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Development of Prediction Models for Sick Leave Due to Musculoskeletal Disorders

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Abstract

Purpose The aim of this study was to develop prediction models to determine the risk of sick leave due to musculoskeletal disorders (MSD) in non-sick listed employees and to compare models for short-term (i.e., 3 months) and long-term (i.e., 12 months) predictions. *Methods* Cohort study including 49,158 Dutch employees who participated in occupational health checks between 2009 and 2015 and sick leave data recorded during 12 months follow-up. Prediction models for MSD sick leave within 3 and 12 months after the health check were developed with logistic regression analysis using routinely assessed health check variables. The performance of the prediction models was evaluated with explained variance (Nagelkerke's R-square), calibration (Hosmer–Lemeshow test) and discrimination (area under the receiver operating characteristic curve, AUC) measures. *Results* A total of 376 (0.8%) and 1193 (2.4%) employees had MSD sick leave within 3 and 12 months after the health check. The prediction models included similar predictor variables (educational level, musculoskeletal complaints, distress, supervisor social support, work-home interference, intrinsic motivation, development opportunities, and work pace). The explained variances were 7.6% and 8.8% for the model with 3 and 12 months follow-up, respectively. Both prediction models showed adequate calibration and discriminated between employees with and without MSD sick leave 3 months (AUC = 0.761; Interquartile range [IQR] 0.759–0.763) and 12 months (AUC = 0.740; IQR 0.738–0.741) after the health check. *Conclusion* The prediction models could be used to determine the risk of MSD sick leave in non-sick listed employees and invite them to preventive consultations with occupational health providers.

Keywords Absenteeism · Musculoskeletal disease · Prediction models · Prognostic research · Risk assessment

Introduction

Musculoskeletal disorders (MSD) are one of the leading causes of long-term sickness absence and work disability in Europe [1]. Preventing MSD sick leave is therefore of great importance. Risk factors of MSD sick leave have been investigated in a number of studies [2–8]. Common risk factors among these studies were age [3, 5, 6], social support [6, 8], psychological distress [2, 4], control at work [4, 8], and physical work demands [5, 7]. Although these separate risk factors can be informative, it is more useful to combine them in a multivariable model to identify employees at risk of future MSD sick leave, enabling health providers to take preventive measures before employees report sick.

According to Dutch legislation, employers have to offer employees an occupational health check at least once every 4 years. The health checks are conducted with a questionnaire on work and health, followed by a medical examination if appropriate. However, it has not yet been determined whether the variables of the health check questionnaire can be used in a multivariable prediction model to estimate the risk of MSD sick leave. Two studies developed prediction models for all-cause sickness absence based on occupational health checks and one showed poor performance and the

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other fair performance [9, 10]. A recent study on a prediction model for low back pain sick leave in Dutch construction workers also showed poor performance and not sufficient for practical implementation [11].

Therefore the aim of the present study was to develop a prediction model for risk of MSD sick leave among non-sick listed employees, based on variables which are commonly measured in occupational health checks. Furthermore, in previous studies aimed at developing prediction models, different sets of predictors were selected when different follow-up periods are chosen [12–14]. Additionally, lower performance was found with increasing follow-up periods [10]. The secondary aim of this study was to compare models for short-term (i.e., 3 months) and long-term (i.e., 12 months) predictions.

Methods

Study Design and Population

The present study is a prospective cohort study in which the occupational health checks were set as baseline and MSD sick leave was recorded in an occupational health service register during 12 months of follow-up. The study population consisted of 49,158 Dutch employees who participated in health checks and filled in questionnaires between 2009 and 2015. Participants gave consent for the use of their data for reports on group level, but not at the individual level. Therefore, the personal information of employees was removed from the data files before data analysis to ensure anonymity.

Outcome Variable

Sick leave is defined as a temporary paid leave off work due to any (i.e., work-related as well as non-work-related) injury or illness. Sick leaves were certified by an occupational physician (OP) within 6 weeks of reporting sick. In general, employees visit an OP after 4–6 weeks of sick-listing, but in some cases it was possible that an employee visited an OP earlier. OPs certify sick leaves with a diagnostic code related to the 10th International Classification of Diseases (ICD-10). Sick leave OP-certified within the ICD-10 chapter XIII (Diseases of the musculoskeletal system and connective tissue) was defined as MSD sick leave.

