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Framingham score and work-related variables for predicting cardiovascular disease in the working population

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Background:: The Framingham score is commonly used to estimate the risk of cardiovascular disease (CVD). This study investigated whether work-related variables improve Framingham score predictions of sickness absence due to CVD. **Methods:** Eleven occupational health survey variables (descent, marital status, education, work type, work pace, cognitive demands, supervisor support, co-worker support, commitment to work, intrinsic work motivation and distress) and the Framingham Point Score (FPS) were combined into a multi-variable logistic regression model for CVD sickness absence during 1-year follow-up of 19 707 survey participants. The Net Reclassification Index (NRI) was used to investigate the added value of work-related variables to the FPS risk classification. Discrimination between participants with and without CVD sickness absence during follow-up was investigated by the area under the receiver operating characteristic curve (AUC). **Results:** A total of 129 (0.7%) occupational health survey participants had CVD sickness absence during 1-year follow-up. Manual work and high cognitive demands, but not the other work-related variables contributed to the FPS predictions of CVD sickness absence. However, work type and cognitive demands did not improve the FPS classification for risk of CVD sickness absence [NRI = 2.3%; 95% confidence interval (CI) −2.7 to 9.5%; $P = 0.629$]. The FPS discriminated well between participants with and without CVD sickness absence (AUC = 0.759; 95% CI 0.724–0.794). **Conclusions:** Work-related variables did not improve predictions of CVD sickness absence by the FPS. The non-laboratory Framingham score can be used to identify health survey participants at risk of CVD sickness absence.

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Introduction

The World Health Organization estimates that 17.7 million people worldwide died from cardiovascular disease (CVD) in 2015, representing 31% of all global deaths.[1] Of these deaths, an estimated 7.4 million were due to coronary heart disease and 6.7 million were due to stroke. In Europe, CVD caused 3.9 million deaths, which accounts for 45% of all deaths in 2015.[2] Moreover, CVDs are responsible for the loss of more than 64 million disability-adjusted life years, which is about a quarter of all disability-adjusted life years lost due to disease in Europe.[2] Most CVDs can be prevented by addressing lifestyle risks such as tobacco use, unhealthy diet, overweight and physical inactivity. People who are at high CVD risk need early detection and management by counseling and medicines.[1]

In the past seven decades, the Framingham heart study has identified age, sex, high blood pressure, smoking, dyslipidemia and diabetes as the major risk factors for developing CVD.[3] The point scores on these risk factors were combined into a Framingham score which is predictive of the 10-year CVD risk.[4,5] Framingham scores are widely used in primary health care to early detect people at risk of CVD when they consult their general practitioner (GP). The use of Framingham scores in public and occupational health care is restricted, because the scores rely on blood pressure measurements and blood cholesterol levels. D'Agostino et al.[4] developed a non-laboratory version of the Framingham score, in which blood pressure measurement is replaced by patient-reported systolic blood pressure and blood cholesterol measurements are replaced by the body mass index calculated from patient-reported length and weight. The non-laboratory Framingham score predicts CVD as accurately as the original, and therefore it was concluded that the non-laboratory Framingham score can be used for CVD risk assessments in situations where laboratory testing is inconvenient or unavailable.[6–8] Potentially large numbers of individuals at risk of CVD could be detected if the non-laboratory Framingham score were implemented in occupational health surveys.

Occupational health surveys focus on health risks and work stress. In a recent overview of systematic reviews, Fishta and Backé[9] found that work stress was significantly associated with an increased CVD risk. In a review of 27 cohort studies in Europe, the USA and Japan, Kivimäki and Kawachi[10] found evidence that job strain and long working hours were associated with work stress and elevated risk of both coronary heart disease and stroke. The excess risk for

exposed workers was 10–40% compared with those free of work stressors. These results accentuate the potential added value of work-related variables when assessing the risk of CVD among participants in occupational health surveys.

The aim of this study was to investigate whether work-related variables improve the Framingham risk predictions of sickness absence due to CVD among occupational health survey participants.

Methods

Study setting and design

In The Netherlands, employers have to enable their staff to participate in an occupational health survey at least once every 4 years. Occupational health surveys consist of a questionnaire, followed by a consultation with an occupational health provider, if appropriate. The contents of the occupational health survey questionnaire vary across organizations. Psychosocial working conditions are addressed in most organizations. The further contents are determined by the working conditions in an organization. For example, in industry the survey questionnaire contains items on standing, bending, and heavy lifting, while in office work there will be items on sedentary work. On request of the management and staff representatives of an organization, questions on lifestyle and the non-laboratory Framingham score can be added to the survey questionnaire.

