Development and Validation of a Logistic Regression Model to Estimate the Risk of WMSDs in Portuguese Home Care Nurses

Ana C. Braga(✉) and Paula Carneiro

ALGORITMI Centre, University of Minho, 4710-057 Braga, Portugal
{acb,pcarneiro}@dps.uminho.pt

Abstract. Multivariable prediction models are being developed, validated, updated, and implemented in different domains, with the aim of assisting professionals in estimating probabilities and potentially influence their decision making. The main goal of this work was to develop and validate a logistic regression model that would predict the risk of musculoskeletal complaints involving the lumbar region in nurses working at the Health Centres of Northern Portugal and providing home-based care. The main methodology used was a questionnaire developed in electronic format, which was based on the Standardized Nordic Questionnaire for the analysis of musculoskeletal symptoms.

Internal and external validation methods were used, and their performances were compared with the ROC (Receiver Operating Characteristic) methodology.

Keywords: Logistic regression · Development · Validation · ROC curve

1 Introduction

Work-related musculoskeletal disorders (WMSDs) have been described by the scientific community as the most important occupational health problem affecting nursing professionals [2,19]. The high prevalence of symptoms and injuries associated with the musculoskeletal system of these professionals constitutes an evidence of the referred problem [1,3,10]. The high-risk level of WMSDs results from physical requirements and also from the various risk factors in the working context. Musculoskeletal disorders negatively influence many aspects of the nurses' lives, such as their productivity level, absenteeism rate, well-being, and quality of life [2,4,7].

Most studies focus on professionals who develop their activity in the hospital setting, thus excluding the group of nurses who provide home health care. This group has unique characteristics when compared with hospital professionals, as they work in a poorly controlled/standardized working environment. At the patient's home, nurses experience an increased physical demand, and consequently experience more musculoskeletal symptoms [5,14,18,20]. Several studies have revealed that WMSDs are a serious problem for nurses and nursing assistants who provide home care, affecting mainly their back [8,12,20].

O. Gervasi et al. (Eds.): ICCSA 2016, Part I, LNCS 9786, pp. 97–109, 2016.
DOI: 10.1007/978-3-319-42085-1_8

Although back problems have a multi-factorial etiology, including physical, psychosocial, and individual factors, the manual handling of patients (physical risk factor) is considered one of its main causes [14].

2 Problem Description

Taking into account the scarcity of studies addressing musculoskeletal problems in home care nurses, Carneiro [4] developed a study to characterize the musculoskeletal complaints of these professionals. That author found out that providing home care increases the likelihood of having lower back complaints. Based on that result, that author proposed to identify the main risk factors for lower back complaints. Thus Carneiro [4] developed a logistic regression model to predict which risk factors could contribute to the occurrence of complaints involving the lumbar region in home care nurses.

After an exhaustive univariate analysis, the final multivariate model contained seven variables that, when acting together, could contribute, negatively or positively, to the risk of having lower back complaints (Table 1).

The variables that integrate the proposed statistical model are usually associated with back complaints, some more than others, and thus contribute to the credibility of the statistical model. For example, the use of assistive devices by

Table 1. Variables of the logistic regression model and their contribution to lower back complaints, according to Carneiro [4].

Variable	Description	Contribution
X_1	Forearm posture	The adoption of a posture different from the reference posture may contribute to the absence of complaints
X_2	Static postures	The maintenance of static postures for more than 1 min may contribute to the occurrence of complaints
X_3	Arm posture	The adoption of a posture different from the reference posture may contribute to the occurrence of complaints
X_4	Arm supported	Working with the arm supported may contribute to the absence of complaints
X_5	Height of the bed	Working with a bed at an inadequate height may contribute to the occurrence of complaints
X_6	Job satisfaction	Job satisfaction may contribute to the absence of complaints
X_7	Assistive devices for moving or transferring patients	Using assistive devices to move patients may contribute to the absence of complaints

nurses for lifting/transferring patients (X_7) whenever possible, has been encouraged to decrease the risk of musculoskeletal complaints [11,13]. Job satisfaction (X_6) has also been referred in the literature as a factor that might contribute to the occurrence of WMSDs. Namely, Daraiseh et al. [9], reported that dissatisfaction with the working conditions may lead to the occurrence of musculoskeletal symptoms. Moreover, in a study involving Japanese nurses, Smith et al. [19] concluded that more importance should be given to job satisfaction, work organization, and occupational stress, in parallel with the more traditional risk reduction strategies that emphasize manual handling tasks and other occupational factors. Maintaining the same posture for more than a minute (X_2) has also been recognized as a WMSDs risk factor, and this is particularly relevant in the home care context, where the maintenance of static postures may occur in several situations, such as dressing in a limited workspace [5].

