

## NIH Public Access

Author Manuscript

J Occup Environ Hyg. Author manuscript; available in PMC 2013 December 01.

Published in final edited form as: *J Occup Environ Hyg.* 2012 December ; 9(12): 691–698. doi:10.1080/15459624.2012.728927.

### Developing a Framework for Predicting Upper Extremity Muscle Activities, Postures, Velocities, and Accelerations During Computer Use: The Effect of Keyboard Use, Mouse Use, and Individual Factors on Physical Exposures

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#### Abstract

Prediction models were developed based on keyboard and mouse use in combination with individual factors that could be used to predict median upper extremity muscle activities, postures, velocities, and accelerations experienced during computer use. In the laboratory, 25 participants performed five simulated computer trials with different amounts of keyboard and mouse use ranging from a highly keyboard-intensive trial to a highly mouse-intensive trial. During each trial, muscle activity and postures of the shoulder and wrist and velocities and accelerations of the wrists along with percentage keyboard and mouse use were measured. Four individual factors (hand length, shoulder width, age, and gender) were also measured on the day of data collection. Percentage keyboard and mouse use explained a large amount of the variability in wrist velocities and accelerations. Although hand length, shoulder width, and age were each significant predictors of at least one median muscle activity, posture, velocity, or acceleration exposure, these individual factors explained very little additional variability in any of the physical exposures investigated. The amount of variability explained for models predicting median wrist velocities and accelerations ranged from 75 to 84% but were much lower for median muscle activities and postures (0-50%). RMS errors ranged between 8 to 13% of the range observed. While the predictions for wrist velocities and accelerations may be able to be used to improve exposure assessment for future epidemiologic studies, more research is needed to identify other factors that may improve the predictions for muscle activities and postures.

#### Keywords

anthropometry; biomechanics; task-based exposure assessment

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#### A INTRODUCTION

Although many studies have reported associations between computer use and musculoskeletal disorders (MSDs), the evidence identifying specific physical and individual exposures during computer use that may explain these associations is limited.<sup>(1)</sup> One challenge in attempting to link exposures and outcomes in epidemiologic studies is the collection of accurate measurements of these exposures.<sup>(2)</sup>

Physical exposures such as the muscle activities, postures, velocities, and accelerations experienced during computer use are particularly difficult to measure accurately. Questionnaires, which require participants to self-report their perceived physical exposures during computer use, have the advantage of enabling data collection in large samples of workers at a reasonable cost. However, previous studies have reported low agreement between exposures assessed through self-report methods compared with direct measurements of physical exposures during computer use.<sup>(3-5)</sup> Direct measurements, the preferred method of exposure assessment in terms of accuracy, are expensive, time consuming, and often impractical for the large epidemiologic studies needed to make associations with MSDs.<sup>(2)</sup> Direct measurements are also needed to collect enough data to determine the median values of physical exposures, a common metric that has been presented in many previous studies.<sup>(6-8)</sup>

Exposure prediction models have been proposed as an alternative means of generating exposure data that is difficult to measure directly. Chen et al.<sup>(9)</sup> used mixed-effect modeling to predict taxi drivers' exposure to whole body vibration based on a set of known predictors of vibration, including engine size, driver's weight, and seat cushion type, and found acceptably low prediction error. It is possible that predictions can be generated using this strategy for physical exposures including muscle activities, postures, velocities, and accelerations of the upper extremity during computer use.

A task-based approach to exposure prediction modeling takes advantage of the variability in exposures across tasks inherent to many jobs to calculate predictions of exposures. The primary tasks that many modern office workers complete are computer tasks (compared with non-computer work), which can further be broken into keyboard tasks and mouse tasks (prolonged interactions with the computer using each input device), as well as idle tasks (active interaction with the computer without use of an input device).<sup>(10,11)</sup> Previous studies have shown that there is variability in physical exposures across computer tasks; for example, keyboard use is associated with increased muscle efforts and wrist velocities and accelerations, and mouse use is associated with non-neutral shoulder postures.<sup>(12,13)</sup>

The large inter-subject variability inherent to many physical exposures, which cannot be explained by task, has limited the usefulness of the task-based approach.<sup>(14)</sup> Thus, factors that could explain some of this variability could be used to improve estimates generated from task-based models. During computer use, physical exposures have varied with hand length,<sup>(6,8)</sup> gender,<sup>(7,8)</sup> age,<sup>(15)</sup> and shoulder width.<sup>(8,16)</sup>

The goal of this study, therefore, was to develop models based on keyboard and mouse use in combination with individual factors that could be used to predict median upper extremity muscle activities, postures, velocities, and accelerations experienced during computer use. The models were used to determine which keyboard use, mouse use, or individual factors were predictors of median upper extremity muscle activities, postures, velocities, and accelerations, as well as the strength and directions of the associations. The predictive capabilities of the models were also evaluated.