Predictor Variables

The occupational health check questionnaire addresses sociodemographic characteristics, and health-, social- and work-related variables. The contents of an occupational health check are determined by the occupational health service in consultation with a company's management and staff representatives. Consequently, some companies administered more elaborate health check questionnaires than others. In order to obtain a most comprehensive sample of employees, only predictor variables administered in the majority of the companies and known to be associated with sick leave due to MSD according to previous literature [2–8] were selected from the health checks.

Sociodemographic variables included gender, age, educational level, and country of birth (Netherlands or other). Educational level was measured on a seven grade scale and was categorised in low (none, primary education and junior vocational education), medium (secondary general education and senior vocational education) and high (higher professional education and university) education.

Health-related variables included musculoskeletal complaints, i.e., pain/stiffness in the back, arms/neck/shoulders, hand/wrist, and hip/knee/ankle/foot. Response options for each type of complaint ranged from 1 "not" to 4 "most of the time" and were averaged resulting in a range of 1–4 (Cronbach's $\alpha = 0.64$).

Mental health-related variables included work engagement, burnout, and distress. Work engagement was measured with the 9-item "Utrecht Work Engagement Scale" (UWES-9) [15]. Items were answered on a frequency scale ranging from 1 "never" to 7 "always"; responses were summed and then averaged into a UWES score with a range of 1–7. Burnout was measured by the 15-item Dutch version of the "Maslach Burnout Inventory-general survey" (MBI-GS) [16]. The items had the same response options as the UWES-9 and were also summed and averaged, resulting in a score with a range of 1–7. Distress was measured by a Dutch questionnaire "Four Dimensional Symptom Questionnaire-Distress" (4DSQ-Distress) [17], containing 16 items, such as: "Were you more irritable this month?" or "Did you suffer from depression last week?", with the response options ranging from 0 "no" to 2 "frequently to very often or always". The responses were summed, leading to a score with a range of 0–32 (Cronbach's $\alpha = 0.93$).

Social-related variables included social support by supervisor, colleagues, and by family/friends, and were measured with the Dutch version of the Questionnaire on the Experience and Evaluation of Work (QEEW) [18]. Each scale consisted of three items with response options ranging from 1 "no" to 5 "very often or always"; items were summed and averaged to scores with a range 1–5 (Cronbach's $\alpha = 0.90$, $\alpha = 0.88$, and $\alpha = 0.78$ for social support by supervisor, colleagues, and family/friends, respectively). Work-home interference was assessed by the "Dutch version of the Survey Work-home Interference Nijmegen" (SWING) [19] containing seven items, such as: "How often are you irritable at home, because your work is demanding?". Response options ranged from 1 "never" to 5 "very often or always";

responses were summed and averaged, resulting in a range of 1–5 (Cronbach's α = 0.89).

Work-related variables included irregular working hours (no = 0, yes = 1), and satisfaction with work, which was measured with three items on satisfaction with current job, pleasure in current job, and general satisfaction with work (Cronbach's α = 0.92); response options on a 5-point Likert scale from 1 "totally disagree" to 5 "totally agree" and were averaged so that satisfaction with work ranged 1–5. Intrinsic motivation for work was assessed with the seven items interest/enjoyment subscale of the Intrinsic Motivation Inventory [20] with items such as: "I experience a lot of fun at work" with response options 1 "very false" to 7 "very true". Responses were summed and averaged, resulting in an intrinsic motivation score ranging from 1 to 7.

From the Dutch questionnaire QEEW [18] the following were assessed: organization commitment (5 items, Cronbach's α = 0.79), emotional demands (3 items, Cronbach's α = 0.80), cognitive demands (5 items, Cronbach's α = 0.82), developmental opportunities (4 items, Cronbach's α = 0.87), work variation (6 items, Cronbach's α = 0.86), work pace (5 items, Cronbach's α = 0.86), task clarity (5 items, Cronbach's α = 0.85), and progress of employment (4 items, Cronbach's α = 0.91). The response options for all the items were range from 1 "not/never" to 5 "always"; responses were summed and averaged per scale, resulting in scale scores between 1 and 5.