According to the model, working with patients' beds at inadequate heights may contribute to the onset of complaints involving the lumbar region. The inadequate height of the bed contributes to the adoption of inadequate postures and, therefore, to the occurrence of musculoskeletal problems. In general, the beds at patients' homes are typically low. Accordingly, Owen and Staehler [17] found that the major sources of back problems for home care workers were the height and width of the beds, their location, and the impossibility of adjusting them.

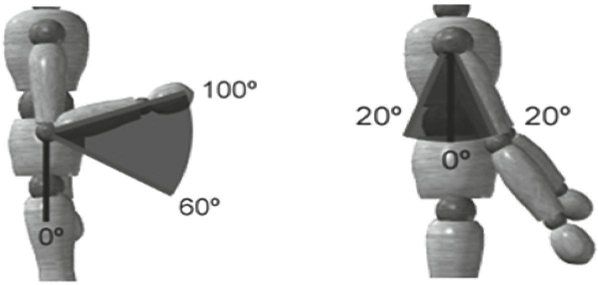
The other variables of the statistical model are less emphasized in the scientific literature as potential factors for the occurrence of musculoskeletal complaints. These Variables are the "arm's posture" (X_3), the "forearm's posture" (X_1), and the "arm supported" (X_4). For both the arm and the forearm, some postures may be favorable to reduce the moment generated on the lumbar spine, hence resulting in decreased stress on it and a consequent reduced likelihood of complaints. According to the final statistical model, and in order to minimize the complaints involving the lumbar region, nurses should avoid working with the forearm in the reference posture, which is between 60° and 100° of flexion (Fig. 1(a)), and should work with the arm in the reference posture, i.e., between 20° of extension and 20° of flexion (Fig. 1(b)). Working with the arm supported is also favorable for reducing the moment generated on the lumbar spine.

3 Model Development

Model development studies aim to derive a prediction model by selecting predictors and combining them into a multivariable model. Logistic regression is a technique commonly used in cross-sectional (diagnostic) and short-term studies [6].

Using a binary dependent variable and p independent predictors, $\mathbf{x}$, the logistic regression model, in terms of expected probability, $\pi(\mathbf{x})$, can be written as shown below in Eq. 1:

$$\pi(\mathbf{x}) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)} \quad (1)$$



(a) Forearm reference posture. (b) Arm reference posture.

Fig. 1. Reference postures for X_1 and X_4.

The transformation of $\pi(\mathbf{x})$ is usually called *logit* transformation and is defined in terms of $\pi(\mathbf{x})$, as shown below (Eq. 2):

$$g(\mathbf{x}) = \ln\left(\frac{\pi(\mathbf{x})}{1-\pi(\mathbf{x})}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \tag{2}$$

The *logit* transformation is important due to being a linear function of the parameters β.

The construction of a model is an art; it depends not only on gathering a set of requirements and assumptions that should be statistically evaluated but also on the intuition and knowledge of the researcher.

Generally, the researcher must evaluate the association of each variable with the binary outcome. This work is exhaustive, and some researchers opt for selection techniques based on error criteria, like stepwise procedures.

3.1 Sample Size Considerations

The estimation of a sample size for logistic regression is a complex problem. Nevertheless, based on the work of Peduzzi et al. [16] a guideline for a minimum number of cases to include in this kind of study can be suggested. That guideline is described below.

Let p be the smallest of the proportions of negative or positive cases in the population and k the number of covariates (the number of independent variables or predictors), then the minimum number of cases to include is:

$$N = 10 * \frac{k}{p}$$

Thus, for example, if we have seven covariates to include in the model and the proportion of positive cases in the population is 0.60 (60 %), the minimum number of cases required is

$$N = 10 * \frac{7}{0.6} = 117$$

If the resulting number is inferior to 100 Peduzzi et al. [16] suggest increasing it to 100.

4 Model Validation

According to Terrin et al. [21] the utility of predictive models depends on their generality, which can be separated into two components: internal validity (reproducibility) and external validity (transportability).

