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Multicentre validation of frequent sickness absence predictions

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Background	A prediction model including age, self-rated health (SRH) and prior sickness absence (SA) has previously been found to predict frequent SA.
Aims	To further validate the model and develop it for clinical use.
Methods	A multicentre study of care of the elderly workers employed at one of 14 centres in Aarhus (Denmark). SA episodes recorded in the year prior to baseline and both age and SRH at baseline were included in a prediction model for frequent (three or more) SA episodes during a 1-year follow-up period. The prediction model was developed in the largest centre. Risk predictions and discrimination between high- and low-risk workers were investigated in the other centres. The prediction rule 'SRH–prior SA' was derived from the prediction model and prognostic properties of the prediction rule were investigated for each centre, using score <0 as cut-off.
Results	Of 2562 workers, 1930 had complete data for analysis. Predictions were accurate in 4 of 13 centres; discrimination was good in five and fair in another five centres. Prediction rule scores <0 identified workers at risk of frequent SA with sensitivities of 0.17–0.54, specificities of 0.86–0.96 and positive predictive values of 0.54–0.87 across centres.
Conclusions	The prediction model discriminated between workers at high and low risk of frequent SA in the majority of centres. The prediction rule 'SRH–prior SA' can be used in clinical practice specifically to identify workers at high risk of frequent SA.
Key words	Absenteeism; external validity; generalization; prediction model; prediction rule; sick leave.

Introduction

In the healthcare sector, sickness absence (SA) reduces the efficiency and quality of care [1]. Frequent SA adversely affects work schedules and may generate feelings of mistrust and blame in colleagues [2]. In a randomized controlled trial, healthcare workers had fewer SA episodes in the year after receiving seven to nine 1-h coaching sessions compared to a control group without such coaching [3]. Preventive coaching is time-consuming and should therefore be targeted at high-risk workers.

Roelen *et al.* [4] showed that a prediction model including age, self-rated health (SRH) and prior SA correctly identified Dutch hospital workers at risk of frequent SA in 83% of cases. The development of a prediction model involves four stages: internal validation, external validation, validation in multiple settings and assessment of clinical usefulness [5]. At external validation, the prediction model correctly identified Danish care of the elderly workers at risk of frequent SA in 79% of cases [6]. The objective of this multicentre study was to develop the prediction model further and derive a prediction rule for clinical practice.

Methods

The Working in Eldercare Survey questionnaire was sent to 4536 Danish care of the elderly workers [6,7]. A total of 3444 (76%) participants returned the questionnaire,

the date of which was set as baseline. For our study, 882 participants were excluded because they were either employed for less than 1 year or were on sick or parental leave at baseline. The Danish Data Protection Agency approved the use of survey data for this study.

We calculated age from the personal number assigned to every Danish citizen. SRH was measured with the question: In general, would you say your health is excellent (5), very good (4), good (3), moderate (2) or poor (1)? This is widely used in health research and has been associated with various morbidity and mortality measures [8]. SA episodes were obtained from employers' records at the individual level, irrespective of duration as in previous studies [4,6]. The number of SA episodes in the year before baseline was the predictor variable 'prior SA'. SA episodes in the year following baseline were used as the outcome variable 'frequent SA', defined as three or more SA episodes as in previous studies [4,6].

Statistical analyses were done in R (Project for Statistical Computing) using the Regression Modelling Strategies package [9]. Data clustering at centre level was minimal (intra-class coefficient 0.03) ruling out the need for multilevel analysis. Logistic regression analysis yielded the linear predictor (LP) = 0.281 − 0.031 × age − 0.122 × SRH + 0.200 × prior SA for the largest care of the elderly centre (N = 278). LP was used to predict the risk of frequent SA in the other centres with the formula $1/(1 + e^{-LP})$.

The accuracy of risk predictions was investigated with calibration graphs, plotting mean predicted risks (x-axis) against observed risks (y-axis) of frequent SA. If risk predictions are perfect, then the calibration graph is a straight line with intercept = 0 and slope = 1. Risk predictions were considered accurate if the test of the calibration slope $P \geq 0.05$ (i.e. the calibration slope did not differ significantly from slope = 1) [6,10]. Miscalibration was concluded for calibration slope test $P < 0.05$, meaning that risk predictions deviated too far from the observed risks. The prediction model's ability to discriminate between workers at high and low risk of frequent SA was examined with receiver operating characteristic (ROC) curves; area under the ROC curve ≥ 0.90 represented excellent, 0.80–0.89 good, 0.70–0.79 fair, 0.60–0.69 poor and <0.60 failing discrimination [6].

