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Predicting Forearm Physical Exposures During Computer Work Using Self-Reports, Software-Recorded Computer Usage Patterns, and Anthropometric and Workstation Measurements

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Abstract

Objectives: Alternative techniques to assess physical exposures, such as prediction models, could facilitate more efficient epidemiological assessments in future large cohort studies examining physical exposures in relation to work-related musculoskeletal symptoms. The aim of this study was to evaluate two types of models that predict arm-wrist-hand physical exposures (i.e. muscle activity, wrist postures and kinematics, and keyboard and mouse forces) during computer use, which only differed with respect to the candidate predicting variables; (i) a full set of predicting variables, including self-reported factors, software-recorded computer usage patterns, and worksite measurements of anthropometrics and workstation set-up (full models); and (ii) a practical set of predicting

variables, only including the self-reported factors and software-recorded computer usage patterns, that are relatively easy to assess (practical models).
Methods: Prediction models were build using data from a field study among 117 office workers who were symptom-free at the time of measurement. Arm-wrist-hand physical exposures were measured for approximately two hours while workers performed their own computer work. Each worker's anthropometry and workstation set-up were measured by an experimenter, computer usage patterns were recorded using software and self-reported factors (including individual factors, job characteristics, computer work behaviours, psychosocial factors, workstation set-up characteristics, and leisure-time activities) were collected by an online questionnaire. We determined the predictive quality of the models in terms of R^2 and root mean squared (RMS) values and exposure classification agreement to low-, medium-, and high-exposure categories (in the practical model only).
Results: The full models had R^2 values that ranged from 0.16 to 0.80, whereas for the practical models values ranged from 0.05 to 0.43. Interquartile ranges were not that different for the two models, indicating that only for some physical exposures the full models performed better. Relative RMS errors ranged between 5% and 19% for the full models, and between 10% and 19% for the practical model. When the predicted physical exposures were classified into low, medium, and high, classification agreement ranged from 26% to 71%.
Conclusion: The full prediction models, based on self-reported factors, software-recorded computer usage patterns, and additional measurements of anthropometrics and workstation set-up, show a better predictive quality as compared to the practical models based on self-reported factors and recorded computer usage patterns only. However, predictive quality varied largely across different arm-wrist-hand exposure parameters. Future exploration of the relation between predicted physical exposure and symptoms is therefore only recommended for physical exposures that can be reasonably well predicted.

Keywords: arm-wrist-hand exposures; computer use; exposure assessment; forearm physical exposures; prediction models; prediction model evaluation; predictive quality; work-related musculoskeletal symptoms; occupational; upper extremity

Introduction

Work-related upper extremity symptoms are a prevalent and expensive problem among office workers (Blatter *et al.*, 2005; Eltayeb *et al.*, 2009; Hagberg *et al.*, 2007; Van den Heuvel *et al.*, 2007). Better knowledge of exposure-response relationships during computer use can guide efforts to reduce the occurrence of symptoms. The most accepted possible injury mechanism states that individual and occupational factors could increase physical exposure of the worker (e.g. muscle activity, forceful exertions or non-neutral body postures), which over time could result in tissue damage and upper extremity symptoms (Gerr *et al.*, 2004; Punnett and Wegman, 2004; Gerr *et al.*, 2006; Visser and Van Dieën, 2006; Bleecker and Barnes, 2012). The plausibility of this hypothesis should be investigated by relating accurately assessed physical exposure to upper extremity symptoms, preferably in large cohorts with longitudinal data.

Direct measurements of exposures, such as by electromyography (EMG), video analyses and motion capture systems, are considered superior to self-reported measurements because they are more accurate and less subject to bias (Winkel and Mathiassen, 1994). However, such measurements can be expensive, time consuming, and difficult to use at worksites (Hansson *et al.*, 2001; Balogh *et al.*, 2004; Trask *et al.*, 2007; Trask *et al.*, 2014). Therefore, in large longitudinal cohort studies, researchers tend to rely on self-reports of physical exposure. An alternative physical exposure assessment method may be to estimate exposure through the use of prediction models (Chen *et al.*, 2004; Bruno Garza *et al.*, 2014; Heiden *et al.*, 2016).

Recently, the predictive quality of prediction models developed to assess office workers' neck-shoulder physical exposures (i.e. trapezius muscle activity and shoulder, head, neck, and torso postures) was examined in the PRedicting Occupational biomechanics in OFfice workers (PROOF) study, demonstrating the feasibility of such models (Bruno Garza *et al.*, 2014). These models were based on self-reported individual, psychosocial and work characteristics, software-recorded computer usage patterns, and measurements of anthropometrics and workstation set-up. The results from this study indicated that some of the exposure outcomes could be reasonably well predicted (maximum R^2 = 0.59). Compared to neck-shoulder physical exposures, arm-wrist-hand exposures are expected to be more task-related and computer usage characteristics (i.e. % keyboard use, % mouse use, and % idle time) might affect the predictive quality of arm-wrist-hand and neck-shoulder prediction models differently.

