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Development of Prediction Models for Sickness Absence Due to Mental Disorders in the General Working Population

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Abstract

Purpose This study investigated if and how occupational health survey variables can be used to identify workers at risk of long-term sickness absence (LTSA) due to mental disorders. *Methods* Cohort study including 53,833 non-sicklisted participants in occupational health surveys between 2010 and 2013. Twenty-seven survey variables were included in a backward stepwise logistic regression analysis with mental LTSA at 1-year follow-up as outcome variable. The same variables were also used for decision tree analysis. Discrimination between participants with and without mental LTSA during follow-up was investigated by using the area under the receiver operating characteristic curve (AUC); the AUC was internally validated in 100 bootstrap samples. *Results* 30,857 (57%) participants had complete data for analysis; 450 (1.5%) participants had mental LTSA during follow-up. Discrimination by an 11-predictor logistic regression model (gender, marital status, economic sector, years employed at the company, role clarity, cognitive demands, learning opportunities, co-worker support, social support from family/friends, work satisfaction, and distress) was AUC = 0.713 (95% CI 0.692–0.732). A 3-node decision tree (distress, gender, work satisfaction, and work pace) also discriminated between participants with and without mental LTSA at follow-up (AUC = 0.709; 95% CI 0.615–0.804). *Conclusions* An 11-predictor regression model and a 3-node decision tree equally well identified workers at risk of mental LTSA. The decision tree provides better insight into the mental LTSA risk groups and is easier to use in occupational health care practice.

Keywords Decision-tree analysis · Health surveys · Logistic regression · Mental health · ROC analysis

Introduction

Mental disorders account for a large and growing burden of disease worldwide, particularly among individuals of working age: it affects one-fifth of the working population at any given moment [1]. Workers with mental disorders have poorer work outcomes than those in good mental health [2]. They are at risk of long-term sickness absence (LTSA i.e., sickness absence episodes of 6 weeks or longer), which disconnects them from the workplace, leading to work disability, unemployment and poverty [3]. Mental disorders also have economic consequences. Employers struggle with productivity losses and high absence rates. At the societal level, the costs of social and health care expenditures on mental disorders amount up to 4% of the gross national product [1]. Given the significant burden for individuals, companies, and societies, the Organization of Economic Cooperation and Development (OECD) pleaded that mental disorders need to become a priority for stakeholders in the workplace.

If stakeholders in the workplace recognize mental disorders among non-sicklisted workers, they could accommodate work duties or times to prevent LTSA due to mental disorders. Previous studies have shown that mental health symptoms measured with the 4-Dimensional Symptom Questionnaire (4DSQ) can identify non-sick-listed workers who are at increased risk of mental LTSA [4–6]. Roelen et al. [4]. showed that the 4DSQ distress subscale discriminated office

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workers with mental LTSA from those without mental LTSA during 1-year follow up, with an area under the receiver operating characteristic curve (AUC) of 0.71; the 4DSQ subscales for depression (AUC = 0.66), anxiety (AUC = 0.64) and somatization (AUC = 0.68) showed poorer discrimination. In a later study, the 4DSQ distress scale was also found to discriminate between postal workers with and without mental LTSA (AUC = 0.75), whereas depressive symptoms (AUC = 0.64) and fatigue (AUC = 0.61) did not discriminate between postal workers with and without mental LTSA during 2-year follow-up [5]. The 4DSQ distress scale could be a promising tool identify workers at risk of mental LTSA, although additional predictor variables are needed to improve discrimination between workers with and without mental LTSA [6].

In a Swedish population study, the risk of mental LTSA was higher in women, workers aged 30–39 years and in families with underage children [7]. Furthermore, workers in health care, education and social services had an elevated mental LTSA risk. The Oslo Health Study revealed that women had a higher risk of mental LTSA than men [8]. Distress, low education, and low supervisor support increased the risk of mental LTSA, although the effect of supervisor support was mediated through distress. Supervisor support and other psychosocial work factors have been associated with the risk of mental disorders. In a systematic review of the literature, Nieuwenhuijsen et al. [9] reported that high job demands, low decision latitude, low co-worker support, and a high effort-reward imbalance predicted the incidence of stress-related mental disorders.