The prediction rule 'SRH–prior SA' was derived from the prediction model and tested as a tool for identifying workers at risk of frequent SA in clinical practice. Care of the elderly workers with prediction rule scores <0 were considered at high risk of frequent SA.

Results

The study population included 2562 care of the elderly workers of whom 632 (25%), particularly male students, left employment during the 1-year follow-up. Therefore, 1930 workers were included in the analyses and 688 (36%) of them had frequent SA during follow-up. Risk predictions were accurate in 4 of 13 care of the elderly centres; discrimination was good in five centres and fair in another five centres (Table 1).

Table 1. Prediction model and rule for frequent sickness absence

Centre	N	Baseline			Follow-up		Prediction model			Prediction rule			
		Age, mean (SD)	SRH, mean (SD)	Prior SA, mean (range)	Lost, n (%)	High SA, n (%)	R^2	Calibration slope (SE)	Discrimination AUC (95% CI)	High risk, n (%)	Sens	Spec	PPV
Centre 1[a]	278	45.2 (9.4)	3.4 (0.9)	2.5 (0–12)	64 (23)	82 (38)	0.20	1.00	0.74 (0.67–0.81)	56 (26)	0.45	0.86	0.66
Centre 2	271	46.7 (9.2)	3.4 (0.9)	2.6 (0–14)	69 (25)	78 (39)	0.21	1.55 (0.26)	0.74 (0.67–0.80)	44 (22)	0.36	0.89	0.70
Centre 3	239	47.4 (8.4)	3.4 (0.9)	2.0 (0–9)	61 (26)	66 (37)	0.28	2.17 (0.34)	0.83 (0.77–0.89)	27 (15)	0.32	0.95	0.78
Centre 4	205	46.8 (8.9)	3.5 (0.8)	2.2 (0–16)	55 (27)	54 (36)	0.35	2.10 (0.44)	0.80 (0.72–0.87)	27 (18)	0.43	0.96	0.85
Centre 5	195	47.3 98.6)	3.6 (0.9)	1.9 (0–7)	46 (24)	47 (32)	0.38	2.10 (0.40)	0.78 (0.69–0.86)	19 (13)	0.32	0.96	0.79
Centre 6	188	45.5 (9.6)	3.6 (0.9)	2.3 (0–9)	49 (26)	48 (35)	0.25	2.36 (0.42)	0.79 (0.71–0.87)	36 (26)	0.54	0.89	0.72
Centre 7	188	45.0 (9.5)	3.3 (0.9)	2.2 (0–8)	48 (26)	52 (37)	0.33	1.66 (0.32)	0.79 (0.72–0.87)	24 (17)	0.31	0.91	0.67
Centre 8	181	46.7 (10.2)	3.6 (0.8)	1.8 (0–8)	45 (25)	52 (38)	0.38	1.50 (0.30)[b]	0.76 (0.67–0.84)	30 (22)	0.40	0.89	0.70
Centre 9	180	46.2 (9.3)	3.6 (0.9)	2.4 (0–8)	39 (22)	42 (30)	0.31	1.14 (0.30)[b]	0.69 (0.60–0.78)	13 (9)	0.17	0.94	0.54
Centre 10	149	47.1 (9.3)	3.4 (1.0)	2.1 (0–7)	44 (30)	35 (33)	0.39	0.87 (0.44)[b]	0.68 (0.57–0.78)	21 (20)	0.37	0.89	0.62
Centre 11	145	44.8 (9.9)	3.5 (0.8)	2.8 (0–8)	30 (21)	44 (38)	0.35	2.07 (0.40)	0.81 (0.73–0.90)	22 (19)	0.33	0.92	0.77
Centre 12	142	45.6 (9.5)	3.4 (0.9)	2.5 (0–8)	37 (26)	37 (35)	0.34	2.24 (0.48)	0.80 (0.72–0.89)	13 (12)	0.46	0.87	0.65
Centre 13	109	44.4 (9.0)	3.5 (0.8)	2.3 (0–11)	26 (24)	26 (31)	0.35	0.61 (0.32)[b]	0.66 (0.53–0.80)	11 (13)	0.27	0.93	0.64
Centre 14	92	49.1 (9.6)	3.5 (0.8)	2.0 (0–9)	19 (21)	25 (34)	0.51	2.67 (0.61)	0.88 (0.80–0.96)	15 (23)	0.52	0.96	0.87

AUC, area under the curve; AUC ≥ 0.90 reflects excellent, 0.80–0.89 good, 0.70–0.79 fair and 0.60–0.69 moderate discrimination; CI, confidence interval; PPV, positive predictive value; R^2, Nagelkerke's R^2, a measure for the overall predictive performance of the model; SA, sickness absence; prior SA is the number of SA episodes in the year prior to baseline; high SA is ≥3 SA episodes during follow-up; SD, standard deviation; SE, standard error; Sens, sensitivity; Spec, specificity; SRH, self-rated health (score range 1–5).

