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Strategy for finding occupational health survey participants at risk of long-term sickness absence

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Background: When resources are limited, occupational health survey participants are usually invited to consultations based on an occupational health provider's subjective considerations. This study aimed to find health survey participants at risk of long-term (i.e., $\geq$ 42 consecutive days) sickness absence (LTSA) for consultations with occupational health providers (OHPs). **Methods:** The data of 64 011 non-sicklisted participants in occupational health surveys between 2010 and 2015 were used for the study. In a random sample of 40 000 participants, 27 survey variables were included in decision tree analysis (DTA) predicting LTSA at 1-year follow-up. The decision tree was transferred into a strategy to find participants for OHP consultations, which was then tested in the remaining 24 011 participants. **Results:** In the development sample, 1358 (3.4%) participants had LTSA at 1-year follow-up. DTA produced a decision tree with work ability as first splitting variable; company size and sleep problems were the other splitting variables. A strategy differentiating by company size would find 75% of the LTSA cases in small ($\leq$99 workers) companies and 43% of the LTSA cases in medium-sized (100–499 workers) companies. For large companies ($\geq$500 workers), case-finding was only 25%. **Conclusions:** In small and medium-sized companies, work ability and sleep problems can be used to find occupational health survey participants for OHP consultations aimed at preventing LTSA. Research is needed to further develop a case-finding strategy for large companies.

Introduction

The average sickness absence rates across Europe vary between 3% and 6% with societal costs amounting up to 2.5% of a country's gross domestic product.[1] Long-term sickness absence constitutes the major part of these costs and disconnects workers from the workplace, which may ultimately result in disability or unemployment.[2–5] The risk of long-term sickness absence increases with the duration of sickness absence.[4,5] Therefore, workers at risk of long-term sickness absence are preferably identified before they report sick, for example in occupational health surveys. In The Netherlands, employers have to enable their personnel to participate in occupational health surveys at least once every four years. Occupational health surveys are conducted by occupational health services (OHS) and consist of a questionnaire measuring health status, lifestyle and working conditions. After completing the questionnaire, participants are invited to consultations with an occupational health provider (OHP). In practice, however, not all survey participants can be invited to OHP consultations due to limited resources in terms of time and/or money. The current practice is that OHPs invite survey participants based on experience and subjective interpretations of the questionnaire results, rather than the participants' risk of long-term sickness absence.

The risk of long-term sickness absence has been associated with a multitude of health-related, lifestyle, intrapersonal, work-related, and home-related factors. Many of those risk factors are addressed in occupational health surveys; however, little is known about the factors that identify survey participants at increased long-term sickness absence risk. Based on occupational health survey data, Roelen et al.[6] developed a multivariable prediction model for sickness absence $\geq$28 consecutive days in the Danish working population. The prediction model included age, sex, education, prior sickness absence, self-rated health (SRH), mental health, work ability, emotional job demands and recognition by the management as predictor variables. Its performance was moderate, correctly assigning the highest risk to workers with sickness absence $\geq$28 consecutive days in 68% of the cases.

Later, Airaksinen et al.[7] developed a prediction model for sickness absence $\geq$90 consecutive days in the Finnish working population, including age, sex, socioeconomic position, SRH, depression, prior sickness absence, number of chronic diseases, smoking, shift work, working night shift, and quadratic terms for body mass index (BMI) and sleep disturbance. The Finnish prediction model correctly assigned the highest risk to workers with sickness absence ≥90 consecutive days in 73% of the cases. Recently, van der Burg et al.[8] developed a prediction model for sickness absence ≥28 consecutive days in the Dutch working population. Older age, female gender, lower level of education, poor SRH, low weekly physical activity, high self-rated physical job load, knowledge and skills not matching the job, high number of major life events in the previous year, poor work ability, high number of sickness absence days in the previous year, and being self-employed correctly assigned the highest risk to workers with sickness absence ≥28 consecutive days in 76% of the cases.