Psychosocial work factors are commonly addressed in occupational health surveys. Several studies have investigated the use of health survey variables to identify workers at risk of LTSA irrespective of cause. Airaksinen et al. [10] reported that a prediction model including age, gender, socioeconomic position, self-rated health, depression, previous sickness absence, number of chronic diseases, body mass index, smoking, shift work, working night shifts, and sleep disturbance discriminated between Finnish workers with and without LTSA ≥ 90 consecutive days (AUC = 0.73). Roelen et al. [11]. showed that a prediction model including age, gender, education, self-rated health, mental health, prior LTSA, work ability, emotional demands and recognition by the management moderately discriminated between Danish workers with and without LTSA ≥ 28 consecutive days during 1-year follow-up (AUC = 0.68), possibly due to the fact that the authors were not able to differentiate between LTSA causes.

Another explanation for the moderate discrimination by the prediction model might be that important interactions between predictor variables were not taken into account. The assessment of interactions in regression models requires pre-specification of interaction terms. In regression models with many variables, the number of possible interactions that can be investigated is large and may lead to a complicated model that can be difficult to use in healthcare practice [12]. Decision tree analysis (DTA) is a non-parametric statistical method that takes interactions and non-linear relationships among predictor variables into account [13].

The aim of the present study was to develop a multivariable prediction model specifically for mental LTSA by using logistic regression analysis and DTA. The logistic regression model and decision tree were compared in their ability to identify occupational health survey participants with mental LTSA during 1-year follow up.

Methods

Study Population and Design

According to the Dutch Labor Law, companies have to enable their employees to participate in an occupational health survey once every 4 years. Occupational health surveys are conducted by occupational health services (OHS) and consist of an online occupational health survey questionnaire. The questionnaire results are collected and analyzed by the OHS; participants receive an individual feedback and companies receive a survey report presenting the survey results at team/department level. At the request of trade organizations, companies or staff representatives, occupational health survey participants can consult with OHS professionals to discuss their individual questionnaire results, explore work and health risk factors and get an advice on how to reduce risk factors.

The present study used the occupational health survey questionnaire results of 53,833 workers who participated in surveys between 2010 and 2013. A cohort design was used, with the occupational health survey as baseline and sickness absence recorded in the year following the occupational health survey as follow-up. The 2207 survey participants who were on sickness absence at baseline were excluded from the study. Results are presented in line with the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) [14].

Outcome: Mental Long-Term Sickness Absence (LTSA)

Sickness absence was defined as a temporary paid leave from work due to any (i.e., work-related as well as non-work-related) injury or illness, and was recorded from the first to the last sickness absence day in an occupational health service (OHS) register. In The Netherlands, sickness absence is medically certified by an occupational physician (OP) within

6 weeks of reporting sick. Therefore, LTSA was defined as sickness absence lasting 6 weeks or longer.

Based on a consultation with a sick-listed worker, the OP records a diagnostic code derived from the 10th International Classification of Diseases (ICD-10) in the OHS register. Mental LTSA was defined as LTSA with diagnostic codes of the ICD-10 chapter V (Mental and Behavioral Disorders). Mental LTSA during 1-year follow-up was used as the outcome variable.

Predictors: Occupational Health Survey Variables

Sociodemographic Variables

Age, gender, marital status (single, living together/married, other), care for children at home (yes, no) and education (low = primary school and lower vocational education; medium = secondary general or vocational education; high = higher vocational and academic education) were retrieved from the occupational health survey questionnaire.

Work-Related Characteristics

The occupational health survey questionnaire asked for the economic sector (agriculture, manufacturing, commercial services, or public services), number of years employed at the company, the number of years in the present job and the average number of hours worked per week.