Our goal was to develop and evaluate two types of models that predict arm-wrist-hand physical exposures (i.e. muscle activity, wrist postures and kinematics, and keyboard and mouse forces) during computer use. These models differ in the kind of candidate predicting variables that were entered into the model. The first models, using a full set of predicting variables, assessed by self-report, software-recorded compute usage, and additional worksite measurements of anthropometrics and workstation set-up, are aimed at reaching maximum achievable predictive quality (full models). The second models will be build using only predicting variables that are relatively easy to assess, i.e. self-reported factors and software-recorded computer usage patterns (practical models). It was our goal to examine how well both types of models performed in terms of predictive quality compared to direct measurements of physical exposures. Since in epidemiological studies often categorized variables are used, for the practical models we also examined the classification agreement when the predicted exposures of these models were categorized into low, medium, and high. The aims of this study were therefore to:

1. Determine the predictive quality of arm-wrist-hand physical exposures (i.e. muscle activity, wrist postures and kinematics, and keyboard and mouse forces) through prediction models based on the full set of predicting variables (full models).
2. Determine the predictive quality and agreement between predicted and observed exposures if categorized into low, medium, and high, of arm-wrist-hand physical exposures through prediction models based on predicting variables that are relatively easy to assess (practical models).

Methods

Experimental design and selection of participants

This study is part of the PROOF study, in which physical exposures during computer work in a realistic work setting were assessed among 120 office workers (Bruno Garza *et al.*, 2012). Forearm muscle activity, wrist postures, and forces applied to the keyboard and computer mouse were directly measured for ~2 h while the workers performed their own work at their own workstations. Additionally, each worker's anthropometry and set-up of his/her workstation were measured by an experimenter, characteristics of his/her computer use were recorded using a software program installed on the workers' computer. Individual, workstation set-up and job characteristics, computer work behaviours, and psychosocial factors were collected via self-report using an online questionnaire.

All office workers were employed at either VU University (across eight different departments) or VU University Medical Center in Amsterdam, The Netherlands. Workers were invited to participate if their main tasks included computer work, they were free of musculoskeletal symptoms in the neck, shoulders, arms, wrists, and/or hands for at least 1 week prior to data collection, worked at least 20 h per week according to their contract, and were comfortable using a computer mouse with their right hand. Before the start of the data collection, participants gave written consent. All protocols and informed consent forms were approved by the Harvard School of Public Health Human Subjects Committee, the Medical Ethics Committee of the VU University Medical Center, and the Ethics Committee of the Faculty of Human Movement Sciences of VU University Amsterdam.

Data collection and data processing

Computer interaction activities (keyboard use, mouse use, and idle time)

Computer input device usage was recorded using computer interaction monitoring software, assessing each participant's computer activity episodes (i.e. any period within 30 s of pressing a key, clicking a button on the mouse, or moving the mouse) and non-computer activity episodes (i.e. any period without computer input device usage for at least 30 s; Chang *et al.*, 2008; Hwang *et al.*, 2010). We also calculated the percentages of keyboard, mouse, and idle time during computer use. Keyboard activity was defined as a series of keyboard events (key strikes) that had <2 s of inactivity between successive keyboard events. Mouse activity was defined as a series of mouse events (mouse movement, scrolling, or button clicks) with <2 s of inactivity between successive events. Idle time was defined as any period of keyboard or mouse inactivity that lasted at least 2 s but <30 s (Dennerlein and Johnson, 2006; Chang *et al.*, 2008; Yeh *et al.*, 2009).

Physical exposures: wrist extensor muscle activity, wrist postures and kinematics, and forces applied to the computer mouse and keyboard

Left and right extensor carpi radialis (ECR) muscle activity were measured using surface EMG with a wireless logger system (Mega WBA, Mega Electronics LTD, Kupio, Finland). Electrodes (12 mm diameter Ambu Bluesensor N-00-S surface electrodes) were mounted over the muscle bellies with 20 mm inter-electrode spacing (Basmajian, 1989). Data were recorded at 1000 Hz after amplification (bandwidth of 10–500 Hz), then smoothened using a 3-Hz second-order, zero-phase, low–pass Butterworth filter, and down-sampled to 40 samples per second using a mean filtering procedure.

For each participant, three maximum voluntary contractions (MVCs) were collected from the right and left ECR muscle, by radially deviating and extending a fist of his/her hand against resistance applied by the experimenter. There was at least 1 min of rest in between MVCs. Each muscle's MVC was the highest 1-s average of the EMG amplitudes collected from the three measurements.

Median (P50) wrist extensor muscle activity during computer use was calculated for each participant and normalized to the MVC (% MVC). Static (P10) and peak (P90) muscle activity were not analysed, since these measures were expected to be closely correlated to median muscle activity.

Left and right wrist flexion-extension and radial-ulnar deviation were measured using twin axis electrogoniometers (Model SG65, Biometrics Ltd, Gwent, UK), which were mounted over the back of the hand and the forearm with the wrist in a neutral position (i.e. hands pronated, middle metacarpal aligned with the midline of the forearm and dorsal aspect of the hand aligned with dorsal aspect of the forearm). Data were recorded at 1000 Hz with the same wireless data logging system used to collect muscle activity. Wrist posture data were filtered through a 5-Hz second-order, zero-phase, low-pass Butterworth filter, down-sampled to 40 Hz, and expressed as deviations from a participant's neutral posture, which was recorded at the beginning of the data collection.