All these studies used receiver operating characteristic (ROC) analyses to discriminate between workers with and without long-term sickness absence during 1-year follow-up.[6–8] The problem with ROC curves is that there is no optimal cut-off point to find survey participants at increased risk of long-term sickness absence. Decision tree analysis (DTA) is a robust statistical technique to identify risk groups in large datasets.[9] Although frequently used to develop decision-making tools in clinical practice, DTA is scarcely used in occupational healthcare. The aim of the present study was to use DTA to find occupational health survey participants at risk of long-term sickness absence for OHP consultations. In The Netherlands, employers have to make a return-to-work plan of action when workers are sicklisted for 6 weeks or longer. In Dutch occupational health care, sickness absence lasting ≥42 days is commonly considered long-term sickness absence (LTSA). Therefore, LTSA was defined in this study as sickness absence ≥42 gross sickness absence days.

Methods

Study setting and design

Between January 2010 and July 2015, 64 011 non-sicklisted workers participated in occupational health surveys. The study was designed as a split-sample cohort study, setting the occupational health survey as baseline and 1-year follow-up of LTSA recorded in an OHS register as outcome variable. The Medical Ethics Committee of the University Medical Center Groningen granted ethical clearance for the study.

Outcome variable

Sickness absence was defined as a temporary paid leave from work due to work-related and non-work-related injuries or illnesses. Sickness absence was recorded from the day of reporting sick to the day of returning to work in an OHS sickness absence register. Sickness absence episodes with ≥42 consecutive days were defined as LTSA and retrieved at the individual level from the OHS register at 1-year follow-up.

Predictor variables

Sociodemographic factors

Age, sex, education (low = primary school, junior vocational education; medium = senior vocational and secondary general education; high = higher professional and academic education), marital status (single, married, other, e.g. living with parent), children living at home (yes, no) and informal care for parents or elderly family members (yes, no) were used as sociodemographic predictor variables.

Health-related factors

LTSA (≥42 gross sickness absence days) in the 12 months prior to the survey was obtained from the OHS register and used for the predictor variable 'prior LTSA' (yes/no).

The other predictor variables were measured with the occupational health survey questionnaire. SRH was addressed with the question 'In general, do you rate your health excellent (=5), very good (=4), good (=3), moderate (=2) or poor (=1)'. Smoking habits were assessed by the question 'Do you smoke?' with response options 'yes', 'no, I have never smoked' and 'no, I have stopped smoking'. Alcohol use was measured with the AUDIT-C, but responses were missing in 82% of the cases. Therefore, alcohol use was discarded as predictor variable. Exercise was assessed by the question 'How often do you perform sturdy exercise or sports?' with a frequency scale ranging from 'less than once a week' to 'daily'. Body mass index (BMI) was calculated from participant-reported length and weight. BMI was categorized according to the World Health Organization (WHO) classes underweight <18.5, normal weight 18.5–24.9, overweight 25–29.9, and obesity ≥30.0.[10] Sleep problems were measured with the 10-item 'sleep problems' subscale of the Pittsburg Sleep Quality Index. Although originally developed in psychiatric practice,[11] the Pittsburg Sleep Quality Index is one of the most widely used sleep health assessment tools in clinical and non-clinical populations. The sleep problems subscale asked participants: 'During the past month, how often have you had trouble sleeping, because of...' (e.g. 'waking up in the middle of the night', 'coughing or snoring loudly' and 'having bad dreams'). All items had response options 'no' = 1, 'less than once a week' = 2, 'once or twice per week' = 3 and 'three or more times per week' = 4. Responses were summed (Cronbach's $\alpha = 0.88$) to a total score and then divided by the number of items so that the score range was between 1 and 4, with higher scores reflecting more sleep problems.

Mental health was measured with the 16-item distress subscale of the Four-Dimensional Symptom Questionnaire.[12] Participants rated distress symptoms in the past two weeks with response options 'no' (=0), 'sometimes' (=1), 'regularly' (=2), 'often' (=2) or 'very often/constantly' (=2). Responses were summed to a distress score (range 0–32; $\alpha = 0.94$). Musculoskeletal pain was measured with items on pain/stiffness in the back, neck/shoulder/arm, wrist/hand and hip/knee/ankle/foot. Responses were scored on a 4-point frequency scale ranging from 'never' (=1) to 'most of the time' (=4) and summed to a musculoskeletal pain score (range 4–16; $\alpha = 0.74$).