Work pace (5 items, Cronbach's $\alpha = 0.87$), cognitive demands (5 items, $\alpha = 0.82$), emotional demands (3 items, $\alpha = 0.80$), variety in work (6 items; $\alpha = 0.86$), role clarity (5 items; $\alpha = 0.85$), learning opportunities (4 items; $\alpha = 0.87$), supervisor support (3 items; $\alpha = 0.90$), co-worker support (3 items; $\alpha = 0.88$) and organizational commitment (5 items; $\alpha = 0.79$) were measured with the Questionnaire on the Experience and Evaluation of Work [16]. Survey participants responded on a five-point frequency scale ranging from 'never' (= 1) to 'always' (= 5) and item scores were summed to a total subscale score, which was then divided by the number of items in the scale. Consequently, all psychosocial work characteristics had a score range between 1 (= low) and 5 (= high).

Social support from family and friends was assessed with 3 QEEW items (Can you count on the support of partner/family/friends when you have some difficulty at work? Is work at home taken out of your hands if you are busier at work? Do you feel appreciated by your partner/family/friends? $\alpha = 0.77$). Survey participants responded on a five-point frequency scale ranging from 'never' (= 1) to 'always' (= 5) and item scores were summed and averaged so that social support from family/friends ranged between 1 (= low) and 5 (= high).

Work–family interference was assessed with 7 QEEW items (e.g., How often does your job interfere with responsibilities at home? How often does your job prevent you from spending time with family and friends? $\alpha = 0.88$). Responses were given on 5-point frequency scales ranging from 'never' (= 1) to 'always' (= 5); item scores were summed and averaged so that work family interference ranged between 1 (= low) and 5 (= high).

Work satisfaction was measured with 6 QEEW items ($\alpha = 0.87$) about pleasure in work (e.g., I am pleased to start my day's work; I find my work stimulating; I enjoy my work). Responses were given on 5-point frequency scales ranging from 'never' (= 1) to 'always' (= 5). Items scores were summed and averaged, so that work satisfaction ranged between 1 (= low) and 5 (= high).

Intrinsic work motivation was measured with the 7-item interest/enjoyment subscale of the Intrinsic Motivation Inventory [17]. This subscale asks survey participants 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 work motivation score ($\alpha = 0.89$), which was then averaged to a score range between 1 (= low) to 7 (= high).

Work ability was measured with a shortened version of the Work Ability Index covering items on current work ability compared with lifetime best, work ability in relation to the (physical and mental) demands of work, number of physician-diagnosed diseases, impaired work performance due to illness, sickness absence in the past 12 months, expected work ability in the forthcoming 2 years, and mental resources [18]. The item scores were summed to a total work ability score ranging from 7 (= poor) to 49 (= excellent).

Work engagement was measured with a 9-item short form of the Utrecht Work Engagement Scale [19]. The items were scored on a 6-point frequency scale ranging from 'never' (= 0), 'scarcely' (= 1), 'sometimes' (= 2), 'regularly' (= 3), 'often' (= 4), 'very often' (= 5), and 'always' (= 6). The items scores were summed and averaged to a work engagement score between 0 (= low) and 6 (= high). Burnout was measured with the 15-item Dutch version of the Maslach Burnout Inventory—General Scale [20]. Items were scored on a 6-point frequency scale, summed and averaged into a burnout score between 0 (= low) to 6 (= high).

Distress was measured with the Four-Dimensional Symptom Questionnaire (4DSQ), which was included in the occupational health survey questionnaire. The distress scale consisted of 16 items addressing symptoms elicited by stressors or the efforts to maintain psychosocial functioning, such as worry, irritability, tension, listlessness, poor concentration, sleeping problems, and demoralization [21, 22]. Survey participants were asked if they experienced these symptoms in the past week, 'no' (= 0), 'sometimes' (= 1), 'regularly' (= 2), 'often' (= 2), or 'very often/constantly' (= 2). Item scores were summed (score range 0–32; Cronbach's α = 0.94) so that higher scores reflected higher levels of distress. Terluin et al. [23] defined scores ≤ 10 as low, 11–20 as moderate, and > 20 as high distress.

LTSA episodes in the year prior to the occupational health survey were retrieved from the OHS register regardless of cause, and used for the predictor variable 'prior LTSA' (yes = 1, no = 0).