After selecting the best set of predictors to include in the model, the researcher must evaluate the statistical significance of the estimated parameters and the diagnostic value of the resulting model. Measures such as significant p values for the parameters test and no significant p value for the Hosmer-Lemeshow goodness-of-fit statistical test suggest that the model fits the data reasonably well.

The term *"validation"*, although widely used, is misleading, because it indicates that model validation studies would result in a "yes" (good validation) or "no" (poor validation) answer to the evaluation of the model's performance. Instead, the aim of model validation is to quantitatively evaluate the model's predictive performance either on the resampled participant data of the developed dataset (often referred to as internal validation) or on the independent participant data that were not used to develop the model (often referred to as external validation) [6].

According to Collins et al. [6], the quantification of a model's predictability with the same data used to develop the model (often referred as apparent performance, Fig. 2) tends to give an optimistic estimate of performance, due to overfitting (too few outcome events in relation to the number of candidate predictors) and to the use of predictor selection strategies [6]. Studies developing new prediction models should therefore always include some form of internal validation to quantify any optimism in the predictive performance (for example, calibration and discrimination) of the developed model and adjust the model for overfitting. Internal validation techniques use only the original sample of the study and include methods such as bootstrapping and cross-validation.

Therefore, after developing a prediction model, the evaluation of its performance with participant data different from that used in the model development – external validation – is strongly recommended (Fig. 2) [6]. This type of model validation requires that, for each individual in the new participant data set, outcome predictions be made using the original model (i.e., the published model or regression formula) and compared with the observed outcomes.

The external validation of the model may be performed using participant data collected by the same investigators, typically using the same predictor and outcome definitions and measurements, but obtained later (in time or with narrow validation).

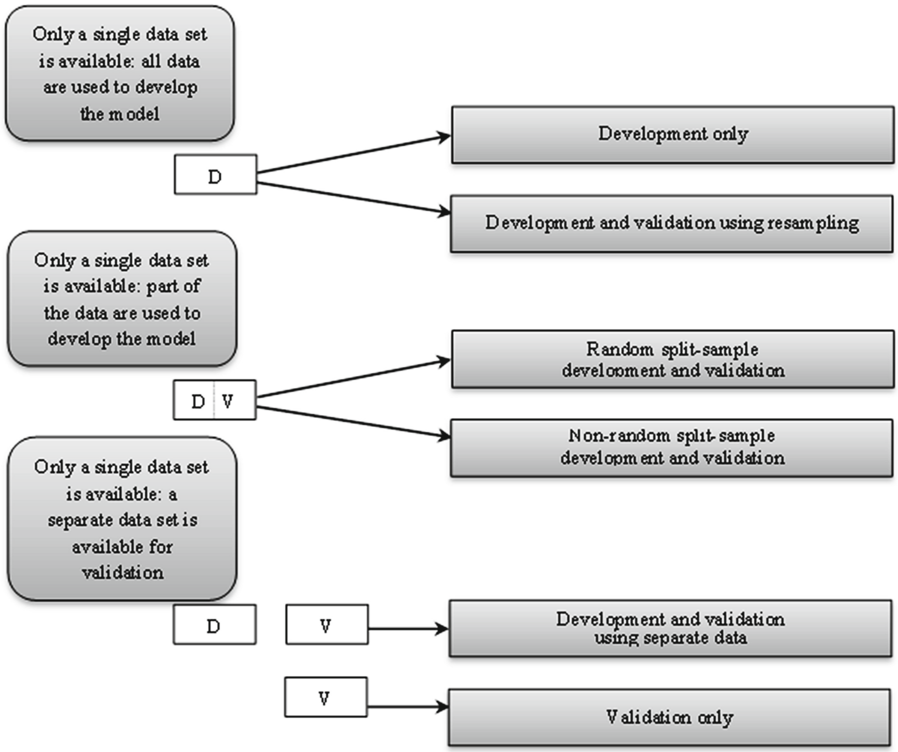


Fig. 2. Types of prediction model studies (adapted from [6]).

5 Materials and Methods

While conducting this study, we faced some difficulties, particularly in the data collection, which resulted in a small sample with many variables. We chose to develop a model starting with a univariate analysis in order to exclude variables that had little information, and/or that did not show statistical significance for the dependent variable (lower back complaints by nurses working in health centers and providing home care). This part of the study is described in more detail in Carneiro [4].