Median (P50) wrist postures, expressed in degrees, were calculated for each participant. Wrist velocities and accelerations were calculated by digitally differentiating the posture data and expressed in root mean squared (RMS) values. Only data of wrist postures, velocities, and accelerations during computer interactions were used.

Keyboard force was measured by placing each participant's keyboard on top of a force plate with three miniature compression load cells (ELFF-B4-10L, Measurement Specialties, Hampton, VA, USA) mounted underneath in a triangular pattern (Asundi *et al.*, 2009). Mouse grip force was measured using a modified USB mouse with scroll wheel (Model 3902C693, Microsoft, Inc., Redmond, WA, USA). Three compression load cells (ELW-D1-10L, Measurement Specialties, Hampton, VA, USA) were mounted inside the mouse (Johnson *et al.*, 2000). This force-sensing mouse was designed to be operated with the right hand, measuring thumb forces applied to the mouse. Participants were asked to use this force-sensing mouse instead of their own computer mouse for the duration of the measurements.

Keyboard and the mouse force data were collected with USB backplanes (NI cDAQ-9172; National Instruments: Austin, TX, USA) and sampled at 10 000 Hz, then low-pass filtered at 20 Hz (6th order Butterworth filter), down-sampled to 40 Hz. Three maximum voluntary force (MVFs) exertions were collected per participant, with 1 min of rest in between. Maximal keyboard force was measured by requiring a participant to maximally press down the "J" key with their right index finger for 5 s, and maximal mouse force by requiring a participant to maximally squeeze the mouse for 5 s. Maximum forces were measured while a participant adopted the same posture as during actual keyboard or mouse work. MVF values were the highest 1-s averages of the three collected MVFs. For each participant median (P50) keyboard and mouse force were calculated.

Predicting variables: Questionnaire, anthropometry, and workstation set-up

Self-reported factors, including (i) individual factors, (ii) job characteristics, (iii) computer work behaviours, (iv) psychosocial factors (Cohen *et al.*, 1983; Siegrist, 1996; Schreurs and De Ridder, 1997; Karasek *et al.*, 1998; Sluiter *et al.*, 1999; Van Veldhoven and Broersen, 2003; Siegrist *et al.*, 2004), (v) workstation set-up characteristics, and (vi) leisure-time activities, were collected through an online questionnaire (IJmker *et al.*, 2006). Measures of anthropometry (item 12–16, Part 3 of the Supplementary Material, available at *Annals of Work Exposures and Health* online) and workstation set-up (item 77–92, Part 3 of the Supplementary Material, available at *Annals of Work Exposures and Health* online) were observed using a tape-measure and collected by the same experimenter for all participants throughout the whole data collection. For the anthropometry measures, definitions of Won and colleagues (2009) were used, while the workstation set-up measures were derived from Marcus and colleagues (2002). All predicting variables were theoretically related to physical exposures or upper extremity symptoms and are listed in Part 3 of the Supplementary Material (available at *Annals of Work Exposures and Health* online), including the response categories and references.

Prediction models

A: Full models; predictions based on self-reported factors, software-recorded computer usage patterns, and additional worksite measurements of anthropometrics and workstation set-up

Predictions of continuous arm-wrist-hand physical exposures (i.e. ECR muscle activity, wrist postures and kinematics, and keyboard and mouse forces) were calculated from linear regression models (IBM SPSS Statistics 20). In the prediction models, both continuous and categorical variables were used. For continuous variables, effects sizes (e.g., betas and corresponding *P* values) were modelled per unit of the variable, while for categorical variables effect sizes were modelled across categories. At the start of the selection procedure, we assigned all 98 variables to six different categories (individual characteristics, job characteristics, computer work behaviours, psychosocial factors, workstation set-up, and leisure-time activities, see Part 3 of the Supplementary Material, available at *Annals of Work Exposures and Health* online). Because we had a large number of predicting variables, we developed the prediction models following a three-step procedure, comparable to the procedure of Bruno Garza and colleagues (2014) for developing neck-shoulder physical exposure prediction models.

Step 1: We determined the univariate associations between all 98 predicting and the physical exposure outcomes. Associations with a two-tailed significance level of P <0.20 were identified and selected for further analyses.

Step 2: Per category, all remaining variables from Step 1 were included in a backward selection procedure with P removal set at P <0.20. This tolerant P value was chosen in order to retain sufficient variables for the final selection step. Prior to this, however, pairwise correlations between all factors within each category were calculated. In cases where two variables were strongly correlated (with a Pearson $r \geq 0.70$), only the variable with the largest relative dispersion (i.e. the highest coefficient of variation) within the data set was retained to avoid collinearity, as per earlier work (Heiden *et al.*, 2016).

Step 3: The variables remaining after Step 2 from all six categories were included in another backward selection procedure with a P removal set at P <0.10 for the selection of the final set of variables for each prediction model. A P value of P <0.10 was chosen following the Akaike Information Criterion and the Schwarz Bayesian Criterion. Also, prior to this this step, pairwise correlations between all factors was calculated, while only the variable with the largest relative dispersion within the data set was retained in case of strong correlation.

To determine the predictive quality of the final models, R^2 values, absolute, and relative RMS errors were calculated. We calculated the relative RMS error by dividing the RMS error by the range of the observed values and then multiplying by 100 percent (Table 1). Also, beta, standard error, and P value depicting the association of each of the factors with the outcome in each model were outputted. In order to internally validate the final models, a bootstrap procedure was conducted, in which a total of 1000 samples were drawn from the original data set. Average beta, standard error, and P values over these samples from each of the studied associations were estimated.