For this study, we used a convenience sample of 19 707 (25%) workers who completed occupational health survey questionnaires including the non-laboratory Framingham score in the period January 2013–July 2017. The study was designed as a cohort study with the occupational health survey set as baseline and CVD during 1-year follow-up as outcome variable. The Medical Ethics Committee of the University Medical Center Groningen granted ethical clearance for this study. The results are presented in line with TRIPOD, the Transparent Reporting of a multi-variable prediction model for Individual Prognosis Or Diagnosis.[11]

Outcome variable

CVD was operationalized as sickness absence due to CVD. In The Netherlands, sickness absence is medically certified by an occupational physician (OP) within 6 weeks of reporting sick using diagnostic codes related to the 10th version of the International Classification of Diseases (ICD-10). Sickness absence episodes OP-certified within the ICD-10 chapter Diseases of the circulatory system (I00–I99) were retrieved from an occupational health service register. The Framingham score is commonly used to predict the risk of CVD with an atherosclerotic pathogenesis. Therefore, sickness absence episodes OP-certified as myocardial infarction (ICD-10 I21), angina pectoris (I20), ischemic heart disease (I24) and cerebrovascular disease (I60–69) were used for the composite outcome variable 'CVD sickness absence'.

Predictor variables

The point scores on the non-laboratory Framingham items age, gender, length and weight (to calculate body mass index), systolic blood pressure, anti-hypertensive medication use (yes or no), diabetes diagnosis (yes or no) and current smoking (yes or no) were summed to a total Framingham point score (FPS).[12]

Based on the literature of work factors associated with CVD, 12 variables were selected from the occupational health survey questionnaire as potential CVD predictors. The FRS is age- and sex-specific and therefore age and gender were not included as CVD predictors. Descent (both parents Dutch, one parent Dutch, no parents Dutch), marital status (single, married/living together, other, e.g. living with family), education (low = no education, primary school, junior vocational training; medium = senior vocational training, junior general education; high = higher vocational training and university) and work type (manual or non-manual) were retrieved from the occupational health survey questionnaire.

Work pace (5 items; Cronbach's $\alpha = 0.87$), cognitive demands (5 items; $\alpha = 0.82$), supervisor support (3 items; $\alpha = 0.90$), co-worker support (3 items; $\alpha = 0.88$), job autonomy (9 items; $\alpha = 0.92$) and commitment to work (5 items; $\alpha = 0.78$) were measured with the Questionnaire on the Evaluation and Experience of Work.[13] All work characteristics were scored on a Likert scale ranging from 'totally disagree' (=1) to 'totally agree' (=5). Items were summed and divided by the number of items so that each work characteristic had a score between 1 and 5, with higher scores indicating higher levels of the work characteristic.

The intrinsic motivation for work was measured with the 7-item interest/enjoyment subscale of the Intrinsic Motivation Inventory.[14] This subscale asks workers to rate statements, such as 'I enjoy my work' and 'I like to do my job' on a Likert scale ranging from 'not true at all' (=1) to 'totally true' (=7). The items were summed to an intrinsic motivation score ($\alpha = 0.89$) and divided by the number of items so that the intrinsic motivation score ranged between 1 and 7, with higher scores representing more intrinsic motivation for work.

Distress was measured with the 16-item distress subscale of the Four-Dimensional Symptom Questionnaire, addressing symptoms elicited by stressors or the efforts to maintain psychosocial functioning, such as irritability, tension, poor concentration and sleep problems.[15] Workers were asked if they experienced these symptoms in the past month, 'no' (=0), 'sometimes' (=1), 'regularly' (=2), 'often' (=2) or 'very often/constantly' (=2). Item scores were summed (score range 0–32; $\alpha = 0.94$) so that higher scores reflect higher levels of distress.

Missing data

Job autonomy was excluded as predictor variable because the scale had 84% missing responses. For the other predictor variables, missing responses were imputed by using Harrell's Miscellaneous package.[16]

Sample size

The study used a convenience sample without a-priori sample size calculations. To prevent overfitting, we adhered to the criterion of at least 10 outcome events per variable in the statistical model.[17] There were 129 workers with CVD sickness absence during 1-year follow-up. Consequently, the FPS and 11 occupational health survey variables could all be included together in a multi-variable logistic regression model.

Statistical analysis

All statistical analyses were done in R for Windows, version 3.5.1.