Missing Data

Of the 51,626 non-sicklisted occupational health survey participants, 20,769 had missing responses on one or more predictor variables. Missing data analysis showed that missingness was not related to the risk of mental LTSA. Therefore, it is reasonable to assume that complete cases analysis will be unbiased. If all 27 occupational health survey variables were included in a model, 270 mental LTSA events would be needed to fulfill the rule of 10 outcome events per variable [24]. The 30,857 participants with complete data had 450 mental LTSA events, which was more than sufficient for estimating stable regression coefficients.

Statistical Analysis

The logistic regression model and decision tree were developed using IBM SPSS Statistics for Windows, version 24 (released 2016; IBM Corp. Armonk, NY).

Logistic Regression Analysis

Twenty-seven occupational health survey variables were included in a multivariable logistic regression model as candidate predictor variables. Gender, marital status, care for children at home, education, prior mental LTSA, economic sector, and distress were included as categorical variables. Age, the number of years employed at the company and in the present job, average number of hours worked per week, work pace, cognitive demands, emotional demands, variety in work, role clarity, learning opportunities, supervisor support, co-worker support, organizational commitment, social support from family/friends, work—family interference, intrinsic work motivation, work satisfaction, work ability, work engagement, and burnout were included as continuous variables in a multivariable logistic regression model with mental LTSA at follow-up (no = 0, yes = 1) as outcome variable. The full 27-predictor model was reduced by a backward stepwise procedure, using Akaike's Information Criterion as stopping rule.

Decision Tree Analysis (DTA)

The same 27 predictor variables were entered in DTA, using the Chi square Automatic Interaction Detector (CHAID) algorithm to partition the data. CHAID is a multi-way tree algorithm that analyses each potential predictor and all possible cut-off points to split the data [24]. Partitioning starts with the predictor variable which splits the population into subsets that differ most in their risk of mental LTSA. After the first split, subsets are partitioned over and over again by other predictor variables until no further significant partitioning is possible. Large decision trees tend to be unstable and are prone to overfitting [12, 13, 25]. Therefore, partitioning was stopped if groups included less than 1000 participants and/or less than 50 mental LTSA events.

Logistic Regression Versus Decision Tree

Discrimination between survey participants with and without mental LTSA was investigated by using receiver operating characteristic (ROC) analysis. The area under the ROC-curve (AUC) represented discrimination between survey participants with and without mental LTSA in the year following the occupational health survey. AUC is the probability that a randomly chosen survey participant with mental LTSA has a higher risk score than a randomly chosen participant without mental LTSA. In the present study, AUC < 0.60 represents failing, 0.60–0.69 poor, 0.70–0.79 fair, 0.80–0.89 good, and 0.90–1.00 perfect discrimination.

The AUCs were validated in 100 bootstrap samples by using the regression modeling strategies (rms) package in R (statistical computing) for Windows, version 3.5.1 [15]. The internally validated AUC better than the non-validated AUC reflects discrimination that can be expected in new samples of occupational health survey participants.

Results

The 30,857 (57%) non-sicklisted occupational health survey participants with complete data and were more often female, married, higher educated, working for a shorter time at the company, and in their present job as compared to those excluded because of missing data, although the differences were small (Table 1).

Logistic Regression Analysis

Of the 30,857 occupational health survey participants with complete data, 450 (1.5%) had mental LTSA during 1-year follow-up. When all 27 occupational health survey variables were included in the logistic regression model, distress and gender were the strongest predictors of mental LTSA

Table 1 Population characteristics (N = 53,833)