B: Practical models; predictions based on self-reported factors and software-recorded computer usage patterns

For the practical models, that estimated continuous arm-wrist-hand exposures based on self-reported factors and software-recorded computer usage only, we followed the exact same three-step procedure as described above. At the start of this procedure, all 21 manually recorded anthropometry and workstation set-up variables were removed from the complete set of 98 variables. The variables body weight and calculated BMI, for which we used manually recorded data in the prediction models under A, were substituted with self-reported data. Even though the 3-step procedure was exactly the same for the full models and the practical models, the content of these models in terms of predicting variables ending up in the final models is likely to be different, because of the difference in candidate predicting variables that were entered into the models.

Other than for the full models, we classified all observed and predicted physical exposure outcomes from the prediction models based on self-reported factors and software-recorded computer usage patterns into low, medium, and high categories, using tertiles. We then determined the classification agreement between observed and predicted outcomes by calculating the percentage of agreement per group (Table 3).

Results

In the analyses of muscle activity and wrist posture, out of 120 participants, data of 117 participants were included. Seventy-two percent of the participants were female, with a mean (standard deviation) age of 41 (12) years, height of 174 (12) cm, weight of 73 (15) kg, and with a median of 5–10 years in a job with daily computer use. In the analyses of the wrist kinematics, data of 116 participants were included and in the analyses of forces on mouse and keyboard data of 114 participants were included. Data were excluded from the analyses because of technical failures and in one case because the participant had only 5 min of computer interaction time.

A: Full models; quality of predictions based on self-reported factors, software-recorded computer usage patterns, and additional worksite measurements of anthropometrics and workstation set-up

The prediction models for median wrist muscle activity showed R^2 values of 0.40 and 0.41 for the right and left

Table 1. Prediction models based on self-reported factors, software-recorded computer usage patterns, and anthropometric and workstation measurements, using exposure data of 117 office workers collected during computer work at their own workstation.

	R^2	RMS	Relative RMS (%)	Individual factors	Job characteristics	Computer work behaviors	Psychosocial factors	Workstation set-up	Leisure-time activities	Total number of predicting variables
Wrist muscle activity (%MVC)										
Left ECR	0.41	1.8	16	7, **16**	28	38, 41, 46	58	63, 65, 75		10
Right ECR	0.40	2.4	19	1, **16**	20,25	39, 45	52	76	97	9
Wrist Posture (degrees)										
Left flexion-extension	0.16	10.6	13	6, 7		42		75		4
Left radial-ulnar deviation	0.34	7.7	11	8	18,19,22,25	36, 46		76, **88**		9
Right flexion-extension	0.23	10.5	12			42, 48		74, 75, **87, 91**	98	7
Right radial-ulnar deviation	0.19	6.9	12	1		42, 47	56	**81**		5
Wrist velocity (degrees/s)										
Left flexion-extension	0.24	5.1	13	**15**	18	33	63		97	5
Left radial-ulnar deviation	0.26	2.8	15	6, **13**	20			**78, 88, 90**		5
Right flexion-extension	0.38	6.8	11	**15**	24,26	41, 46		**81**	94, 97	8
Right radial-ulnar deviation	0.56	3.2	9	**12, 13, 14, 15**	20,27	43, 47, 48	57, 65	**87, 91**	97	14
Wrist acceleration (degrees/s^2)										
Left flexion-extension	0.38	71.1	13	2, **13**	18,19	33, 38	54, 63		97	9
Left radial-ulnar deviation	0.38	35.1	15	**13**	28	46	53, 54	**78, 86, 88, 90**		9
Right flexion-extension	0.52	99.9	11	2, **13, 15**	18,24,26	41, 46	54	**80**	94, 95, 97	13
Right radial-ulnar deviation	0.39	54.5	10	**12**	19	47, 48	57, 65			6
Force (%MVF)										
Keyboard	0.80	0.6	5	**10, 14**				67	97	4
Mouse	0.48	0.4	10	**10**	35	46	49, 57, 64	79, **84**	98	9

Predictor numbers refer to Part 3 of the Supplementary Material (available at *Annals of Work Exposures and Health* online). Numbers printed in bold represent additional worksite measurements of anthropometrics and workstation set-up, which were excluded from selection for the prediction models of Table 2.

Table 2. Prediction models based on self-reported factors and software-recorded computer usage patterns (practical models), using exposure data of 117 office workers collected during computer work at their own workstation.