Selection of work-related variables

The FPS and 11 occupational health survey variables were included in a multi-variable logistic regression model with sickness absence due to CVD during follow-up (no = 0, yes = 1) as outcome variable, using Harrell's regression modeling strategies package.[18] The association between the FPS and CVD sickness absence was non-linear; therefore the FPS was included in logistic regression analysis as a 3-knot spline function. Descent, marital status, education and work type were included as categorical predictors. Work pace, cognitive work demands, supervisor support, co-worker support, commitment to work, intrinsic motivation for work and distress were inserted as continuous predictors.

To select the most important CVD predictors, the full 12-predictor model was reduced by backward stepwise regression analysis with Akaike's Information Criterion as stopping rule, implicating that variables with $P < 0.157$ remained in the final model.

Risk reclassification

The added value of the work-related variables in the final model was investigated with risk reclassification analysis, using the predictABEL package.[19] The European Society of Cardiology has defined the following CVD risk groups: low <1.0%, moderate 1.0–4.9%, high 5.0–9.9% and very high ≥10% risk of CVD during 10-year follow-up.[20] This study had a 1-year follow-up and we therefore used 0.1, 0.5 and 1% as cutoff points for the risk reclassification analysis, i.e. survey participants with a predicted 1-year risk <0.1% were classified as low risk, 0.10–0.49% as moderate risk, 0.50–0.99% as high risk and those with a 1-year predicted risk ≥1.0% as very high risk. Risk reclassification analysis addresses the reclassification of participants after adding work-related variables to the FPS. For those with CVD sickness absence during follow-up, reclassification into higher risk categories is correct. Alternatively, reclassification into lower risk categories is correct for participants without CVD sickness absence during follow-up. The Net Reclassification Index (NRI) measures overall risk reclassification.[17,21–23] The NRI varies between −100 and 100%; risk reclassification is significant if NRI = 0 is outside the 95% confidence interval (CI). Positive NRIs reflect improved classification and negative NRIs reflect poorer risk classification.

Discrimination

The ability of the model with FPS and additional variables to discriminate between occupational health survey participants with and without CVD sickness absence during follow-up was investigated with receiver operation characteristic (ROC) analysis. The area under the ROC-curve (AUC) was used as discrimination measure; AUC = 0.50 represents no discrimination above chance and an AUC ≥ 0.75 was considered useful for practice.[17]

Internal validation

Generally, discrimination is best for the subjects used to develop the model. Therefore, predictions based on the development population are likely to be too optimistic for new samples of survey participants.[17] To adjust for this optimism, discrimination was internally validated in 250 bootstrap samples. The internally validated AUC better represents discrimination between individuals with and without CVD sickness absence during 1-year follow-up of new samples of occupational health survey participants.

Results

The characteristics of the occupational health survey participants are shown in table 1.

At 1-year follow-up, 129 (0.7%) occupational health survey participants had CVD sickness absence due to myocardial infarction (ICD-10 I21; $n = 59$), other ischemic heart diseases (I24; $n = 26$), angina pectoris (I20; $n = 15$) and cerebrovascular diseases (I60–69; $n = 29$).

Selection of work-related variables

When all predictor variables were included in the logistic regression model, the FPS had the highest Wald-statistic indicating that it was the strongest predictor of CVD sickness absence (table 2). After backward stepwise regression analysis, the FPS, work type and cognitive demands remained in the final model.

Risk reclassification

The logistic regression formula of the model including only FPS was used to estimate CVD sickness absence risks; $n = 11\,409$ (58%) survey participants had a low, $n = 5300$ (27%) moderate, $n = 2945$ (15%) high risk and $n = 53$ (0%) very high risk of CVD sickness absence. Table 3 shows that three participants with CVD sickness absence during follow-up were correctly reclassified from moderate

Table 1 Characteristics of occupational health survey participants (*N* = 19 707)

	Mean (SD)	*n* (%)
Age	46.4 (10.7)	
Sex		
Men		14 776 (75)
Women		4931 (25)
Descent		
Both parents Dutch		16 502 (84)
One parent Dutch		961 (5)
No parents Dutch		2244 (11)
Marital status		
Single		2141 (11)
Married		15 682 (81)
Other		1584 (8)
Education		
Low		3615 (18)
Medium		9195 (47)
High		6897 (35)
Type of work		
Manual		6895 (35)
Non-manual		12 812 (65)
Work pace (range 1–5)	2.7 (0.9)	
Cognitive demands (range 1–5)	3.5 (0.8)	
Supervisor support (range 1–5)	3.9 (0.8)	
Co-worker support (range 1–5)	3.6 (1.0)	
Job autonomy (range 1–5)	2.7 (0.9)	
Commitment to work (range 1–5)	3.2 (0.7)	
Intrinsic motivation (range 1–7)	5.9 (1.0)	
Distress (range 0–32)	9.7 (9.9)	
Framingham risk score (range 0–100)	18.1 (12.3)	