	Complete cases analysis (n = 30,857)				Excluded because of missing data (n = 22,976)			
	Mean	SD[a]	n	%	Mean	SD	n	%
Sociodemographic variables								
Age	45.2	10.1			44.7	10.9		
Gender								
Men			23,710	77			18,363	80
Women			7147	23			4492	20
Missing			–				121	
Marital status								
Single			3129	10			2837	12
Relationship, but living apart			2516	8			1951	9
Living together/married			24,556	80			16,443	72
Other			656	2			1,09	5
Missing			–				654	
Care for children at home								
No			12,648	41			7573	40
Yes			18,209	59			11,215	60
Missing			–				4188	
Education								
Low			5114	17			4337	19
Medium			13,219	43			10,390	46
High			12,522	40			7751	34
Missing			–				498	
Years employed at company	14.4	11.5			17.0	12.5		
Years in present job	8.4	8.3			9.0	9.1		
Work hours per week	38.4	7.7			37.6	7.3		
Prior mental LTSA[b]								
Yes			461	2			362	2
No			30,396	98			22,614	98
Missing			–				–	
Psychosocial work factors (range 1–)								
Work pace	2.8	0.7			2.7	0.8		
Cognitive demands	3.6	0.7			3.5	0.7		
Emotional demands	1.7	0.6			1.7	0.6		
Variety in work	3.6	0.8			3.6	0.8		
Role clarity	4.0	0.7			4.0	0.7		
Learning opportunities	3.1	1.0			3.0	1.0		
Support supervisor	3.6	1.0			3.6	1.0		
Support co-workers	3.9	0.8			3.9	0.8		
Organizational commitment	3.2	0.7			3.1	0.7		
Social support family/friends (range 1–5)	3.6	1.0			3.5	1.0		
Work–family interference (range 1–5)	1.7	0.6			1.6	0.6		
Intrinsic work motivation (1–7)	5.9	1.0			5.9	1.0		
Work satisfaction (range 1–5)	3.9	0.8			3.9	0.8		
Work ability (7–49)	42.2	4.2			42.2	4.2		
Work engagement (range 0–6)	3.8	1.1			3.7	1.1		
Burnout (range 0–6)	2.4	0.5			2.4	0.5		
Distress								
Low			22,008	71			16,065	73
Medium			6449	21			4455	20
High			2400	8			1600	7
Missing			–				1053	

[a]Standard deviation

[b]Long-term sickness absence due to mental disorders in the 12 months before baseline

(Table 2). After backward stepwise logistic regression analysis, gender, marital status, economic sector, years employed at the company, role clarity, cognitive demands, learning opportunities, co-worker support, social support from family/friends, work satisfaction, and distress remained in the final logistic regression model for mental LTSA.

Decision-Tree Analysis (DTA)

DTA revealed distress as the first node of the decision tree, indicating that it was the strongest predictor of mental LTSA. Survey participants with low distress scores had a 0.8% risk of mental LTSA and survey participants with moderate distress scores had a 2.3% risk of mental LTSA (Fig. 1). Survey participants with high distress scores had a 5.0% risk of mental LTSA, which is more than 3 times higher than the 1.5% population risk.

Of the survey participants with low distress scores, only women reporting low work satisfaction had an increased risk of mental LTSA as compared to the population risk. Amongst survey participants with moderate distress scores, women were at increased 3.3% risk of mental LTSA, particularly those experiencing a high work pace who had a 6.7% risk of mental LTSA. Survey participants with high distress scores and low work satisfaction had a 6.6% risk of mental LTSA during follow-up.

Logistic Regression Versus Decision Tree

ROC analysis showed that the final 11-predictor logistic regression model fairly discriminated (AUC = 0.740; 95% CI 0.711–0.768) between survey participants with and without mental LTSA during follow-up; the bootstrap validated AUC was 0.713 (95% CI 0.692–0.732). In comparison, discrimination by the decision tree was AUC = 0.727 (95% CI 0.701–0.753) and the bootstrap validated AUC was 0.709 (95% CI 0.615–0.804). Figure 2 shows that the discriminative ability of the decision tree was as good as that of the logistic regression model.

Discussion

The present study used occupational health survey variables to predict mental LTSA during 1-year follow-up of survey participants. An 11-predictor logistic regression model including gender, marital status, economic sector, years employed at the company, role clarity, cognitive demands, learning opportunities, co-worker support, social support from family/friends, work satisfaction, and distress discriminated between survey participants with and without mental LTSA during follow-up. Discrimination by the logistic regression model was of the same magnitude as discrimination found in previous studies [4–6]. Although decision tree analysis takes interactions between predictor variables into account, a decision tree based on distress, gender, work satisfaction and work pace did not result in better mental LTSA predictions. This may indicate that interactions between the 27 occupational health survey variables did not contribute to mental LTSA predictions.

