Glucose	5.59^{C}	$5.46^{C,D}$	9.60^{D}	5.69
Smoking	1.03^{C}	1.11^{C}	15.31^{D}	0.76
Alcohol intake	1.25^{D}	1.38^{D}	1.07^{D}	11.08

Note. Age, sex, and BMI were entered as covariates at first for individual health indicators; age was found to be nonsignificant predictor and was excluded from the analyses as a covariate. Letters in superscripts indicate significant pairwise comparisons between the respective profiles. Written in **bold** indicates a significant overall χ^2 test. FRSB = Framingham Risk Score, calculated using BMI; FRSL = Framingham Risk Score, calculated using blood lipids; HDL = High-density lipids.

each other) as well as quantitatively (in absolute levels) in their experiences of WLI.

Regarding the second research question, the *High Interference* profile was identified as a risk group in terms of work-related well-being, specifically emotional exhaustion. This indicates that the employees, who experience high cognitive, behavioral, and performance WLI, are likely to experience emotional exhaustion as well. On the contrary, the *Low Performance Interference* profile shows the lowest risk of emotional exhaustion. In terms of the E–R model (Meijman & Mulder, 1998), our findings demonstrate that high levels of WLI may impede the recovery process, resulting in emotional exhaustion. Low levels of WLI, on the contrary, may provide enough opportunity for employees to recover. Our findings are in accord with previous literature, which has identified emotional exhaustion as one of the outcomes of WLI (Geurts et al., 2003), and provided meta-analytic evidence of the relationship between reduced recovery (e.g., poor detachment) and emotional exhaustion (Wendsche & Lohmann-Haislah, 2017).

Regarding cardiometabolic risk (the third research question), we found that the *Low Performance Interference* and the *Moderate Interference* profiles showed the lowest overall cardiometabolic risk. This indicates that low interference seems most favorable in terms of cardiometabolic risk. These results are in accordance with the E–R (Meijman & Mulder, 1998) and the AL model (McEwen, 1998), which propose that the absence of work-related stressors is necessary for recovery and health. Similar seems to be true for the *Moderate Interference* profile, indicating that moderate levels of WLI seem to be manageable in terms of recovery and health. This finding additionally supports the E–R model (Meijman & Mulder, 1998) with respect to the notion of the ratio between external load and an individual's maximum capacity. Apparently, individuals can endure a certain amount of stressors without notable psychological or physiological costs as long as they remain within one's limits of capacity.

The two profiles with the highest cardiometabolic risk across several categories of indicators were the *Low Behavioral Interference* and the *High Interference* profiles, indicating that these "combinations" of forms of WLI relate to the highest cardiometabolic health risk. Turning again to the E–R model (Meijman & Mulder, 1998), the results indicate that employees who think about work in their private time, bring work home, and experience diminished functionality in private life (the *High Interference* profile) have fewer opportunities to recover from work-related stressors and demands on a physiological level. Interestingly, the *Low Behavioral Interference* profile shows cardiovascular risk most consistently across objective indicators, even though it experiences the same level of cognitive and performance WLI as the *Moderate Interference* profile, which shows the lowest risk most consistently. Low behavioral WLI paired with higher levels of cognitive and performance WLI seem to be detrimental for health, even more detrimental than experiencing moderate levels of WLI. Specifically, it is possible that low behavioral WLI is experienced due to the nature of the work, making it unfeasible for work to enter private life, and not due to an adequate work–life balance. Hence, when work cannot be brought home, low behavioral WLI could intensify the experiences of stress when employees have unfinished work (known as the Zeigarnik effect; Zeigarnik, 1938). Previous studies in the work context have shown that unfinished work relates to increased perseverative cognition and other negative outcomes (Cropley & Millward, 2009; Syrek & Antoni, 2014). Therefore, although work is not behaviorally present in this profile, it does not necessarily indicate the absence of stress and the opportunity for recovery, especially when an employee is still cognitively occupied by work but is unable to tackle it behaviorally. This assumption is somewhat corroborated by the demographic properties of the profile, as it involves the lowest level of education, the highest percentage of nonservice sector employees, and the lowest rates of leadership position, indicative of passive, blue-collar occupations or job positions. In addition, it seems feasible that the profile covers predominantly passive jobs (as indicated by the demographics), which have been identified as a risk for health (e.g., Karasek, 1979). Specifically, Gimeno et al. (2009) found that passive jobs encourage a passive lifestyle in men, while Slopen et al. (2012) found elevated cardiovascular risk in women with passive jobs.