For this study the model with seven variables proposed by Carneiro [4] was considered. Using this same set of data, we restarted the development process, taking into account the missing values and dealing with them firstly.

A questionnaire based on the one developed by Carneiro [4] was used to collect the information necessary for the external validation of the model. However, changes were made to simplify and shorten the questionnaire.

That electronic questionnaire was sent to nurses during the year of 2014, and the posterior methodology was based on respondent-driven sampling. This methodology combines snowball sampling with a mathematical model that comprises a sampling method to compensate the sample being randomly collected. Thus, it allows easier access to specific groups, thereby leading to a more accurate representation of the professional group, in this case, nurses working in Health Centres in Northern Portugal.

The development of the model and its process validation were carried out in the STATA® 13.1 software using the logistic regression command `.logistic` with post estimation evaluation.

6 Results

Two datasets were used in this study, one from Carneiro [4] - *Dataset 1* - and other from the study conducted in 2014 - *Dataset 2*.

Table 2 summarizes the descriptive data of some variables of interest in the two datasets. For qualitative variables, the values are expressed in percentages and/or counts, for quantitative variables, the mean value and the standard deviation value (between brackets) are presented.

Table 2. Summary of the two datasets.

n		*Dataset 1*	*Dataset 2*
		147	83
Home health care		85 % (125)	100 % (83)
Region	North	125	50
Female		88 %	80 %
Age		34.7 years (8.01)	40.4 years (7.28)
Seniority in the profession Complaints:		11.9 years (7.60)	17.1 years (6.70)
	Cervical	73.6 %	74.0 %
	Lower back	68.8 %	86.0 %
	Dorsal	50.4 %	18.0 %
	Shoulders	48.0 %	44.0 %
	Elbows	8.8 %	8.4 %
	Wrists/hands	31.2 %	24.0 %
	Thighs	16.8 %	4.0 %
	Knees	20.8 %	20.0 %
	Ankles/feet	13.6 %	12.0 %

The dependent variable is musculoskeletal complaints involving the lower back reported by nursing professionals. This variable has two levels: 0 = absence of musculoskeletal complaints involving the lower back and 1 = musculoskeletal complaints involving the lower back. The considered predictor variables are also binary.

Table 3 presents the distribution for the reference level ($X_i = 0$) of each predictor in the two datasets.

Table 3. Distribution of the predictors by dataset.

Variable	Dataset 1 (Total = 79)		Dataset 2 (Total = 50)	
	%	(n)	%	(n)
X_1	20.0 %	(25)	56.0 %	(28)
X_2	9.6 %	(12)	18.0 %	(9)
X_3	6.4 %	(8)	12.0 %	(6)
X_4	56.8 %	(71)	92.0 %	(46)
X_5	16.5 %	(13)	96.0 %	(48)
X_6	20.3 %	(16)	38.0 %	(19)
X_7	97.5 %	(77)	98.0 %	(49)

We carried out the study using the following procedure:

1. developing the logistic models based on Dataset 1, using all of the seven predictors (model 1);
2. developing alternative models based on Dataset 1, using more restrictive statistical criteria for testing the parameters' significance (p *values* < 0.1);
3. validating the models generated in the development process, using Dataset 2;
4. evaluating the apparent and external validation using ROC analysis.

The first developed model included all seven candidate predictors. The corresponding results of the estimated coefficients of the logit model, the standard errors, and the significance test for the coefficients (z-statistic and corresponding bilateral p values) are listed in Table 4. Then, the variable X_7 was excluded from the model due to the low percentage of associated cases, and $p > 0.2$, thus generating the Model 2 (Table 5). Considering the values of Model 2, we tried to assess the model's behaviour without the variable with a higher p value in the statistical significance tests for the coefficients. Thus, we obtained Model 3 (Table 6).

The measures of the goodness-of-fit test for each model are evaluated and resumed in Table 7.

In Table 7, $\boldsymbol{X^2}$ represents the Pearson's goodness-of-fit test or the Hosmer-Lemeshow's goodness-of-fit test. Values of $p > 0.05$ indicate that the model seems to fit quite well. The **LL** values correspond to the log likelihood of the final model. The individual value has no meaning in and of itself; regarding models comparison, the values are of the same order of magnitude.