SD, standard deviation.

to high risk and six participants from high to very high risk after adding work type and cognitive demands to the FPS. Alternatively, six participants were incorrectly reclassified from high to moderate risk and another six participants were incorrectly reclassified from very high to high risk.

Of the participants without CVD sickness absence during follow-up, 866 were correctly reclassified from moderate to low risk and 425 from high to moderate risk after adding work type and cognitive demands to the FPS. Alternatively, 760 participants without CVD sickness absence were incorrectly reclassified from low to moderate risk and 528 from moderate to high risk. Altogether, the adding of cognitive demands and work type did not improve the FPS risk classification of occupational health survey participants (NRI = 2.3%; 95% CI − 2.7–9.5%; *P* = 0.629).

Discrimination and internal validation

Figure 1 shows that discrimination by the 3-predictor model including FPS, work type and cognitive demands (AUC = 0.761; 95% CI 0.726–0.797) was comparable to discrimination by the FPS model (AUC = 0.759; 95% CI 0.724–0.794). The internally validated AUCs were 0.756 and 0.754, respectively.

Discussion

Work-related variables did not improve CVD sickness absence risk classifications by the FPS. The FPS correctly identified occupational health survey participants at increased risk of CVD in 75.4% of the cases.

A high FPS was the strongest predictor of CVD sickness absence, followed by work type and cognitive demands. The finding that manual workers were at higher risk than non-manual workers is in line with previous results of Biering et al.[24] Manual workers are more likely to be of low socioeconomic status, and a low socioeconomic status is strongly inversely related to CVD as a

Table 2 Backward stepwise selection of work-related variables (*N* = 19 707)

	Full model		Final model	
	Wald	OR (95% CI)	Wald	OR (95% CI)
Descent both parents Dutch		1		
One parent Dutch	−0.49	0.62 (0.31–1.23)		
No parents Dutch	0.01	1.00 (0.44–2.30)		
Marital status single		1		
Married	−1.12	0.94 (0.54–1.63)		
Other	0.59	1.21 (0.78–9.22)		
Education low		1		
Medium	−0.12	0.97 (0.63–1.49)		
High	−0.38	0.90 (0.50–1.59)		
Type of work manual		1		1
Non-manual	−1.36	0.86 (0.48–1.55)	−1.68	0.74 (0.52–1.05)
Work pace (range 1–5)	0.31	1.04 (0.81–1.33)		
Cognitive demands (range 1–5)	1.57	1.24 (0.95–1.63)	1.60	1.21 (0.96–1.52)
Supervisor support (range 1–5)	−0.71	0.93 (0.77–1.13)		
Co-worker support (range 1–5)	−0.26	0.97 (0.77–1.22)		
Commitment to work (range 1–5)	0.27	1.04 (0.79–1.36)		
Intrinsic motivation (range 1–7)	0.89	1.11 (0.88–1.40)		
Distress (range 0–32)	−0.08	1.00 (0.98–1.02)		
Framingham risk score	5.25	1.23 (1.14–1.33)	5.45	1.24 (1.15–1.33)
Restricted cubic spline	−4.15	0.84 (0.77–0.91)	−4.29	0.84 (0.77–0.91)

OR (95% CI), odds ratio (95% confidence interval).

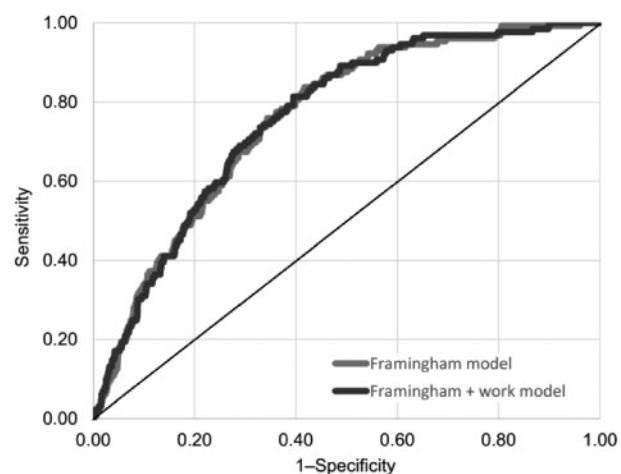**Table 3** Risk reclassification (*N* = 19 707)