#### A METHODS

#### **B Experimental Protocol**

Twenty-five participants (13 males) volunteered to take part in this study. All participants were experienced computer users who were comfortable using the mouse with their right hand during the measurement period. The experimental collection protocol for this study has been previously described.<sup>(12)</sup> The Harvard School of Public Health Human Subjects Committee approved all protocols and consent forms.

**C Individual Factors**—In total, four individual factors were measured as part of the experimental protocol. The individual factors considered for this study were chosen because each factor had been identified in a previous study as being associated with at least one physical exposure of interest during computer use.<sup>(6–8,15,16)</sup> Each participant's hand length and shoulder width were measured as the shortest distance between anatomical landmarks.<sup>(17)</sup> Hand length was measured as the distance from the ulnar styloid to the third metacarpophalangeal joint. Shoulder width was measured as the distance across acromioclavicular joints. Participants self-reported their age and gender. The distribution of participant's individual factors is shown in Table I.

C Computer Trials—During the study, participants performed five trials designed to provide contrasting percentages of keyboard and mouse use. The trials ranged from a highly keyboard-intensive trial in which participants were required to type a piece of text (called TYPE in this manuscript), to a highly mouse-intensive trial in which participants browsed a local intranet web page (called WEB in this manuscript). The other three trials ranged from being more keyboard intensive to more mouse intensive: participants filled in a series of text boxes (called FORM in this manuscript), deleted and corrected mistakes in a word processing document (called EDIT in this manuscript), and sorted and resized objects (called GRAPH in this manuscript). As reported in Dennerlein et al., (12) the various trials resulted in significant differences in percentage keyboard and mouse use. The distribution of percentage keyboard and mouse use for each task is shown in Table II. The duration of each trial was 5 min, and trials were presented to participants in a random order. Participants performed these five trials at a height-adjustable computer desk with an adjustable monitor stand and adjustable chair. The chair, desk, and monitor were adjusted for each individual in accordance with guidelines put forth by ANSI-HFS and Occupational Safety and Health Administration.(18,19)

A computer interaction monitoring software program written in LabView (National Instruments, Austin, Texas) recorded the beginning and end times of any keyboard or mouse use time by monitoring the keyboard and mouse events captured by the Windows operating system. "Keyboard use" was defined as any series of keystrikes that had less than 2 sec of inactivity between successive keystrikes. Similarly, "mouse use" was defined as a series of mouse events (mouse movement, scrolling, or button clicks) that had less than 2 sec of inactivity between successive mouse events. Percentage keyboard and mouse use were calculated for each trial as the amount of time spent using the keyboard or mouse, respectively, divided by the total amount of time spent performing each trial. While there is no extant standard for defining keyboard or mouse activities, 2 sec was chosen as being a long enough time period to separate keyboard and mouse use time from idle time. Cutoffs between 1.5 and 4.5 sec have been validated as having low relative error compared to direct observation.<sup>(20,21)</sup> Periods characterized by two or more seconds in which there was no kevboard or mouse activity for at least 2 sec were considered "idle time." The combination of "keyboard use time," "mouse use time," and "idle time" added up to the total time spent performing each trial, or 100%.

**C Electromyography**—Surface electromyographic (EMG) activity was measured for four muscles of the right forearm and three muscles of the right shoulder. The forearm muscles measured included the flexor carpi radialis, flexor carpi ulnaris, extensor carpi radialis, and extensor carpi ulnaris. The shoulder muscles measured included the anterior deltoid, medial deltoid, and upper trapezius. Surface electrodes (DE-2.1 Single Differential Electrode; Delsys, Boston, Mass.) were placed on top of the muscle bellies in accordance with the anatomical locations as identified by Perotto.<sup>(22)</sup> After amplification (Bandwidth of 20-450 Hz, Bagnoli-Eight Amplifier; Delsys, Boston, Mass.) data were recorded to a personal computer at a sampling rate of 1000 samples/sec, and the EMG amplitude was represented by a root mean squared (RMS) value calculated over a 0.2-sec moving window. All EMG activity was normalized based on the amplitude of the participant's EMG signals during maximum voluntary contractions obtained from three experimenter-resisted. 3-5 sec contractions for each muscle with 1 min rest in between. For the forearm muscles, the postures and directions of movements were those defined by Buchanan et al.<sup>(23)</sup> With the upper arm near the neutral posture (at rest and vertically aligned with the torso) for the anterior deltoid, the experimenter resisted shoulder flexion; for the medial deltoid, shoulder abduction was resisted. For the trapezius muscle, subjects attempted to lift/shrug their shoulders with the direction of the resistance being applied vertically downward at the acromion. Participants rested for 1 min between contractions. The median RMS EMG value for each forearm and shoulder muscle was calculated for each participant.