Statistical Analysis

Prediction Model Development

The prediction models were developed using multivariable logistic regression for the outcome MSD sick leave (no = 0, yes = 1) measured at 3 and 12 months after the occupational health check of 49,158 employees. With the maximum of 23 potential predictors, of which education had three categories, the criterion of 10–15 events per variable [21] was met with 376 employees reporting MSD sick leave within 3 months and 1193 employees within 12 months.

From the selected potential predictor variables, musculoskeletal complaints were not administered in all occupational health checks, resulting in 26.8% missing values. Several factors were associated with missing values in musculoskeletal complaints, however the associations did not indicate that the employees with missing values in musculoskeletal complaints were necessarily healthier employees. Furthermore, the large part of the associations were weak. The other potential predictor variables were administered in all occupational health checks, but had missing responses in up to 11% of the cases. To deal with missing responses on variables, multiple imputation was applied by using the Multivariate Imputation by Chained Equations (MICE) package in R statistical software [22] on the variables total scores. According to White, Royston [23], the number of imputations can be derived from the percentage of incomplete cases. When using the 23 selected predictor variables, the dataset contained 43% incomplete cases and therefore 43 imputed datasets were generated.

The full multivariable logistic regression models were reduced using backward stepwise selection for a more easy to use model. The variable selection was done based on the Rubin's Rules for pooled estimates over the imputed datasets [24]. Akaike Information Criterion (AIC) was used as stopping rule for the exclusion of predictors so that all variables with $p < 0.157$ remained in the model [25].

Internal Validation of the Prediction Models

In general, prediction models perform better in the sample used for the development of the model than in an external sample, because the model is fitted to the data of the development sample. This phenomenon is called optimism [26]. To correct for this optimism, the final prediction models were internally validated by using bootstrapping techniques. We have drawn 250 bootstrap samples from each imputed dataset and compared the performance of the prediction models in the bootstrap samples with the performance in the original sample [26]. This resulted in a shrinkage factor, which was used to adjust prediction model performance for optimism.

Performance of the Prediction Models

The Nagelkerke's R-square was regarded as a measure for the explained variance and the overall predictive performance [27]. The Nagelkerke's R-square was corrected for optimism in each imputed dataset and the median and interquartile range (IQR) was presented as the combined estimate of the explained variance of the prediction model [28].

The agreement between predicted and observed MSD sick leave risks is considered as the calibration of the models and was assessed by the Hosmer–Lemeshow goodness-of-fit-test. The Chi square values of the Hosmer–Lemeshow test were pooled over the imputed datasets [28]. In this test $p \geq 0.05$ indicates that the predicted risk are not significantly different from the observed risks, which is an indication of adequate calibration.

The discrimination of the models is the ability to discriminate between the employees with and without sick leave due to MSD. Discrimination was evaluated with receiver operating characteristic (ROC) analysis. The area under the ROC-curve (AUC) reflects the degree of discrimination; AUC < 0.60 reflects failing, 0.60–0.69 poor, 0.70–0.79 fair, 0.80–0.89 good, and ≥ 0.90 excellent discrimination. The AUC was corrected for optimism in each imputed dataset and the median and IQR of these AUCs was presented as the overall estimate of discrimination by the prediction models.

All the analyses were performed by using R, version 3.2.5 (R Project for Statistical Computing).

Results

The characteristics of the 49,158 employees participating in occupational health checks are presented in Table 1. Of them, 376 (0.8%) had MSD sick leave within 3 months and 1193 employees (2.4%) within 12 months after the occupational health check.