Work-related factors

The economic sector (agriculture/mining, manufacturing, commercial services, public services), number of years employed at the present company, company size (small ≤99, medium-sized 100–499 and large ≥500 workers), average number of work hours per week, and irregular work hours (yes, no) were obtained from the occupational health survey questionnaire.

Work ability was measured with a short version of the Work Ability Index,[13] covering current work ability compared with lifetime best, work ability in relation to the demands of work, number of physician-diagnosed diseases, impaired work performance due to disease, sickness absence in the past 12 months, expected work ability in the forthcoming two years and mental resources. The items were summed to a work ability score ranging from 7 (=poor) to 49 (=excellent).

Work pace (five items, $\alpha = 0.87$), cognitive demands (five items, $\alpha = 0.82$), emotional demands (three items, $\alpha = 0.80$), task variety (six items, $\alpha = 0.86$), learning opportunities (four items; $\alpha = 0.87$), supervisor support (three items; $\alpha = 0.90$) and co-worker support (three items; $\alpha = 0.88$) were measured with the Questionnaire on the Experience and Evaluation of Work.[14] Items were scored on a five-point frequency response scale ranging from 'never' (=1) to 'always'

(=5). The item scores were summed and averaged, so that scores ranged from 1 (=low) to 5 (= high).

Sample size calculations

Twenty-seven occupational health survey variables were included in the analyses. Based on a 50 events per variable assumption[15] and the 3.4% LTSA incidence in the study population, a total of (27*50)/ 0.034 = 39 706 participants would be needed to develop the decision tree. Consequently, a random sample of 40 000 participants was drawn from the study population to develop the decision tree. The results from the development sample were then transferred into a practical strategy to find survey participants for OHP consultations. The data of the remaining 24 011 participants not included in the development sample were used to test this strategy. After taking the random sample, all occupational health survey variable means (Mann–Whitney test) and frequencies (Chi-square test) were compared.

Missing data

Missing data were analyzed in DTA as a separate risk category for each variable.[9]

Statistical analysis

DTA was conducted in IBM SPSS Statistics for Windows, version 25 (released 2017). The decision tree was developed in the sample of 40 000 survey participants by entering the 27 occupational health survey questionnaire variables in DTA, using the Chi-square Automatic Interaction Detector (CHAID) algorithm to partition data. CHAID is a non-parametric method that can handle nominal, ordinal, as well as continuous data.[16] CHAID uses the predictor variables to split risk groups until no further significant partitioning is possible. The more complex a decision tree, the less reliable it will be when applied to new samples. Therefore, we set CHAID to stop partitioning when risk groups included less than 1000 participants and/or less than 50 LTSA events.

The developed decision tree was applied to the test sample. The total number of participants and the number of those with LTSA were used for risk calculations in each group of the developed decision tree.

Results

The occupational health survey participants (75% men) had a mean age of 44.7 (standard deviation [SD] 10.6) years and worked on average 38.1 (SD = 7.7) hours per week in agriculture/mining (2%), manufacturing (55%), commercial services (16%), public services (17%) and other economic sectors (10%). Table 1 presents the study population characteristics. No significant differences were found between the development ($n = 40\,000$) and test ($n = 24\,011$) samples.

Development of a decision tree for LTSA (n = 40 000)

At 1-year follow-up, 1358 (3.4%) participants in the development sample had LTSA: 38% mental LTSA, 29% musculoskeletal LTSA and 33% LTSA due to other somatic disorders, particularly cardiovascular and respiratory disorders. Of all 27 occupational health survey variables, DTA showed that work ability split the population into four risk groups. Survey participants with excellent, good, moderate to poor work ability had 2.0%, 4.0%, 8.2% LTSA risks, respectively (figure 1). For survey participants reporting good work ability, company size was a significant splitting variable, with those working in small companies being at highest LTSA risk. For participants working in medium-sized companies, sleep problems was a significant splitting variable.