	R^2	RMS	Relative RMS (%)	Individual factors	Job characteristics	Computer work behaviors	Psychosocial factors	Workstation set-up	Leisure-time activities	Total number of predicting variables
Wrist muscle activity (%MVC)										
Left ECR	0.43	1.7	15	2,7	28	38, 41, 46	58, 63, 65	75	97	11
Right ECR	0.36	2.5	19	1	20, 25	45	52	71, 76	97	8
Wrist Posture (degrees)										
Left flexion-extension	0.16	10.6	13	6,7		42		75		4
Left radial-ulnar deviation	0.30	7.9	11		19, 22, 25	36, 46	57	76		7
Right flexion-extension	0.17	10.8	12			42, 48		74, 75	98	5
Right radial-ulnar deviation	0.18	6.9	12	1,10	25	42	56			5
Wrist velocity (degrees/s)										
Left flexion-extension	0.21	5.2	13		18	33	63		97	4
Left radial-ulnar deviation	0.08	3.1	16		23			72		2
Right flexion-extension	0.32	7.1	12	7	18, 24, 26	41, 46	54	75	97	9
Right radial-ulnar deviation	0.34	3.7	11	2		31, 36, 43, 47, 48	57			7
Wrist acceleration (degrees/s^2)										
Left flexion-extension	0.31	74.3	14	4		33, 38, 48	54, 63		97	7
Left radial-ulnar deviation	0.23	37.8	16	4,9	23	46	54	72		6
Right flexion-extension	0.38	111.0	12	2	18,24	41, 48	54		94, 95, 97	9
Right radial-ulnar deviation	0.35	56.0	10	3	19	47, 48	57, 65			6
Force (%MVF)										
Keyboard	0.05	1.2	10	10	67					2
Mouse	0.34	0.5	11	10	35	46, 47	57, 64		98	7

Predictor numbers refer to Part 3 of the Supplementary Material (available at *Annals of Work Exposures and Health* online).

Table 3. Agreement of classifying observed and predicted exposures to low, medium, and high tertiles.

	Low	Medium	High
	% Correctly predicted[a]	% Correctly predicted[a]	% Correctly predicted[a]
Wrist muscle activity (%MVC)			
Left ECR	71.1	53.8	61.5
Right ECR	55.3	46.2	71.1
Wrist Posture (degrees)			
Left flexion-extension	48.7	35.9	48.7
Left radial-ulnar deviation	56.4	43.6	51.3
Right flexion-extension	38.5	38.5	
Right radial-ulnar deviation	55.3	36.8	46.2
Wrist velocity (degrees/s)			
Left flexion-extension	50.0	38.5	65.8
Left radial-ulnar deviation	71.4	34.8	50.0
Right flexion-extension	56.4	35.1	61.5
Right radial-ulnar deviation	59.5	46.2	61.5
Wrist acceleration (degrees/s^2)			
Left flexion-extension	47.4	31.6	57.9
Left radial-ulnar deviation	46.2	38.5	54.1
Right flexion-extension	60.5	36.8	64.1
Right radial-ulnar deviation	57.9	38.5	56.8
Force (%MVF)			
Keyboard	41.0	26.3	52.5
Mouse	63.2	46.2	64.1

Observed and predicted exposures based on data of 117 office workers, collected during computer work at their own workstation. Means (SD) and ranges of limits of exposure are given for observed physical exposures. Predictions are based on self-reported factors and software-recorded computer usage patterns. Abbreviation: SD = standard deviation.

[a]% Observed from total % predicted low, medium, or high.

ECR, respectively. The predictive quality for wrist postures revealed R^2 values ranging between 0.16 and 0.23, except for left wrist radial-ulnar deviation, which had an R^2 of 0.34. The models predicting wrist velocity for the right hand showed higher R^2 values (0.38 and 0.56 for flexion-extension and radial-ulnar deviation, respectively) compared to the models predicting wrist posture. The predictive quality of the wrist acceleration models was higher than the quality of the wrist velocity predictions, except for right radial-ulnar deviation, which was lower. Keyboard and mouse force prediction models had the highest predictive quality, with R^2 values of 0.80 and 0.48, respectively. Keyboard force was predicted by only four predicting variables, of which two were additionally measured anthropometrical factors (i.e. body weight and hand length).

RMS errors for right and left ECR muscle activity were 2.4 %MVC and 1.8 %MVC, respectively. RMS errors for wrist postures ranged from 6.9 to 10.6 degrees, for wrist velocities from 3.2 to 6.8 degrees/s, and for wrist accelerations from 35.1 to 99.9 degrees/s^2. The prediction models for keyboard force and mouse force had RMS errors of 0.6 and 0.4 %MVF, respectively. Relative RMS errors ranged from 5 to 24% for the 16 prediction models based on data collected through self-reported factors, software-recorded computer usage patterns, and additional worksite measurements of anthropometrics and workstation set-up.

Of each of the final models, beta, standard error, and *P* values from the full data set, as well as from the bootstrapping procedure are shown in Part 1 of the Supplementary Material (available at *Annals of Work Exposures and Health* online). These findings show reasonable consistency, with only small differences in predictive quality of the identified predicting variables.

B: Practical models; quality and classification agreement of predictions based on self-reported factors and software-recorded computer usage patterns

Compared to the full models, the predictive quality of all practical models decreased to some extent.

Median muscle activity prediction models were not much influenced and revealed comparable quality for the right and left ECR, with the predicting variables still explaining 36% and 43% of the variance in right and left ECR muscle activity, respectively (Table 2). Regarding wrist postures and kinematics, the R^2 values of wrist posture predictions and flexion-extension wrist velocity predictions remained comparable to the full models, the R^2 values for wrist radial-ulnar velocity predictions and wrist acceleration predictions reduced. Without the additional worksite measurements of anthropometrics and workstation set-up as predicting variables in the models, keyboard and mouse force did not remain the best predictable outcomes. The predictive quality of keyboard force dropped considerably, i.e. from an R^2 value of 0.80 to 0.05, and the quality of mouse force predictions dropped from an R^2 value of 0.48 to 0.34.