Risk predicted by FPS	Risk predicted by FPS + additional variables			
	Low	Moderate	High	Very high
Survey participants with CVD sickness absence (*n* = 129)				
Low (*n* = 6)	6	0	0	0
Moderate (*n* = 21)	0	18	3	0
High (*n* = 49)	0	6	43	6
Very high (*n* = 53)	0	0	6	47
Survey participants without CVD sickness absence (*n* = 19 578)				
Low (*n* = 11 403)	10 643	760	0	0
Moderate (*n* = 5279)	866	3, 885	528	0
High (*n* = 2896)	0	425	2, 471	0
Very high (*n* = 0)	0	0	0	0

The table shows the number of occupational health survey participants at low (<0.10%), moderate (0.10–0.49%), high (0.50–0.99%) and very high (≥1.00%) risk of CVD sickness absence predicted by the FPS before (left column) and after adding the work-related variables (work type and cognitive demands).

Figure 1 Receiver operating characteristic curve representing discrimination between occupational health survey participants with and without sickness absence due to cardiovascular disease during follow-up; the diagonal indicates no discrimination above chance

result of the compounding effects of multiple behavioral and psychosocial risk factors.[25] Furthermore, high cognitive demands contributed to risk predictions of CVD sickness absence, which corroborates previous research on associations between work stress and CVD risk.[9,10] However, work-related variables did not significantly improve the CVD sickness absence risk classification of occupational health survey participants by the FPS. This may be due to the follow-up period. Previous research among patients treated for ischemic heart disease showed that high work pace, low commitment to the workplace, low recognition and low job control were associated with sickness absence at 3 months, but not after 1 year.[24]

Strengths and weaknesses

The prospective study design and the use of OP-certified instead of worker-reported CVD sickness absence were strengths of the study. The large sample of survey participants employed in various economic sectors was another strength of the study, although those who completed occupational health survey questionnaires including the non-laboratory Framingham score were older than those completing occupational health survey questionnaires without Framingham score (mean age 44.6, SD 10.3 years; *t*-test *P* < 0.01). Furthermore, 53% of the study population was employed in the industrial sector as compared to 39% industrial workers (Chi-square *P* < 0.01) in occupational health surveys without Framingham score. In addition, the results of the study may have been biased by a 'healthy volunteer effect' if workers with health complaints were less inclined to participate in occupational health surveys.

Despite the large sample of survey participants, there were relatively few (*n* = 129) outcome events. We dealt with the limited statistical power by including a maximum of 12 predictor variables in a multi-variable logistic regression model. Framingham scores are often stratified into risks for men and women. Our study population included 25% women, of whom only three had CVD sickness absence during 1-year follow-up. Therefore, we could not stratify

our analyses by sex, which is a limitation of our study. A further limitation is that we used logistic regression analysis to predict the risk of CVD sickness absence during 1-year follow-up. Most studies of Framingham predictions use Cox regression analyses to estimate 10-year CVD risks. The different outcomes (CVD sickness absence versus CVD) and techniques (logistic regression vs. Cox regression) restrict comparing the present results with those of previous Framingham studies.

Risk reclassification analysis relies on predefined cutoff points. Cutoffs have been defined for the 10-year CVD risk.[20] These predefined cutoffs might not extrapolate to 1-year risk classifications of CVD sickness absence. When using various data driven cutoffs, however, risk reclassification remained non-significant [data not shown]. Therefore, it is not likely that work type and cognitive demands would improve risk classification when using other cutoffs to define the risk categories.

Practical implications

The World Health Organization advises to early detect people at increased risk of CVD.[1] GPs use the Framingham score to estimate a 10-year CVD risk, but not all people consult a GP. Occupational health surveys could be used as a population-wide strategy to screen for risk of CVD in working populations. This study showed that the non-laboratory Framingham score correctly identified occupational health survey participants at highest risk of CVD in 75.4% of the cases. Although the population is not representative of the total workforce, the Framingham score has been shown to provide valid CVD risk predictions in various settings. Further external validation of this study results may not be necessary to recommend adding the non-laboratory Framingham score to health surveys of working populations.