Of the 1358 participants with LTSA during follow-up, 556 (40.9%) reported good work ability at the time of the survey. The variable 'sleep problems' split the participants with good work ability in medium-sized, but not small or large companies. Therefore, a strategy based on company size was developed to invite survey participants to preventive OHP consultations.

Testing a strategy to find survey participants at risk of LTSA (n = 24 011)

In small companies, 175 (7%) participants reported poor or moderate work ability and 1088 (48%) reported good work ability (table 2). If the 1263 (55%) participants with poor, moderate or good work ability were invited, then 75% of all LTSA cases potentially visit OHP consultations.

In medium-sized companies, 313 (8%) participants reported poor or moderate work ability and 1915 (48%) reported good work ability. Among the participants with good work ability, 73 (3.8%) reported sleep problems, as reflected in a Pittsburg Sleep Quality subscale score >3. If participants with poor or moderate work ability and those with good work ability experiencing sleep problems were invited, a total of 386 (20%) participants would visit OHP consultations, potentially finding 43% of all LTSA cases.

In large companies, 584 (10%) participants reported poor or moderate work ability and 2903 (47%) reported good work ability. DTA found no other survey variables splitting the group of participants reporting good work ability into further risk subgroups. If the participants reporting poor to moderate work ability were invited to OHP consultations, 25% of the LTSA cases could be found implicating that the majority (75%) would be missed.

Discussion

DTA showed that work ability defined four LTSA risk groups. Occupational health survey participants with excellent work ability were at lowest risk of LTSA and those with moderate and poor work ability were at highest LTSA risk. Previous research has shown that poor work ability was a risk factor for LTSA and disability pension.[17–20] Later studies reported that work ability scores discriminated between workers with and without LTSA.[21–23] Recently, Palmlöf et al.[24] found that poor work ability increased the LTSA risk over a period of 10 years, particularly in older age groups. The authors showed a 6-fold increased LTSA risk in the oldest age group of workers in the Swedish public sector reporting poor physical work ability and a 4-fold increased LTSA risk in the oldest age group of those reporting poor mental work ability. The present study showed that of all 27 occupational health survey variables, work ability was the first and most important variable to assign occupational health survey participants to LTSA risk groups. Duchemin et al.[25] hierarchized chronic disease, perceived health and handicap as major LTSA determinants amongst workers in the French private sector. As chronic diseases, health and handicap in terms of work-limitations are part of the work ability construct, this finding corroborates our present results. Sleep problems were also recognized by Duchemin and colleagues as one of the main LTSA determinants. However, company size was not a major determinant of LTSA. This may be due to differences in social security and sickness absence policies between France and The Netherlands. In The Netherlands, return to work is usually facilitated by temporary accommodations in work tasks and/or times. Large companies have more opportunities to accommodate work tasks and work times than small companies. Hence, it is not surprising that company size is an LTSA determinant in the Dutch context, with workers in small companies being at higher risk of LTSA than those working in large companies. In the previously developed multivariable LTSA prediction models, work ability was a predictor variable in the Danish and Dutch models, and sleep disturbances in the Finnish model.[6–8] The Danish, Dutch and Finnish prediction models had age, sex, SRH, and prior

Table 1 Occupational health survey variables in the study population ($n = 64\,011$)