The pseudo $\boldsymbol{R^2}$ is a qualitative measure of the quality of fit of the models. It is difficult to find a rule to establish the limits of McFadden R^2 values. Nevertheless, Louviere et al. [15], on page 55 of his book, indicates the following: *"Values of rho-squared between 0.2–0.4 are considered to be indicative of extremely*

Table 4. RL model: Model 1.

Predictor	Coef., B	Std. Err	z	$P >\| z \|$	[95 % CI for B]	
X_1	−2.1630	1.0691	−2.02	0.043	−4.2585	−0.0675
X_2	1.4273	0.8709	1.64	0.101	−0.2796	3.1342
X_3	3.6061	1.3750	2.62	0.009	0.9111	6.3011
X_4	−3.1618	1.0787	−2.93	0.003	−5.2760	−1.0475
X_5	−1.1283	0.8785	−1.28	0.199	−2.8501	0.5936
X_6	−2.1931	1.2081	−1.82	0.069	−4.5608	0.1746
X_7	−2.2730	1.7873	−1.27	0.203	−5.7761	1.2301
Constant	0.7105	1.6611	0.43	0.669	−2.5452	3.9661

Table 5. RL model: Model 2.

Predictor	Coef., B	Std. Err	z	$P >\| z \|$	[95 % CI for B]	
X_1	−1.5914	0.8636	−1.84	0.065	−3.2841	0.1013
X_2	1.4259	0.8792	1.62	0.105	−0.2973	3.1492
X_3	3.1884	1.2129	2.63	0.009	0.8112	5.5657
X_4	−2.9448	1.0294	−2.86	0.004	−4.9625	−0.9271
X_5	−1.3600	0.8836	−1.54	0.124	−3.0917	0.3717
X_6	−2.2053	1.1777	−1.87	0.061	−4.5135	0.1029
Constant	0.5793	1.6162	0.36	0.720	−2.5884	3.7470

Table 6. RL model: Model 3.

Predictor	Coef., B	Std. Err	z	$P >\| z \|$	[95 % CI for B]	
X_1	−1.8993	0.8707	−2.18	0.029	−3.6062	−0.1924
X_2	1.74488	0.8265	2.11	0.035	0.1250	3.3648
X_3	3.3086	1.2214	2.71	0.007	0.9146	5.7025
X_4	−2.9934	1.0114	−2.96	0.003	−4.9757	−1.0111
X_6	−2.3202	1.1944	−1.94	0.052	−4.6612	0.0207
Constant	0.3406	1.5853	0.21	0.830	−2.7664	3.4479

good model fits. Simulations by Domenich and McFadden (1975) equivalence this range to 0.7 to 0.9 for a linear function". Taking this into account, the values obtained for pseudo R^2 for the three models reveal good model fits.

Finally, the measures of the information criteria - AIC and BIC - allow comparing the models in terms of maximum likelihood. These two measures only differ in the complexity term. So, given that two models fit in the same data, the model with the smaller value of the information criterion is considered to be better. The values of AIC listed in Table 7 are similar, but Model 3 has the smaller value for BIC.

Table 7. Summary of the goodness-of-fit test.

	Model 1	Model 2	Model 3
# predictors	7	6	5
$\boldsymbol{X^2}$	15.06	17.60	16.09
*p*value	0.4470	0.2843	0.0650
LL	−30.3319	−31.1240	−32.2996
Pseudo $\boldsymbol{R^2}$	0.3634	0.3468	0.3221
Correctly classified	83.5 %	84.8 %	84.8 %
Sensitivity	92.9 %	94.6 %	94.6 %
Specificity	60.9 %	60.9 %	60.9 %
AIC	76.6638	76.2481	76.5999
BIC	95.6936	92.8342	90.8166

Table 8. Summary of the ROC analysis for each model.

		External validation	***Apparent validation***
Model 1	AUC	0.7492	0.8649
	SE(AUC)	0.0842	0.0460
	chi2(1)	1.46	
	p value	0.2276	
Model 2	AUC	0.7658	0.8505
	SE(AUC)	0.0807	0.0493
	chi2(1)	0.8	
	p value	0.3700	
Model 3	AUC	0.7641	0.8412
	SE(AUC)	0.0816	0.0513
	chi2(1)	0.64	
	p value	0.4237	

When using the Dataset 2 for external validation, we compared the models in terms of area under the ROC curve (AUC). we evaluated the apparent validation in terms of AUC, and, considering the Dataset 2, we calculated the predicted probabilities for each model and calculated the AUC index for external validation. The summary results are listed in Table 8.