Adhering to cutoff risks extrapolated from the European Society of Cardiology, 27% of the occupational health survey participants had a moderate CVD risk. They could be counseled on the lifestyle risk factors defined in the European cardiovascular risk assessment model.[20] A total of 2998 (15%) occupational health survey participants had a high or very high CVD risk and 102 (3.4%) of them had CVD sickness absence during follow-up. Thus, their CVD sickness absence risk was almost five times the population risk (i.e. 0.7%). The (very) high-risk occupational health survey participants could be invited for a preventive consultation with the OP to explore the major CVD risk factors and determine whether or not further examination and treatment are appropriate.

Conclusion

Manual work and high cognitive demands added to predictions of CVD sickness absence, but did not improve the CVD sickness absence risk classification by the Framingham score. Implementing the non-laboratory Framingham score in occupational health surveys provides an opportunity to screen working populations for risk of CVD.

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Conflicts of interest: None declared.

Key points

- The Framingham score is commonly used to predict the risk of cardiovascular disease.
- Manual work and high cognitive demands were associated with a higher risk of cardiovascular disease, but did not

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- improve the classification of occupational health survey participants for risk of cardiovascular disease.
- The non-laboratory Framingham score will correctly identify occupational health survey participants at risk of cardiovascular disease in 75.4% of the cases.
- The occupational health survey participants with a moderate risk of cardiovascular disease could be counseled about lifestyle changes.
- The occupational health survey participants with a (very) high risk of cardiovascular disease should be invited for preventive consultations with occupational physicians.

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Physical workload and bodily fatigue after work: cross-sectional study among 5000 workers

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Background: Persistent bodily fatigue after working days may indicate an imbalance between work demands and capacity of the workers. This study aimed to investigate associations between physical exposures at work and bodily fatigue after work. **Methods:** Danish workers with physical work (*N*=5377) answered questions about various physical exposures during work and bodily fatigue after work in the 2010 round of the Danish Work Environment Cohort Study. Associations were modeled using binary logistic regression controlled for various confounders. **Results:** Mean age among the younger (<50 years) and older (≥50 years) workers was 36 and 56 years, respectively. Younger and older workers exposed to various physical exposures (e.g. 'bending/twisting the back') for more than a quarter of the workday were more fatigued after work. An exposure–response relationship was observed between the number of physical exposures and bodily fatigue, with odds ratios (OR) for fatigue in the body among younger workers being 1.01 (95%CI 0.63–1.63), 1.59 (95%CI 1.01–2.50), 2.37 (95%CI 1.54–3.66) and 2.84 (95%CI 1.85–5.36) for 1, 2, 3 and ≥4 types of combined physical exposures, respectively. Correspondingly, for older workers, ORs were 1.95 (95%CI 1.09–3.51), 4.06 (95%CI 2.32–7.12), 4.10 (95%CI 2.28–7.37) and 4.90 (95%CI 2.72–8.82) for 1, 2, 3 and ≥4 exposures, respectively. **Conclusion:** While some of the single factor exposures were associated with increased bodily fatigue, the most marked associations were found when summing the number of different exposures. These results indicate that workplaces should focus on the sum of combined physical exposures rather than focusing solely on single exposures.

Introduction

Fatigue after work is commonly experienced by workers engaged in physical work[1] and is defined as a feeling of tiredness, lack of energy and exhaustion.[2] Fatigue can affect both physical and cognitive functioning.[2] In the Danish Work Environment Cohort Study (DWECS) conducted in 2016 among the general working population, 66% felt somewhat tired to completely exhausted after a workday.[1] Additionally, in a national random-digital-dial telephone survey among a random sample of US workers, 38% experienced a lack of energy, poor sleep and fatigue in the past 2 weeks.[3] That study had a sampling frame of 28 902 workers and reported that the health-related and economic consequences of fatigue in workers are enormous and that fatigued workers cost employers $101.0 billion annually more than

non-fatigued workers in health-related lost productive time.[3] The US study used a computer-assisted telephone data collection instrument that calculates lost productive time based on answers on e.g. occupational status, health conditions, lifestyle factors and demographic characteristics.[3] Lost productive time was calculated as a sum of self-reported absence from work due to health-reasons and self-reported reduced performance at work due to health-reasons.[3]

Physical work is inherently associated with a higher level of physical exertion than sedentary work[4,5] and has been associated with increased risk of long-term sickness absence, premature exit from the labor market and even earlier death.[6–9] Moreover, associations have been observed between physical exposures at work in specific body regions and development of musculoskeletal disorders, indicating that physical work particularly affects the exposed body regions.[10] Physical exposures