Variable	Mean	SD[a]	*n*	%	Missing data *n*	Missing data %
Age	44.7	10.6			1820	3
Sex						
Men			47 466	75	764	1
Women			15 781	25		
Education						
Low			10 392	17	990	2
Medium			26 527	42		
High			26 102	41		
Marital status						
Single			12 543	20	1807	3
Living together/Married			47 625	77		
Other			2036	3		
Children at home						
No			24 177	39	2003	3
Yes			37 831	61		
Informal care						
No			47 781	90	11 135	17
Yes			5095	10		
Prior LTSA[b]						
No			60 618	95	–	–
Yes			3393	5		
General health	3.8	0.6			13 648	21
Smoking						
Yes			11 139	20	7809	12
No, never smoked			27 512	49		
No, stopped smoking			17 551	31		
Exercise						
Less than once a week			16 909	31	8934	14
1 to 2 times a week			23 848	43		
3 to 4 times a week			11 401	21		
5 or more times a week			2919	5		
Body mass index						
Underweight			10 235	20	12 801	20
Normal weight			18 786	37		
Overweight			17 116	33		
Obesity			5073	10		
Sleep problems (range 1–4)	1.5	0.6			6214	10
Distress (range 0–32)	7.9	7.3			3472	5
Musculoskeletal pain (range 4–16)	6.5	2.2			15 077	24
Sector						
Agriculture/mining			976	2	15 714	25
Manufacturing			26 721	55		
Commercial services			7498	16		
Public services			8196	17		
Other			4906	10		
Years employed at company	15.2	11.9			2559	4
Company size						
≤99 workers			6987	15	17 989	28
100–499 workers			12 647	28		
≥500 workers			26 388	57		
Years employed in present job	8.3	8.5			2106	3
Work hours per week	38.1	7.7			2710	4
Irregular work hours						
Yes			14 622	27	10 529	16
No			38 860	73		
Work ability						
Excellent			20 565	44	17 206	27
Good			22 298	48		
Moderate			3536	8		
Poor			406	1		
Work pace (range 1–5)	2.8	0.9			2814	4
Cognitive demands (range 1–5)	3.6	0.7			1453	2
Emotional demands (range 1–5)	1.7	0.6			4131	6
Task variety (range 1–5)	3.6	0.8			2461	4
Learning opportunities (range 1–5)	3.1	1.0			2485	4
Supervisor support (range 1–5)	3.6	1.0			1620	3
Co-worker support (range 1–5)	3.9	0.8			1973	3

a: Standard deviation.
b: Long-term (≥42 consecutive days) sickness absence.

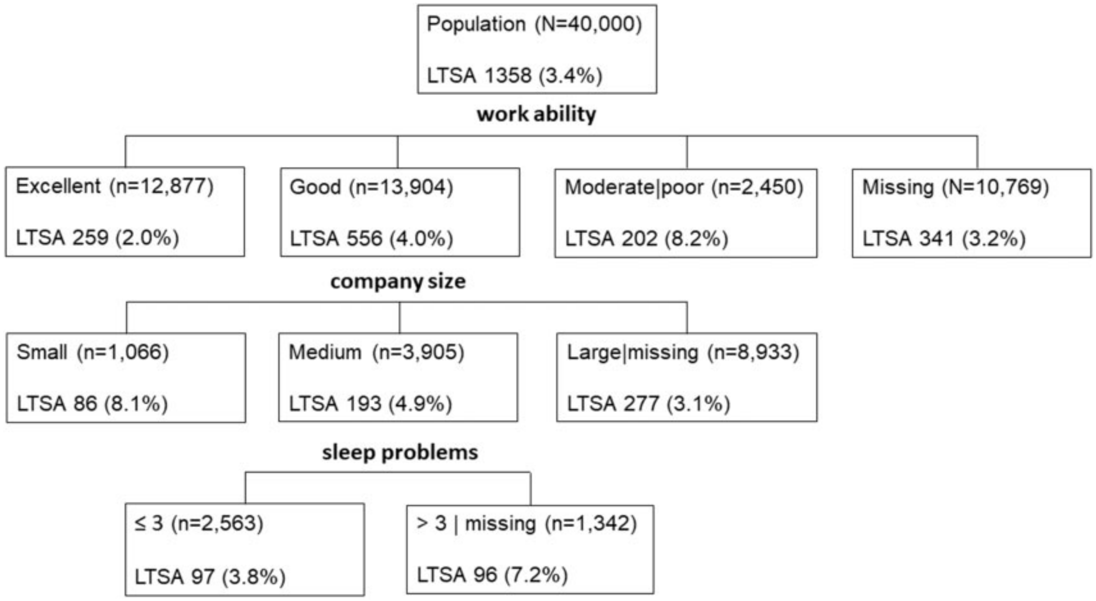

Figure 1 Decision tree for long-term sickness absence

Table 2 Work ability scores and LTSA in the validation sample ($n = 24\,011$) stratified by company size