RMS errors for right and left ECR muscle activity were 2.5 %MVC and 1.7 %MVC, respectively. RMS errors for wrist postures ranged from 6.9 to 10.8 degrees, for wrist velocities from 3.1 to 7.1 degrees/s, and for wrist accelerations from 37.8 to 111.0 degrees/s^2. The prediction models for keyboard force and mouse force had RMS errors of 1.2 and 0.5 %MVF, respectively. Relative RMS errors ranged from 10 to 19% for the 16 prediction models based on data collected through self-reported factors and software-recorded computer usage patterns.

Comparing classification of the predicted and observed exposure outcomes in high, medium, and low groups, percentages of agreement varied largely across the different outcomes (Table 3). Range in both the predicted and observed exposures are shown in Table 4, while a typical example of a classification agreement is presented in Table 5. Percentages correctly classified predictions ranged from 33% to 69%. Overall, the highest percentages correctly classified cases were found in the low and high groups, and the lowest percentages in the medium group. In other words, most misclassification appeared in adjacent categories (i.e. low-medium and medium-high categories). The amount of misclassification between the low and high categories was on average 13.6%. The highest percentages of misclassification between the low and high categories were found for left wrist radial-ulnar deviation and for right flexion extension, revealing both 23.1% low-high/high-low misclassification, respectively.

The bootstrapping procedure showed internal consistency of the results, with comparable betas, standard errors, and *P* values of the final practical models and the bootstrapping procedure (found in Part 2 of the Supplementary Material, available at *Annals of Work Exposures and Health* online).

Discussion

Summary of main results

By comparison with direct measurements in real-life work-settings, the aim of this study was to develop and evaluate prediction models of arm-wrist-hand exposures during computer use from self-reported factors, software-recorded computer usage patterns, and additional worksite measurements of anthropometrics and workstation set-up. In addition, we aimed to evaluate the differences in predictive quality of models based on self-reported factors and software-recorded computer usage patterns alone (practical models). The practical models, which do not require direct researcher observation, did not perform as well as the full models based on the full set of predicting variables in terms of the R^2 values, especially not for wrist velocity, wrist acceleration, and force predictions, but did show overall comparable RMS errors and relative RMS errors. When observed and predicted physical exposures of the practical models were classified into low, medium, and high, classification agreement revealed highest percentage correctly predicted exposures in the low and high categories, with percentages of agreement above what would be expected by chance alone, i.e. above 33.3%. This means that even though the predictive quality of the practical models was in general not large, especially the high and low groups could be correctly classified.

Given the results of the present study, the usability of the reported prediction models as a tool for arm-wrist-hand physical exposure assessment remains uncertain, especially since currently no evaluation standards are available. Based on R^2 values that were mainly below 0.20, Svendsen and colleagues (2005) concluded that their task-based exposure predictions were unsuccessful. The R^2 values of our prediction models ranged from 0.16 to 0.80 when possible predicting variables from additional measurements of anthropometrics and workstation set-up measurements were included in the selection procedure of the prediction model development, and R^2 values ranged from 0.05 to 0.43 without these additional measurements. However, the interquartile ranges were not that different between the full and the practical models, indicating that only for some physical exposures the full models performed substantially better; i.e. for keyboard force, right radial-ulnar deviation, and for right flexion-extension acceleration. The predictive quality of the prediction models in the present paper was better than the models from the above mentioned study, but worse than

Table 4. Range in exposure in the low-, medium-, and high-exposure categories; for observed exposures as well as predicted exposures.