In Table 8, "AUC" stands for the index of the area under the empirical ROC curve, "SE(AUC)" represents the standard error associated with this estimative, "chi2" is the test statistic that corresponds to testing the null hypothesis - $H_0 : AUC(external) = AUC(apparent)$ - and the p value is the probability,

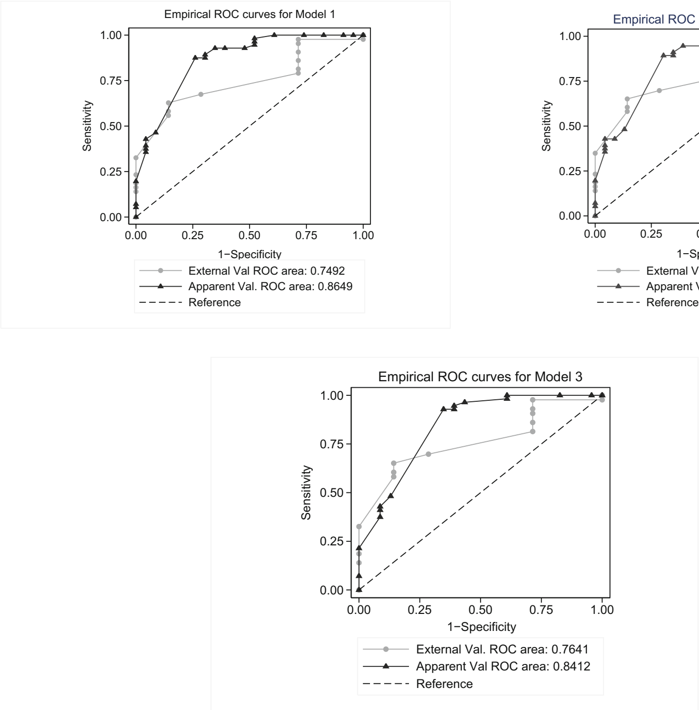


Fig. 3. Empirical ROC curves comparison.

considering this hypothesis, of obtaining a result equal to or higher than what was actually observed $Pr(\chi^2 \geq chi2)$ (Fig. 3).

7 Conclusion

According to the results obtained in the developed model, the "best" model to fit the data in the initial dataset was Model 3. The dimension of the sample, the measures evaluated in the goodness-of-fit test, and the values of the area under the ROC curves for the apparent internal validation justify this choice. In the validation process, we could conclude that the internal validation in the same dataset - the apparent validation - led to more "optimistic" values of AUC and better performance, but with no statistical differences from the corresponding results obtained in the external validation.

Therefore, taking into account these results, the model chosen to predict the risk of musculoskeletal complaints involving the lumbar region in nurses working at the Health Centres of Northern Portugal and providing home-based care, was Model 3, which contained five variables: X_1, X_2, X_3, X_4 and X_6. The contribution of each variable to this model was the same encountered by Carneiro [4] regarding sign in the logit model. However, we tried to minimize the overfitting and to maximize the information contained in the complete sample, by discarding the missing values in data used to develop the model.

The dimension of the sample represented a limitation of this study. Nevertheless, we concluded that Model 3 can be used as a prediction model for the proposed goal, because its performance with participant data different from those used for the model development was evaluated in same conditions, and showed a good performance.

Acknowledgments. This work was supported by FCT - (Fundação para a Ciência e Tecnologia) within the Project Scope: UID/CEC/00319/2013.