Company size	Work ability score															
	Excellent				Good				Moderate/poor				Total		Missing	
	n	%	LTSA	%	*n*	%	LTSA	%	*n*	%	LTSA	%	*n*	LTSA	*n*	LTSA
≤ 99 workers	1021	45	27	25	1088	48	64	59	175	7	18	16	2284	109	348	15
100–499 workers	1765	44	45	27	1915	48	96	57	313	8	27	16	3993	168	774	26
≥500 workers	2641	43	36	22	2903	47	87	53	584	10	42	25	6128	165	3714	130
Missing	2261	44	30	23	2488	48	76	58	420	8	26	19	5169	132	1601	44

The table shows number (*n*) and row percentage (%) of occupational health survey participants with excellent, good or moderate/poor work ability and the number and row% of participants with long-term sickness absence (LTSA) during 1-year follow-up, stratified by company size.

LTSA in common, but none of these factors was a splitting variable in the LTSA decision tree. Apparently, they fail to significantly further partition the work ability-based risk groups.

Study strengths and weaknesses

DTA based on CHAID is a non-parametric approach to extract information from large datasets without distributional assumptions. CHAID can use both categorical and continuous variables and takes interactions between variables into account. Furthermore, DTA treats missing data as a separate category for each variable, which prevents participants with missing data being excluded from the analyses. DTA results are displayed into easy-to-understand decision trees, which is important for their implementation into health care practice.[26] Strong correlations between independent and splitting variables could result in the selection of variables that are not causally related to LTSA. Hence, the decision tree cannot be used to make causal inferences or test causal hypotheses. A further disadvantage of DTA is that decision tree was fitted to a study sample of occupational health survey participants who were older and more frequently male as compared to the total Dutch workforce (mean age 41.7 years; 64% men) in 2013.[27] In addition, participants in occupational health surveys may be healthier than non-participants, a phenomenon known as the 'healthy volunteer effect'. Over-representation of healthy participants may have biased associations between survey variables and LTSA to the null. Consequently, the decision tree applies to occupational health survey participants rather than the general working population.

We only asked the survey participants' consent to retrieve their sickness absence data from the OHS register. Although available, we could not retrieve information on OHP consultations. This will not have biased the current results, because we did not aim to investigate a preventive effect of OHP consultations. Previous studies have already shown that OHP consultations are successful in reducing sickness absence among occupational health survey participants at high risk of future LTSA.[28,29]

Practical implications

In the test sample, work ability scores were available for 17 574 (73%) participants. Of the participants reporting excellent, good and moderate/poor work ability, 138, 323 and 113, respectively, had LTSA during follow-up. If those reporting poor and moderate work ability visited OHP consultations, then 113 (20%) of the 574 LTSA cases could be found whereas 80% of the LTSA cases would be missed. This is in line with previous results of Reeuwijk et al.[21] who reported that LTSA cases are missed because of the low sensitivity of the work ability index. In our study, most participants with LTSA at 1-year follow-up reported good work ability at the time of the survey. This raises the question whether or not to use work ability to identify workers at increased risk of LTSA, especially because LTSA is not a very prevalent problem in the working population. However, considering the consequences of LTSA for workers and the costs for employers and society, every prevented LTSA case helps. Bearing in mind an average gross yearly income of 58 000 Euros per worker in The Netherlands in 2013[27] and approximately 225 working days a year, one sickness absence day would cost 258 Euros. Hence, one case of LTSA (i.e. ≥42 consecutive sickness absence days, of which at least 30 are work days) in a fulltime worker costs more than 7700 Euros. For these costs, an OHP could perform approximately 38 one-hour consultations or 76 half-hour consultations. Small companies employ a maximum of 99 workers; inviting those 55% reporting poor, moderate or good work ability would be practically feasible and potentially finds 75% of all LTSA cases. If OHP consultations prevented one LTSA case, this strategy would be cost-effective for the company.