In line with previous studies [4–6], we found that distress was the strongest predictor of mental LTSA. Furthermore, the present results confirmed that female gender and prior LTSA were associated with a significantly higher LTSA risk [10, 11]. Socioeconomic position [10] and education [11] are important LTSA predictors, but in our study education did not remain in the final prediction model for mental LTSA. When we re-analyzed the results with all-cause LTSA as outcome, education did remain in the prediction model [data not shown]. This may indicate that education is an important LTSA predictor, but not specifically of mental LTSA.

The present study also confirmed that the economic sector was an important predictor of mental LTSA. The mental LTSA risk was lower in manufacturing and commercial services as compared agriculture, which was the reference group. In line with the findings, of Lidwall et al. [7], the risk of mental LTSA in public services was higher than in the other economic sectors.

Cognitive job demands were significantly associated with the risk of mental LTSA and remained in the final regression model, which agrees with the results of a review on the psychosocial work environment and stress-related disorders [7]. Co-worker support, but not supervisor support remained in the final regression model. It has been reported that the effect of low supervisor support on mental LTSA is mediated by distress [8], which may explain why supervisor support was removed from a model that also contained distress. The present study showed that low support from family and friends adds to mental LTSA risk predictions.

Strengths and Weaknesses of the Study

The large study sample, prospective study design, the use of recorded OP-certified LTSA and the different statistical methods to analyze large amounts of data are strengths of the study. However, some potential limitations of the study should be discussed. Although large, the study population was not representative of the Dutch workforce as manufacturing and commercial business was over-represented and agriculture and public services were under-represented. Forty-three percent of the participants were excluded because of missing data. We found that missings were not related to mental LTSA and therefore complete cases analysis was acceptable.

Decision trees more than regression models are data-driven and small perturbation in the data could lead to

Table 2 Logistic regression analysis (n = 30,857)

	Full model			Final model	
	Wald[a]	OR[b]	95% CI[b]	OR	95% CI
Age	0.305	1.004	0.989–1.020		
Gender					
Men		1		1	
Women	20.858	2.044	1.504–2.777	1.927	1.475–2.517
Marital status					
Single	6.989	1		1	
Relationship, but living apart	.823	1.239	0.780–1.966	1.239	0.783–1.959
Living together/married	1.550	0.785	0.536–1.150	0.795	0.554–1.140
Other	1.063	0.578	0.204–1.639	0.559	0.198–1.578
Care for children at home					
No		1			
Yes	0.010	0.987	0.762–1.278		
Education					
Low	2.043	1			
Medium	0.618	0.869	0.612–1.233		
High	1.957	0.759	0.517–1.117		
Economic sector					
Agriculture	5.676	1		1	
Manufacturing	1.559	0.727	0.441–1.199	0.738	0.449–1.215
Commercial services	1.448	0.704	0.397–1.247	0.719	0.407–1.269
Public services	0.010	1.028	0.595–1.779	1.044	0.611–1.783
Years employed at company	3.621	0.986	0.971–1.000	0.991	0.979–1.003
Years in present job	0.053	0.998	0.980–1.016		
Work hours per week	0.063	1.002	0.984–1.021		
Prior mental LTSA[c]					
No		1			
Yes	1.210	1.396	0.771–2.527		
Work pace	0.044	1.017	0.866–1.195		
Cognitive demands	4.078	1.218	1.006–1.474	1.248	1.064–1.463
Emotional demands	0.000	0.999	0.833–1.198		
Variety in work	2.131	1.161	0.950–1.420		
Role clarity	2.323	1.157	0.959–1.397	1.140	0.957–1.358
Learning opportunities	1.261	0.904	0.758–1.078		
Support supervisor	0.262	0.963	0.834–1.112		
Support co-workers	1.613	0.907	0.779–1.055	0.880	0.763–1.015
Organizational commitment	2.543	1.171	0.964–1.423		
Social support family/friends	1.802	0.915	0.804–1.042	0.912	0.804–1.035
Work–family interference	0.069	0.973	0.792–1.195		
Intrinsic work motivation	0.366	0.942	0.774–1.145		
Work satisfaction	4.101	0.811	0.663–0.993	0.776	0.666–0.905
Work ability	3.282	0.973	0.944–1.002	0.962	0.936–0.988
Work engagement	0.492	0.979	0.923–1.039		
Burnout	0.521	1.033	0.946–1.127		
Distress					
Low	28.710	1		1	
Medium	18.273	1.921	1.424–2.592	2.021	1.514–2.698
High	25.271	2.802	1.875–4.186	3.124	2.157–4.526