Table 1 Descriptives of the study population

		Missing %
Gender, n (%)		
Men	38,493 (78.3)	
Women	10,665 (21.7)	
Age, mean (sd)	45.7 (10.4)	0.7
Educational level, n (%)		1.0
Low	8675 (17.6)	
Medium	21,339 (43.4)	
High	18,676 (38.0)	
Country of birth, n (%)		11.0
Netherlands	39,782 (80.9)	
Other	3958 (8.1)	
Musculoskeletal complaints, mean (sd)	1.63 (0.55)	26.8
Work engagement, mean (sd)	3.75 (1.08)	2.1
Burnout, mean (sd)	2.38 (0.48)	10.7
Distress, mean (sd)	7.84 (7.27)	1.7
Supervisor social support, mean (sd)	3.61 (1.02)	1.9
Colleague social support, mean (sd)	3.88 (0.83)	2.7
Family social support, mean (sd)	3.54 (1.02)	3.7
Work-home interference, mean (sd)	1.66 (0.62)	2.9
Irregular working hours, n (%)		8.7
Yes	12,904 (26.3)	
No	31,961 (65.0)	
Satisfaction with work, mean (sd)	3.92 (0.78)	4.6
Intrinsic motivation, mean (sd)	5.90 (0.99)	1.7
Organization commitment, mean (sd)	3.20 (0.70)	4.6
Emotional demands, mean (sd)	1.69 (0.64)	2.5
Cognitive demands, mean (sd)	3.53 (0.74)	1.7
Development opportunities, mean (sd)	3.07 (0.97)	2.6
Work variation, mean (sd)	3.59 (0.79)	2.1
Work pace, mean (sd)	2.75 (0.85)	1.2
Task clarity, mean (sd)	3.99 (0.70)	3.0
Progress of employment, mean (sd)	2.17 (0.97)	4.6
Sick leave within 3 months, n (%)	376 (0.8)	0.0
Sick leave within 12 months, n (%)	1193 (2.4)	0.0

The final model predicting MSD sick leave within 3 months after the health check included: educational level, musculoskeletal complaints, burnout, distress, supervisor social support, work-home interference, intrinsic motivation, development opportunities, and work pace and as predictors (Table 2). This model explained 7.6% (IQR 7.5–7.8) of the variance after it was adjusted for optimism. The pooled p-value of the Hosmer–Lemeshow test was 0.625 which indicates adequate calibration of the model. The optimism adjusted AUC was 0.761 (IQR 0.759–0.763).

In the final model predicting MSD sick leave within 12 months family social support was a predictor but burnout not (Table 3). The rest of the model contained the same predictors as the model for MSD sick leave at 3 months follow-up. The prediction model for MSD sick leave within 12 months explained 8.8% (IQR 8.6–8.8) of the variance after adjusting for optimism. The pooled p-value of the Hosmer–Lemeshow test was 0.894 which indicates adequate calibration. The optimism-adjusted AUC was 0.740 (IQR 0.738–0.741).

Discussion

This study aimed to develop and compare prediction models for risk of sick leave due to musculoskeletal disorders (MSD) within 3 and 12 months after an occupational health check. The prediction models for MSD sick leave at 3 and 12 months both included educational level, musculoskeletal complaints, distress, supervisor social support, work-home interference, intrinsic motivation, development opportunities, and work pace as predictor variables and showed comparable fair performance.

Prediction Models for MSD Sick Leave

Both models included educational level, musculoskeletal complaints, distress, supervisor social support, work-home interference, intrinsic motivation, development opportunities, and work pace.

One of the strongest predictors in the models in our study was musculoskeletal complaints at baseline. This finding is supported by a previous study of Hartman et al. [3], who found that former pain was predictive of MSD sick leave. Musculoskeletal complaints have also been reported as a predictor of sick leave due to low back pain [29, 30]. Harrison and Martocchio [31] argue that predictors that remain in models with different follow-ups, are often variables that remain stable over a longer time.

There were also differences between both models. Burnout was included in the model with 3 months follow up, but not in the model with 12 months follow up. Burnout complaints may have a short term effect on MSD sick leave,

Table 2 Univariable estimates* and estimates* in the final model for MSD sick leave within 3 months

	Univariable regression			Final model		
	OR	*p*	95% CI (OR)	OR	*p*	95% CI (OR)
Gender, female	0.78	0.068	0.60–1.02			
Age	1.02	0.000	1.01–1.03			
Educational level						
Low	1			1		
Medium	0.58	0.000	0.47–0.73	0.75	0.011	0.60–0.94
High	0.12	0.000	0.08–0.17	0.22	0.000	0.14–0.32
Country of birth, other	0.86	0.389	0.61–1.21			
Musculoskeletal complaints	2.43	0.000	2.09–2.82	2.03	0.000	1.71–2.42
Work engagement	0.81	0.000	0.74–0.89			
Burnout	1.57	0.000	1.28–1.91	1.18	0.151	0.94–1.47
Distress	1.04	0.000	1.02–1.05	1.01	0.081	1.00–1.03
Supervisor social support	0.77	0.000	0.70–0.85	0.89	0.034	0.79–0.99
Colleague social support	0.94	0.035	0.78–0.99			
Family social support	0.94	0.201	0.85–1.04			
Work-home interference	0.94	0.474	0.79–1.12	0.81	0.044	0.67–0.99
Irregular working hours	0.44	0.000	0.35–0.54	0.55	0.000	0.44–0.70
Satisfaction with work	0.82	0.001	0.73–0.93			
Intrinsic motivation	0.88	0.010	0.80–0.97	1.22	0.002	1.07–1.38
Organization commitment	0.81	0.005	0.70–0.94			
Emotional demands	0.92	0.345	0.78–1.09			
Cognitive demands	0.84	0.012	0.73–0.96			
Development opportunities	0.63	0.000	0.57–0.70	0.79	0.001	0.69–0.91
Work variation	0.68	0.000	0.60–0.77			
Work pace	0.78	0.000	0.69–0.89	0.85	0.024	0.74–0.98
Task clarity	1.06	0.440	0.91–1.07			
Progress of employment	0.86	0.007	0.77–0.96			