In medium-sized companies employing 100–499 workers, it is not feasible to invite all workers who report poor, moderate or good work ability when resources for OHP consultations are limited. A medium-sized company employs a maximum of 499 workers. If workers who report poor or moderate work ability and those with good work ability who experience sleep problems were invited, an OHP consults with 20% (i.e. maximum 100) workers, potentially finding 43% of the LTSA cases in medium-sized companies. Although covering less than half of the LTSA cases, consultations would be cost-effective if two or three LTSA cases were prevented. In large companies, we can only invite those 10% of the workers reporting poor or moderate work ability when resources for OHP consultations are restricted. Case-finding would be restricted to 25% of the LTSA cases. Further research is needed to identify risk factors among workers in large companies, specifically in workplaces with a higher LTSA prevalence to increase the predictive value of work ability. Risk factors should also be sought at other levels. For that purpose, the IGLO (Individual, Groep, Leadership, Organization) model proposed by Nielsen et al.[30] provides an excellent theoretical framework to improve LTSA case-finding.

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The study was not funded.

Conflicts of interest: None declared.

Key points

- Decision tree analysis showed that work ability, company size and sleep problems partitioned the working population into risk groups for long-term sickness absence (LTSA)
- Most workers with LTSA during 1-year follow-up reported good work ability at baseline.
- In small companies (≤99 workers), the workers reporting poor, moderate and good work ability can be invited to consultations aimed at preventing LTSA
- In medium-sized companies (100–499 workers), the workers reporting poor and moderate work ability should be invited, as well as those with good work ability reporting sleep problems.
- In large companies (≥500 workers), further research is needed to identify the workers at increased LTSA risk among those who report good work ability.

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The impact of a COVID-19 lockdown on work productivity under good and poor compliance

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Background: In response to the COVID-19 pandemic, governments across the globe have imposed strict social distancing measures. Public compliance to such measures is essential for their success, yet the economic consequences of compliance are unknown. This is the first study to analyze the effects of good compliance compared with poor compliance to a COVID-19 suppression strategy (i.e. lockdown) on work productivity. **Methods:** We estimate the differences in work productivity comparing a scenario of good compliance with one of poor compliance to the UK government COVID-19 suppression strategy. We use projections of the impact of the UK suppression strategy on mortality and morbidity from an individual-based epidemiological model combined with an economic model representative of the labour force in Wales and England. **Results:** We find that productivity effects of good compliance significantly exceed those of poor compliance and increase with the duration of the lockdown. After 3 months of the lockdown, work productivity in good compliance is £398.58 million higher compared with that of poor compliance; 75% of the differences is explained by productivity effects due to morbidity and non-health reasons and 25% attributed to avoided losses due to pre-mature mortality. **Conclusion:** Good compliance to social distancing measures exceeds positive economic effects, in addition to health benefits. This is an important finding for current economic and health policy. It highlights the importance to set clear guidelines for the public, to build trust and support for the rules and if necessary, to enforce good compliance to social distancing measures.

Introduction

Since the December 2019 outbreak in China, the novel coronavirus virus (COVID-19) has become a global pandemic. The short-term health impact of the pandemic is unprecedented, with nearly 470 000 deaths globally, and about 45 000 of these deaths coming from the UK.[1] In response to control the spread of the pandemic and to minimize both mortality and the strain on NHS hospital capacities, on 23 March 2020, the UK government implemented a 'lockdown'. Lasting until the beginning of June 2020, this period included the non-pharmaceutical interventions (NPIs) case isolation, social distancing of the entire population, household quarantine and business, school and university closure.[2,3] Public compliance with these measures is necessary for the effective suppression of COVID-19, as lockdown ensures that the spread of COVID-19 is lowered. Whilst the health benefits of good public compliance vs. poor compliance to these NPIs in response to pandemic outbreaks have been clearly identified, the economic effects are unknown.[4–6]

Compliance behaviour to laws, orders and public rules can be motivated by demographic, instrumental or normative factors.[7] Demographic factors such as gender or age can predict compliance with research finding that men and younger individuals are less compliant than women and older individuals.[8] Normative factors relate to people's perceived duty to support the authorities and/or to act for the greater good of the society.[9,10] Instrumental factors are motivated by individual returns of compliant behaviour by weighing the benefits of an action against the costs of the action.[11,12] Whilst systematic reviews show that various studies have analyzed the determinants and health effects of compliance to lockdown measures of pandemics that have occurred in the 20th and 21st century,[13,14] none has to our knowledge focused on identifying