		Low	Medium	High
Wrist muscle activity (%MVC)				
Left ECR	Observed	[0.7 to 3.2]	[3.3 to 5.1]	[5.2 to 11.9]
	Predicted	[1.1 to 3.9]	[4.0 to 5.0]	[5.0 to 10.8]
Right ECR	Observed	[1.2 to 4.2]	[4.4 to 6.8]	[6.9 to 14.3]
	Predicted	[1.8 to 5.1]	[5.1 to 6.7]	[6.7 to 12.2]
Wrist posture (degrees)				
Left flexion-extension	Observed	[−9.2 to 13.7]	[14.2 to 23.9]	[24.2 to 73.8]
	Predicted	[4.7 to 17.0]	[17.0 to 21.0]	[21.0 to 28.1]
Left radial-ulnar deviation	Observed	[−48.0 to −2.6]	[−2.3 to 4.6]	[4.6 to 22.7]
	Predicted	[−13.1 to −1.6]	[−1.5 to 3.5]	[3.6 to 15.9]
Right flexion-extension	Observed	[0.0 to 22.4]	[22.8 to 31.1]	[31.2 to 91.3]
	Predicted	[16.0 to 25.0]	[25.0 to 28.6]	[28.9 to 36.6]
Right radial-ulnar deviation	Observed	[−39.3 to 1.1]	[1.2 to 6.0]	[6.1 to 19.4]
	Predicted	[−6.3 to 2.0]	[2.2 to 4.8]	[4.8 to 9.7]
Wrist velocity (degrees/s)				
Left flexion-extension	Observed	[0.0 to 19.0]	[19.1 to 23.1]	[23.2 to 38.4]
	Predicted	[15.4 to 20.3]	[20.3 to 22.8]	[23.0 to 27.7]
Left radial-ulnar deviation	Observed	[0.0 to 11.2]	[11.2 to 14.0]	[14.0 to 19.1]
	Predicted	[10.2 to 12.1]	[12.3 to 12.3]	[14.2 to 16.1]
Right flexion-extension	Observed	[0.0 to 21.9]	[22.0 to 26.1]	[26.2 to 58.8]
	Predicted	[10.9 to 22.8]	[23.0 to 26.8]	[26.8 to 35.9]
Right radial-ulnar deviation	Observed	[0.0 to 13.5]	[13.6 to 16.2]	[16.3 to 34.7]
	Predicted	[9.2 to 14.0]	[14.0 to 15.7]	[15.7 to 25.3]
Wrist acceleration (degrees/s^2)				
Left flexion-extension	Observed	[0.0 to 231.2]	[231.5 to 287.2]	[293.1 to 525.6]
	Predicted	[164.5 to 238.0]	[238.7 to 291.0]	[291.6 to 398.2]
Left radial-ulnar deviation	Observed	[0.0 to 130.3]	[130.6 to 165.7]	[166.3 to 232.5]
	Predicted	[96.7 to 136.0]	[136.2 to 155.5]	[155.7 to 204.4]
Right flexion-extension	Observed	[0.0 to 283.9]	[289.9 to 360.7]	[366.8 to 926.7]
	Predicted	[136.7 to 304.4]	[305.0 to 388.0]	[390.1 to 549.8]
Right radial-ulnar deviation	Observed	[0.0 to 173.2]	[174.0 to 204.7]	[205.4 to 539.2]
	Predicted	[81.7 to 177.2]	[177.9 to 209.8]	[210.0 to 369.6]
Force (%MVF)				
Keyboard	Observed	[0.0 to 0.0]	[0.0 to 0.1]	[0.1 to 12.0]
	Predicted	[−0.3 to 0.2]	[0.2 to 0.5]	[0.5 to 1.6]
Mouse	Observed	[−0.3 to 0.1]	[0.1 to 0.4]	[0.4 to 3.9]
	Predicted	[−0.4 to 0.2]	[0.2 to 0.5]	[0.5 to 1.3]

the prediction models of van der Beek and colleagues (2012), who reported R^2 values between 0.77 and 0.92 and concluded that using these models as assessment tool were promising. Relative RMS errors of 11% have been suggested to indicate sufficient validity of exposure assessments (Chen *et al.*, 2004). We found comparable relative RMS errors in our study for many exposure parameters and even higher values for some others (Tables 1 and 2).

Furthermore, examination of the percentages correctly classified low, medium, and high exposures, which might give valuable information regarding the usability of these models in analyses with categorized variables, revealed only satisfactory percentages of correctly classified predicted exposures in the low- and high-exposure categories. Most misclassification was found between low and medium and between medium and high exposures. Hence, large contrasts within a study population, which are important in testing the relation of arm-wrist-hand exposures and symptom development, could be feasible based on differences between low- and high-risk

Table 5. Typical example of a cross tabulation, showing percentage of agreement between observed and predicted exposures, using data of 117 office workers collected during computer work at their own workstation.

			Observed exposure[a]			Total
			Low	Medium	High	
Predicted exposure[a]	Low	Percentage within Group	**60.5%**	30.8%	10.5%	33.9%
	Medium	Percentage within Group	28.9%	**38.5%**	34.2%	33.9%
	High	Percentage within Group	10.5%	30.8%	**55.3%**	32.2%
Total		Percentage within Group	100.0%	100.0%	100.0%	100.0%

[a]Left wrist flexion-extension acceleration.

groups. Yet, for the majority of the studied physical exposures seem unlikely that dose-response relationships can be studied by the use of prediction models in epidemiological studies.

The additionally measured anthropometrical variables were included in 12 of the 16 models and workstation set-up variables were included in 9 of the 16 models. Removal of these variables had the largest effect on the quality of keyboard and mouse force predictions, and muscle activity predictions were affected the least. The importance of anthropometry in relation to computer use exposures has been indicated by Won and colleagues (2009), who studied gender differences in exposure during computer use.

When comparing the quality of the arm-wrist-hand exposure predictions evaluated in the present study to the quality of neck-shoulder exposure predictions using models that were developed following the same methods (Bruno Garza *et al.*, 2014), neck-shoulder muscle activity and shoulder, neck, and torso postures can be better predicted than forearm extensor muscle activity and wrist postures, which was contrary to what we expected. We expected that the predictive quality of arm-wrist-hand exposure models would be better than neck-shoulder exposure prediction models because arm-wrist-hand exposures were expected to be more task-related and characteristics of computer use could be included as predictor variables in the present study. It might be that the constraints of computer work reduce variance in task performance and thereby in physical exposure of the arms, wrists, and hands between workers. Furthermore, it was striking that individual factors, especially anthropometry, were more important predicting variables in arm-wrist-hand predictions than in neck-shoulder predictions, and psychosocial factors had notably less predictive value in arm-wrist-hand predictions compared to neck-shoulder predictions. These results might also argue for different approaches of future interventions aiming to reduce arm-wrist-hand and neck-shoulder physical exposures during computer use.