*Pooled estimates from the regression analysis in imputed datasets

but not on long term. It was reported that patients with burnout syndrome often suffer from musculoskeletal complaints [32]. Furthermore, family social support was included in the model with 12 month follow up, but not in the model with 3 months follow up, which might suggest that family social support requires a longer period for its effect to be present. Family social support increased the probability of MSD sick leave, which is in agreement with previous studies showing that higher support from family/friends predicted more all-cause sickness absence [33, 34]. Possibly, family and friends advise employees to stay off work when they experience health complaints. In contrast, supervisor social support decreased the probability of MSD sick leave within 3 and 12 months in our study. Thus, the effect of social support on sick leave depends on the source of social support.

Furthermore, higher intrinsic motivation increased the probability on sick leave in both models, which was unexpected because it has been reported that higher motivation decreased the probability of having all-cause sick leaves [35, 36]. This was also unexpected as in the univariate regression, the effect of intrinsic motivation was in opposite direction. No high collinearity was found between the predictors. We did find that several predictors confounded the effect of intrinsic motivation on MSD sick leave: developmental opportunities, distress, burnout, both supervisor and social support, and musculoskeletal complaints. Mainly the predictor developmental opportunities caused the effect of intrinsic motivation to change from direction. Therefore this developmental opportunities can be considered a strong predictor. However no studies were found that included both developmental opportunities and intrinsic motivation in a prediction model. Therefore it remains difficult to explain why higher intrinsic motivation in the prediction models is associated with a higher probability of MSD sick leave. It can be suggested that employees that are more intrinsically motivated are more likely to work too hard and are therefore more likely to get injured or develop a musculoskeletal disorder, which caused sick leave.

Additionally, we found that high work pace decreases the probability of MSD sick leave. In contrary to our findings, it is reported that high work pace and workload is associated with a higher risk on sick leave due to back pain in a case

Table 3 Univariable estimates* and estimates* in the final model for MSD sick leave within 12 months

	Univariable regression			Final model		
	OR	*p*	95% CI (OR)	OR	*p*	95% CI (OR)
Gender, female	0.87	0.066	0.76–1.01			
Age	1.02	0.000	1.02–1.03			
Educational level						
Low	1			1		
Medium	0.56	0.000	0.49–0.63	0.67	0.000	0.59–0.77
High	0.14	0.000	0.11–0.17	0.22	0.000	0.18–0.27
Country of birth, other	0.95	0.597	0.77–1.16			
Musculoskeletal complaints	2.33	0.000	2.12–2.55	2.02	0.000	1.82–2.24
Work engagement	0.83	0.000	0.79–0.88			
Burnout	1.40	0.000	1.24–1.57			
Distress	1.03	0.000	1.02–1.04	1.01	0.002	1.01–1.02
Supervisor social support	0.79	0.000	0.74–0.83	0.87	0.000	0.82–0.93
Colleague social support	0.88	0.000	0.82–0.95			
Family social support	0.95	0.104	0.90–1.01	1.08	0.009	1.02–1.15
Work-home interference	0.90	0.039	0.82–0.99	0.84	0.004	0.75–0.95
Irregular working hours	0.53	0.000	0.47–0.60	0.67	0.000	0.59–0.77
Satisfaction with work	0.85	0.000	0.79–0.91			
Intrinsic motivation	0.88	0.000	0.83–0.93	1.14	0.000	1.06–1.23
Organization commitment	0.81	0.000	0.74–0.88			
Emotional demands	0.96	0.431	0.88–1.06			
Cognitive demands	0.88	0.002	0.82–0.95			
Development opportunities	0.67	0.000	0.63–0.71	0.84	0.000	0.77–0.90
Work variation	0.73	0.000	0.68–0.78			
Work pace	0.78	0.000	0.73–0.84	0.87	0.000	0.80–0.94
Task clarity	1.01	0.840	0.93–1.10			
Progress of employment	0.88	0.000	0.82–0.93			