References

1. Alexopoulos, E.C., Burdorf, A., Kalokerinou, A.: A comparative analysis on musculoskeletal disorders between Greek and Dutch nursing personnel. Int. Arch. Occup. Environ. Health **79**, 82–88 (2006)
2. Barroso, M., Carneiro, P., Braga, A.C.: Characterization of ergonomic issues and musculoskeletal complaints. In a Portuguese District Hospital. In: Proceedings of the International Symposium Risks for Health Care Workers: Prevention Challenges, Athens (2007)
3. Barroso, M.P., Martins, J.: Assessment and analysis of musculoskeletal risk perception among nurses. In: Proceedings of the International Conference HEPS 2008 C Healthcare Systems Ergonomics and Patient Safety, Strasbourg, France, 25–27 June (2008)
4. Carneiro, P.: LME na prestação de cuidados de saúde ao domicílio: avaliação do risco e construção de modelos estatísticos de previsão. Tese de Doutoramento, Universidade do Minho (2012) (in Portuguese)
5. Cheung, K., Gillen, M., Faucett, J., Krause, N.: The prevalence of and risk factors for back pain among home care nursing personnel in Hong Kong. Am. J. Ind. Med. **49**(1), 14–22 (2006)
6. Collins, G.S., Reitsma, J.B., Altman, D.G., Moons, K.G.: Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): the TRIPOD statement. Ann. Intern. Med. **162**, 55–63 (2015). http://dx.doi.org/10.7326/M14-0697
7. Coelho, M.S.R.: Estudo da Frequência das Lesões Músculo-Esqueléticas Relacionadas com o Trabalho (LMERT) em Profissionais de Enfermagem, Proposta de um Programa de Ginástica Laboral. Dissertação de licenciatura da Faculdade de Desporto da Universidade do Porto, Porto (2009). (in Portuguese)
8. Czuba, L.R., Sommerich, C.M., Lavender, S.A.: Ergonomic and safety risk factors in home health care: exploration and assessment of alternative interventions. Work **42**, 341–353 (2012)
9. Daraiseh, N., Genaidy, A.M., Karwowski, W., Davis, L.S., Stambough, J., Huston, R.L.: Musculoskeletal outcomes in multiple body regions and work effects among nurses: the effects of stressful and simulating working conditions. Ergonomics **46**(12), 1178–1199 (2003)
10. Daraiseh, N., Cronin, S., Davis, L., Shell, R., Karwowski, W.: Low back symptoms among hospital nurses, associations to individual factors and pain in multiple body regions. Int. J. Ind. Ergon. **40**, 19–24 (2010)

11. Evanoff, B., Wolf, L., Aton, E., Canos, J., Collins, J.: Reduction in injury rates in nursing personnel through introduction of mechanical lifts in the workplace. Am. J. Ind. Med. **44**(5), 451–457 (2003)
12. Faucett, J., Kang, T., Newcomer, R.: Personal service assistance: musculoskeletal disorders and injuries in consumer-directed home care. Am. J. Ind. Med. **56**, 454–468 (2013)
13. Kromark, K., Dulon, M., Beck, B.-B., Nienhaus, A.: Back disorders and lumbar load in nursing staff in geriatric care: a comparison of home-based care and nursing homes. J. Occup. Med. Toxicol. **4**, 33, 9. http://www.occup-med.com/content/4/1/33. Accessed 15 Mar 2011
14. Lee, S., Faucett, J., Gillen, M., Krause, N.: Musculoskeletal pain among critical-care nurses by availability and use of patient lifting equipment: an analysis of cross-sectional survey data. Int. J. Nurs. Stud. **50**(12), 1648–1657 (2013)
15. Louviere, J.J., Hensher, A.D., Swait, D.J.: Stated Choice Methods: Analysis and Applications. Cambridge University Press, New York (2000)
16. Peduzzi, P., Concato, J., Kemper, E., Holford, T.R., Feinstein, A.R.: A simulation study of the number of events per variable in logistic regression analysis. J. Clin. Epidemiol. **49**, 1373–1379 (1996)
17. Owen, B., Staehler, K.: Decreasing back stress in home care. Home Healthc. Nurse **21**(3), 180–186 (2003)
18. Simon, M., Tackenberg, P., Nienhaus, A., Estryn-Behar, M., Conway, P.M., Hasselhorn, H.M.: Back or neck-pain-related disability of nursing staff in hospitals, nursing homes and home care in seven countries C results from the European NEXT-Study. Int. J. Nurs. Stud. **45**, 24–34 (2008)
19. Smith, D.R., Mihashi, M., Adachi, Y., Koga, H., Ishitake, T.: A detailed analysis of musculoskeletal disorder risk factors among Japanese nurses. J. Saf. Res. **37**, 195–200 (2006)
20. Szeto, G.P.Y., Wong, K.T., Law, K.Y., Lee, E.W.C.: A study of spinal kinematics in community nurses performing nursing tasks. Int. J. Ind. Ergon. **43**, 203–209 (2013)
21. Terrin, N., Schmid, C.H., Griffith, J.L., D'Agostino Sr., R.B., Selker, H.P.: External validity of predictive models: a comparison of logistic regression, classification trees, and neural networks. J. Clin. Epidemiol. **56**(8), 721–729 (2003)