[a]Sample in which prediction model and rule were developed.

[b]Denotes accurate risk predictions.

The prediction rule identified 358 (19%) workers at risk of frequent SA. Across centres, sensitivities varied between 0.17 and 0.54, i.e. 17–54% of the workers with frequent SA had baseline prediction rule scores <0 (Table 1). Specificities between 0.86 and 0.96 indicated that most workers without frequent SA had baseline prediction rule scores ≥0. Positive predictive values ranged from 0.54 to 0.87, reflecting that the majority of workers with baseline prediction rule scores <0 had frequent SA during follow-up.

Discussion

The prediction model showed fair to good discrimination between care of the elderly workers at high and low risk of frequent SA in most eldercare centres. Predictions of frequent SA risk were accurate in only 4 of 13 centres.

The survey response rate was high (76%), but participants had less SA than non-participants [6,7]. Healthy volunteer bias may have attenuated the prediction model and rule's predictive value. Complete case analyses included 43% of workers, who may not be representative of the care of the elderly sector. However, assessing the performance of a prediction model in different settings is more important for prediction model development than the representativeness of the study population.

The prediction model identified workers at high risk of frequent SA in most centres but requires an algorithm to calculate workers' risks, which may restrict its use in clinical practice. The prediction rule 'SRH–prior SA' is a more practical tool to identify workers at high risk of frequent SA. At a cut-off score <0, sensitivity was low meaning that many frequent SA cases would be missed. When clinicians want to identify as many frequent SA cases as possible, they should choose higher cut-off scores at the expense of more false positives. The clinical usefulness of the prediction rule to identify high-risk workers for preventive coaching remains to be investigated.

Key points

- The prediction model including age, self-rated health and prior sickness absence discriminated between care of the elderly workers at high and low risk of frequent sickness absence.
- The prediction model did not accurately predict the risk of frequent sickness absence.
- The prediction rule 'self-rated health–prior sickness absence' can be used in clinical practice to identify workers at high risk of frequent sickness absence.

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Conflicts of interest

None declared.

References

1. Kane RL, Shamliyan TA, Mueller C, Duval S, Wilt TJ. The association of registered nurse staffing levels and patient outcomes: systematic review and meta-analysis. *Med Care* 2007;**45:**1195–1204.
2. Eakin JM, MacEachen E. Health and the social relations of work: a study of the health-related experiences of employees in small workplaces. *Sociol Health Ill* 1998;**20:**896–914.
3. Duijts SF, Kant I, van den Brandt PA, Swaen GM. Effectiveness of a preventive coaching intervention for employees at risk for sickness absence due to psychosocial health complaints: results of a randomized controlled trial. *J Occup Environ Med* 2008;**50:**765–776.
4. Roelen CA, van Rhenen W, Groothoff JW, van der Klink JJ, Bültmann U, Heymans MW. The development and validation of two prediction models to identify employees at risk of high sickness absence. *Eur J Public Health* 2013;**23:**128–133.
5. McGinn TG, Guyatt GH, Wyer PC, Naylor CD, Stiell IG, Richardson WS. Users' guide to the medical literature XXII: how to use articles about clinical prediction rules. *J Am Med Assoc* 2000;**284:**79–84.
6. Roelen CA, Stapelfeldt CM, Heymans MW *et al.* Cross-national validation of prognostic models predicting sickness absence and the added value of work environment variables. *J Occup Rehabil* 2015;**25:**279–287.
7. Stapelfeldt CM, Jensen C, Andersen NT, Fleten N, Nielsen CV. Validation of sick leave measures: self-reported sick leave and sickness benefit data from a Danish national register compared to multiple workplace-registered sick leave spells in a Danish municipality. *BMC Public Health* 2012;**12:**661.
8. Halford C, Wallman T, Welin L *et al.* Effects of self-rated health on sick leave, disability pension, hospital admissions and mortality. A population-based longitudinal study of nearly 15,000 observations among Swedish women and men. *BMC Public Health* 2012;**12:**1103.
9. Harrell FE. *Regression Modelling Strategies*. http://cran.r-project.org/web/packages/rms (30 March 2015, date last accessed).
10. Steyerberg EW, Vickers AJ, Cook NR *et al.* Assessing the performance of prediction models: a framework for traditional and novel measures. *Epidemiology* 2010;**21:**128–138.