*Pooled estimates from the regression analysis in imputed datasets

control study [3]. Another study found that the control over work pace was protective for having low back pain [37]. Control over work pace was not assessed in this study, but may help explain why employees in our study are less likely to take sick leave when their work has a high work pace.

Performance of the Prediction Models for MSD Sick Leave

The two prediction models showed comparable performance. The explained variances of both models were of the same magnitude and both models showed significant and good calibration. The model for 3 months follow-up had a slightly higher AUC than the model with 12 months follow-up, both were fair. A study reported that the AUC gradually decreased with each 1 year increase in follow-up time, however the differences were small [10]. Similarly, two studies which developed prediction models for MSD sick leave also found that the models with different follow-up periods showed a similar performance, although they partially differed in predictors [13, 14].

The explained variances of the prediction models in this study were low, which may be due to the low incidence of MSD sick leave as outcome variable in our study population [26]. This finding was also reported by our previous study which developed a prediction model for sick leave due to low back pain, which reported a very low incidence of 0.79% and explained variance of 3.6% [11]. Despite an incidence of 5.0%, the prediction model for all-cause long term sick leave reported 14% explained variance with 1 year follow-up [9]. Yet, the authors reported poorer discrimination between employees with and without sick leave, as reflected in lower AUCs than our models. A higher incidence was found in a prediction model for all-cause long term sick leave of 18% and they reported 12.5% explained variance in their full model for sick leave of > 90 days [10].

Furthermore, the low explained variance may indicate that important predictors are lacking from the prediction models. For example, physical job demands is an important risk factor for MSD sick leave [5, 7], but was not administered in the large part of the health checks (51.2%) and therefore not included as potential predictor variable in our study.

Strengths and Limitations

The use of registered sick leave data instead of self-reported MSD sick leave was a strength of this study and minimized self-report bias. Another asset of the study was the prospective design which is preferred for developing prognostic prediction models [38]. Furthermore, the heterogeneous sample of employees working in various economic sectors was important for the generalizability of the results. The use of commonly measured occupational health check variables facilitates the practical application and implementation of the prediction models.

Although the use of commonly measured occupational health check and sick leave data is an important strength, it's disadvantage is that not all relevant predictors were measured. In general, occupational health checks are assessed for routine periodical examination, however sometimes also companies or departments of companies ask for an extra occupational health check. We did not have detailed information to distinguish between these two types of health checks. When the latter is the cases, this could have let to selection bias. However, when the prediction models of this are used in practice, they are most likely be used after the occupational health, therefore including employees from the same study population. If these models were to be used in other populations, further research is needed to determine the validity of these models in other populations.

Another limitation of our study is that we were not able to externally validate the prediction models. We dealt with this problem by performing an internal validation with bootstrapping techniques [26]. Nevertheless, bootstrapping only partially solves the problem of optimism because bootstrap samples are derived from the sample in which the prediction models were developed. Therefore, it is still recommended to investigate the performance of the prediction models in other datasets of non-sick listed employees.

The amount of missing data was also a limitation of the study. We dealt with this limitation by imputing missing values in predictors and pooling regression coefficients of the imputed datasets. Thus, incomplete cases still provided information for the prediction models.

Practical Implications and Directions for Further Research

The risk of MSD sick leave can be adequately predicted by using health check variables in the presented prediction models. However these models can not solely be used as a screening tool, but can only be used as a supportive tool, mixed with clinical expertise of the occupational physician to tailor advise for the individual. In consultation with these employees, the occupational healthcare provider can explore risk factors of MSD sick leave and give advices to reduce the exposure to these risk factors.

Further research should aim at validating these prediction models in other study populations. Furthermore, to improve these prediction models other possible predictors could be added to this model, such as physical job demands.

Compliance with Ethical Standards

Conflict of interest The authors declare no conflicts of interests.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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