Last, examining health behavior (fourth research question), we found that the *High Interference* profile performs worst when it comes to alcohol intake, and the *Low Behavioral Interference* profiles perform worst with respect to nicotine intake. It seems that the profiles are more likely to engage in unhealthy behaviors to relieve stress short term due to WLI. Previous studies have come to similar findings, showing that work-related stress increases unhealthy behavior, which temporarily reduces stress (Ng & Jeffery, 2003). Furthermore, as stress can deplete personal resources necessary for making healthy choices (French et al., 2019), it seems feasible that this would also be true for WLI. Hence, the behavioral pathway seems especially relevant for employees experiencing high overall levels of WLI or experiencing cognitive WLI.

Theoretical, Methodological, and Practical Implications

This study was the first (to the best of our knowledge) to explore cognitive, behavioral, and performance interference of work with private life, using the POA. Four distinct profiles of employees were identified on a heterogeneous sample of employees, indicating that cognitive, behavioral, and performance WLI can co-occur differently in distinct groups of employees. Furthermore, specific combinations of cognitive, behavioral, and performance WLI are relevant when considering the well-being and health of employees. We identified two potential risk groups in terms of well-being and cardiometabolic health (the *High* and the *Low Behavioral Interference* profiles), showing that the absence of a specific form of WLI does not necessarily indicate an opportunity to recover (i.e., the *Low Behavioral Interference* profile). Furthermore, the results indicate that tailored workplace prevention or intervention programs might be more effective because not all employees might benefit from the same intervention. For example, the *Low Behavioral Interference* profile may benefit more from an intervention program focused on equipping employees with tools to tackle negative work-related cognitions in private life. On the contrary, interventions designed to reduce overall WLI in terms of prioritizing private life in off-job time may be more beneficial for the *High Interference* profile. Lastly, the results of the study indicate that the combination of low behavioral and higher cognitive and performance WLI could occur more often in the blue-collar work sector, which is a group of employees not often considered when studying the interplay between work and private life.

Limitations and Future Research

Our study is not without limitations. Due to the cross-sectional design, no final conclusions about causality can be made. Applying a longitudinal approach in future studies would not only enable researchers to better understand the processes and mechanisms through which WLI relates to the cardiometabolic risk of employees but would also allow for testing the reverse causal model. Although some studies find that the direct effect of WLI on health seems to be more prominent than the reverse effect (health predicting WLI; van Hooff et al., 2005), the reverse causal model could provide a more thorough understanding of the relationship. Furthermore, certain groups of employees, such as blue-collar workers, may experience WLI differently than service sector employees but are not often studied. Thus, future studies should not only focus on different forms of WLI but include a heterogeneous sample of employees as well. Future research would benefit from considering possible protective factors or processes that employees engage in. As our study finds, not all experiences of WLI relate to poor cardiometabolic health indicators, indicating that compensating mechanisms could be utilized by employees (e.g., positive forms of WLI, such as positive work reflections; or physical activity as compensating mechanisms). Identifying such mechanisms could further inform the relationship between WLI and health. Lastly, future studies should explore what specific job (e.g., unfinished tasks; Syrek & Antoni, 2014) and personal characteristics (e.g., self-regulation capacities; Allen et al., 2014) differentiate profiles of WLI by further taking advantage of person-oriented methodological approaches.

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Appendix

Means, Standard Deviations, and Correlations

	N	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Cognitive WLI	286	2.81	0.80	—											
2. Behavioral WLI	285	2.39	1.20	.31***	—										
3. Performance WLI	285	2.28	1.10	.53***	.24***	—									
4. Emotional exhaustion	285	2.12	1.34	.50***	.17***	.62***	—								
5. FRS-BMI	224	8.43	8.37	−.06	−.04	−.02	.04	—							
6. FRS-lipids	124	9.45	9.02	−.08	−.03	−.03	.01	.96***	—						
7. Total cholesterol	172	5.56	1.12	−.16*	.08	−.02	−.04	.35***	.46***	—					
8. HDL	159	1.44	0.37	.05	−.01	.16*	.11	−.30***	−.41***	.02	—				
9. Triglycerides	163	1.27	0.98	−.06	.10	−.08	−.06	.33***	.46***	.44***	−.41***	—			
10. Glucose	231	5.68	0.96	.07	−.04	−.02	.01	.44***	.43***	.11	−.39***	.23*	—		
11. Smoking	289	3.46	6.33	−.11	−.21***	−.03	.03	.31***	.28***	.09	−.12	.06	.09	—	
12. Alcohol intake	275	1.56	2.53	.04	.04	.14*	.11	.29***	.24***	.10	.05	.05	.14*	.19***	—

Note. FRS-BMI = Framingham Risk Score, calculated with BMI; FRSL = Framingham Risk Score, calculated with lipids. HDL = High-density lipids.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Received March 4, 2020
Revision received November 10, 2020
Accepted November 15, 2020 ■