[a]Wald statistic is calculated as $(B/SE)^2$ where B is the regression coefficient and SE its standard error; higher Wald-statistics represent stronger predictors of mental LTSA

[b]Odds ratio and 95% confidence interval

[c]Long-term sickness absence due to mental disorders in the 12 months before baseline

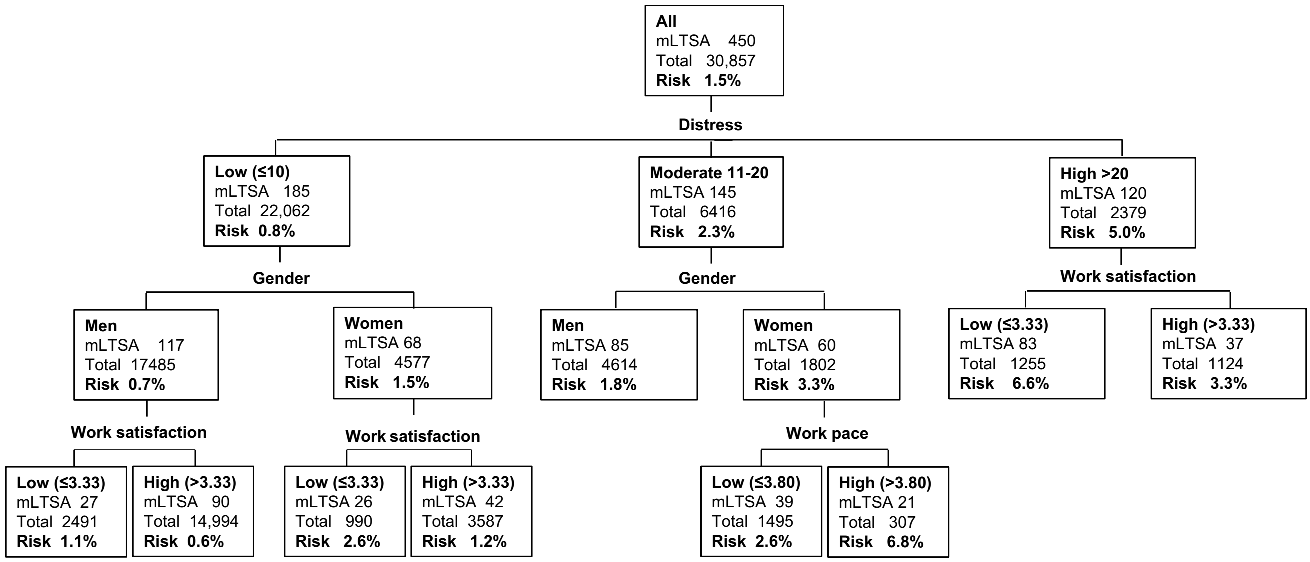

Fig. 1 Decision tree

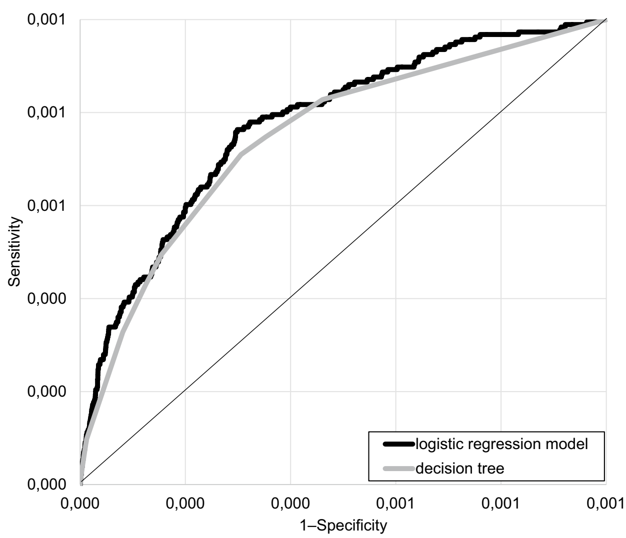

Fig. 2 Discrimination graph

substantial changes in the decision tree [12, 24]. We dealt with this problem by defining cut-offs, stopping recursive partitioning if groups contained less than 1000 participants and/or less than 50 mental LTSA events. This 'pruning' improves the stability and practical use, but reduces the predictive accuracy of decision trees.

The performance of prediction models is overestimated when results are based on the sample of subjects used to develop the models. Bootstrapping has been recommended to estimate the internal validity of a predictive logistic regression model [25]. Discrimination by the regression model and decision tree was validated in 100 bootstrap samples. The bootstrap validated AUCs reflects discrimination between participants with and without mental LTSA in new occupational health survey samples and herewith increased the external validity of our results.

Implications for Practice and Further Research

Based on their disappointing performance, Burdorf [26] pleads for using prediction models to detect predictors of LTSA rather than deliver predictions for individuals at risk. He advocates a population approach to discover and control the causes of LTSA in the workforce. Companies receive an occupational health survey report on the group or department level, which could be used to take actions to prevent mental LTSA in the company's workforce. However, preventive actions aimed at the individual might as well contribute to the prevention of mental LTSA. It is superfluous to advise all occupational health survey participants, as only 1.5% of them develops mental LTSA in the year following the survey. The 11-predictor logistic regression model could be used to identify workers at risk of mental LTSA and provide them with a preventive advice or invite them to a preventive consultation. For that purpose, the occupational health provider has to define a cut-off risk score: participants with a predicted risk above the cut-off score are invited whereas those with a risk below the cut-off score are not invited. However, the problem is that the 11-predictor prediction model does not have an optimal cut-off score. Low risk cut-offs result in the unnecessary invitation of many participants who will not develop mental LTSA. Alternatively, many of the participants who develop mental LTSA are missed if high risk cut-offs were used.