We expected that the variance in arm-wrist-hand physical exposures among office workers would partly be explained by task (i.e. the distribution of keyboard, mouse, and idle time across a work day). However, even though in 10 of the 16 prediction models at least one of the variables % keyboard use, % mouse use, or % idle time were included, the R^2 values were still quite low. It is possible that forearm physical exposures during computer work are not to a large extent explained by the variation in computer task, which is in line with findings of Mathiassen and colleagues (2005), and argues for addressing "total computer use" (i.e. including keyboard, mouse, and idle time) in future exposure assessment studies.

Predictive quality varied largely between the models; where some wrist-arm-hand exposures could sufficiently be predicted, for other physical exposures the predictive quality was poor. In future studies, predictions could be improved when the sources of the unexplained variances are understood. In the present study, a wide set of predicting variables was used, covering many different categories of individual and occupational factors usually measured in etiological and epidemiological studies on physical exposures and neck- and upper-extremity symptoms (IJmker *et al.*, 2006). Nevertheless, it is possible that important variables have been overlooked. Differences in predictive quality between physical exposures cannot be fully explained by the number of variables in the models. In general, the models with most predictive quality had the highest number of predictors, but e.g. keyboard force, the physical exposure measure with the highest explained variance (80%) had only four predictors in the full model. In the practical models, without the two physical measures (measured body weight and hand length), the explained variance of keyboard dropped to 5%, In the model for left radial-ulnar velocity, two predicting variables were identified, explaining only 8% of the variance. It is likely that important predicting variables are missed here. Moreover, it may be that workers adopt different postural strategies during the different aspects of computer use that are not captured by the content of the task and the workstation set-up. As such, a lack of variation in our data may also clarify the relatively poor explained variance in some of the models. Future studies could further explore additional metrics that could be measured at the work site in order to further improve predictive quality of the models or explore the use of different models for mouse use, keyboard use, and idle time.

Strengths and limitations

This is the first study exploring arm-wrist-hand physical exposure predictions during computer use as a possible future exposure assessment tool that is less costly and time consuming than direct measurements. For the development of the prediction models, we collected an abundance of data: 98 possible predicting variables and many different arm-wrist-hand exposures. For the latter, we used reliable measurement systems, which continuously collected data for ~2 h, among a large number of office workers performing their normal computer work. The results of this study provide useful information on the predictive quality of prediction models for arm-wrist-hand exposures that can be reached based on a wide range of predicting variables across different categories. This information can be used as a basis to further develop these prediction models, especially those with relatively large predictive quality. In future studies, also the use of common sets of predictors could be further explored to further reduce the number of predicting variables that need to be collected (make the models even more practical), while at the same time taking into account the effect on the predictive quality of the models. The bootstrapping procedure, as shown in Parts 1 and 2 of the Supplementary Material (available at *Annals of Work Exposures and Health* online), shows reasonable consistency for the identified factors in the final models, suggesting internal validity of the presented findings.

Limitations must be taken into consideration when interpreting the results of this study. First, the results of this study are purely empirical. Since we used a backward selection method predicting variables may have been included in a model by chance, there was a risk of overfitting or included variables may only have fitted the present study population's data (Harrell, 2001). We intended to limit such possible error by performing a pre-selection, based on the single associations between predictor variables and an outcome. All 98 variables were theoretically related to physical exposures or upper extremity symptoms and using a multiple step approach to reduce the number of predicting variables before conducting a multivariate model. Bootstrapping showed that despite the multiple testing the results were quite robust; however, we did not test the developed prediction models in an external data set. When the presented models would be externally validated, it is likely that the R^2 values drop (Harrell, 2001). Furthermore, we would like to note that this study focused on the intensity of exposure only. With regard to musculoskeletal symptoms, duration, and frequency of exposure are other important factors to consider.

Conclusions

As expected, the full prediction models based on self-reported factors, software-recorded computer usage patterns, and additional worksite measurements of anthropometrics and workstation set-up, showed in general a better predictive quality as compared to the practical models based on self-reported factors and software-recorded computer usage patterns only, but results vary largely across different arm-wrist-hand exposure parameters. Future exploration of the relation between predicted physical exposure and symptoms is therefore only recommended for physical exposures that can be reasonably well predicted.

Supplementary Data

Supplementary data are available at *Annals of Work Exposures and Health* online.

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Authors' Contributions

M.A.H.—Study design, data analyses, interpretation of the data, writing of the manuscript. B.H.W.E.—Study design, data acquisition, data processing, data analyses, interpretation of the data, writing of the manuscript. J.L.B.G.—Study design, data processing, interpretation of the data, revision of the manuscript. P.C.—Data analysis, interpretation of the data, revision of the manuscript. B.M.B.—Study design, interpretation of the data, revision of the manuscript. P.W.J.—Study design, data acquisition, interpretation of the data, revision of the manuscript. J.H.D.—Study design, interpretation of the data, revision of the manuscript. A.J.B.—Study design, interpretation of the data, revision of the manuscript. J.T.D.—Study design, data acquisition, data processing, interpretation of the data, revision of the manuscript.

Competing Interests

The authors declare that they have no competing interests.

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