Based on the decision tree, the occupational health provider can more easily decide which occupational health survey participants should be given preventive advices or be invited to preventive consultations, because there is no need to set cut-off scores. The decision tree readily shows the mental LTSA risk groups. For example, an occupational health provider could decide to invite survey participants with moderate and high distress scores to preventive consultations. The decision tree shows that this would implicate that 8795 (29%) of 30,857 occupational health survey participants would be invited, including 265 (59%) of those who have mental LTSA (n = 450) in the year following the survey. If resources are limited, the occupational health provider could decide to only invite female survey participants experiencing moderate distress and high work pace (n = 307) as well as both male and female participants with high distress scores and low work satisfaction (n = 1255). This would involve 5% of all survey participants and 23% of those with mental LTSA in the year following the survey. Thus, the decision tree is a practical tool to identify high-risk groups for preventive consultations. Given the fact that decision trees are data driven and the relatively broad 95% confidence interval of the validated discrimination, the decision tree has to be externally validated in other samples of occupational health survey participants, before we can recommend its use in occupational healthcare practice.

Conclusion

A 3-node decision tree (distress, gender, work satisfaction and work pace) and an 11-predictor regression model (gender, marital status, economic sector, years employed at the company, role clarity, cognitive demands, learning opportunities, co-worker support, social support from family/friends, work satisfaction, and distress) equally well identified occupational health survey participants at increased risk of mental LTSA during 1-year follow-up. If externally validated, the decision tree is more practical than the regression model to identify mental LTSA risk groups in occupational health surveys.

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Compliance with Ethical Standards

Conflicts of interest The authors declare that they have no conflict of interest.

Ethical Approval The Medical Ethics Committee of the University Medical Center Groningen reviewed the study and granted ethical clearance.

Informed Consent All occupational health survey participants agreed to the use of their questionnaire results for scientific research.

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