**C Wrist Posture, Velocity, and Acceleration**—Right and left wrist flexion/extension and radial/ulnar deviation were measured using a two-channel, glove-based electrogoniometry system (Wristsystem; Greenleaf Medical, Palo Alto, Calif.) worn by participants during data collection. The system had a resolution of 0.1 degrees, an accuracy of 2 degrees over a range from –90 to +90 degrees and was calibrated using a wrist jig in accordance with the methods described in Jonsson and Johnson.<sup>(24)</sup> The system and analysis procedure has been used in several previous studies.<sup>(8,12)</sup> Postures were recorded continuously by a data logger at 20 samples/sec during the tasks. Digital differentiation of the data was used to calculate the wrist joint velocities and accelerations after the position data were digitally low-pass filtered at 8 Hz. All postures were calculated with respect to a neutral posture as defined using the wrist posture, velocity, and acceleration were calculated for each participant.

**C Shoulder Posture**—Shoulder abduction, flexion, and rotation postures of the right arm was measured using a three-axis orientation sensor (Model 3DM; Microstrain, Inc., Winooski, Vt.) for the first 15 participants, and an electro-magnetic motion analysis system (MiniBird; Ascension Technology, Burlington, Vt.) for the last 12 participants. The 3DM measured abduction (-70 degrees to +70 degrees) and flexion (-180 degrees to +180 degrees) using inclinometers and rotation (-180 degrees to +180) using a magnetometer. The MiniBird measured the orientation of the upper arm using two sensors, one placed on the forearm and one on the upper arm, midway on the humerus. The second system was introduced when the first system broke. As previously reported, no statistical differences were detected between the shoulder posture measurements recorded from the two systems.<sup>(12)</sup> For both systems, data were recorded through the serial port into a personal computer at 10 samples/sec. All postures were calculated with respect to a neutral posture, measured when a participant was sitting with shoulders relaxed, elbows at their side and palms of the hands resting on the participant.

#### **B Model Development**

To take advantage of the repeated measures design, multilevel linear regression modeling was used to predict each muscle activity, posture, velocity, and acceleration. The data used to form the predictions were the median muscle activity, posture, velocity, or acceleration data from each participant. Analyses were conducted using PROC MIXED in SAS version 9.2 (SAS Institute Inc., Cary, N.C.). The models used to develop the predictions had a random intercept (to account for subject-level correlation), and fixed slopes for covariates. Visual inspection for normality of the residuals for each model confirmed that parametric methods were appropriate.

A backward stepwise selection procedure was used to determine which predictors should be left in the linear regression models. First, percentage keyboard use, percentage mouse use, gender, hand length, shoulder width, and age were introduced individually as predictors into univariate models separately for each muscle activity, posture, velocity, or acceleration measure. Gender was treated as a dichotomous variable and all other individual factors, percentage keyboard use, percentage mouse use, and all muscle activity, posture, velocity, and acceleration measures were treated as continuous variables. Next, all predictors with p-values less than 0.20 in the univariate analyses for each muscle activity, posture, velocity, or acceleration dataset were introduced into multivariate models. Using an iterative process, the predictor with the least-significant p-value was removed at each iteration until only those with p-values less than 0.05 were retained. The resulting models were used to generate predictions for that muscle activity, posture, velocity, or acceleration measure ("full models"). For any full model that included both computer actions and individual factors, a second set of prediction models were generated with only keyboard use and/or mouse use as predictors ("reduced models").

#### **B Model Evaluation**

Beta coefficients, 95% confidence intervals (CI), and p-values were calculated as part of the PROC MIXED procedure. To calculate an R-squared value to determine amount of variability explained by the models, the residual variance was calculated for the finalized prediction model for each median muscle activity, posture, velocity, or acceleration measure, and also for the intercept-only model. The R-squared value was then determined by taking the difference between the residual variance for the intercept-only model and that of the final prediction model divided by the total intercept-only residual variance. R-squared values were calculated for both the "full models" and the "reduced models," and the difference in R-squared between the "full models" and the "reduced models," was also calculated. Root mean squared errors were calculated, and relative RMS errors were determined by dividing by the full range of median values observed.

#### A RESULTS

At least one of the keyboard use, mouse use, or individual factors was a significant predictor of every physical exposure except for left wrist flexion (Tables III and IV). Keyboard use, mouse use, or both, were significant predictors in all models. Fewer (9 out of 22) physical exposures also had individual factors as predictors, and no model had only individual factors as predictors without keyboard use or mouse use.

Muscle activity, wrist velocity, and wrist acceleration all tended to increase as the percentage of keyboard use or mouse use increased. Increased keyboard use decreased shoulder flexion and external rotation. Increased mouse use increased shoulder abduction but was not significant in the other shoulder posture multivariate prediction-rule models (Tables III–VI).

Shoulder rotation was the dependent variable most influenced by individual factors, with a decrease in external rotation of 3.8 degrees for every 1-cm increase in shoulder width (Table IV). Gender was not a significant predictor of any muscle activity, posture, velocity, or acceleration, but all other individual factors were significant predictors of at least one muscle activity, posture, velocity, or acceleration. Hand length and shoulder width were significant predictors of several muscle activity and posture measures (Tables III and IV). Age was a significant predictor of velocity and acceleration in the radial and ulnar deviation directions only for both the left and right hands (Table V).

The combination of percentage keyboard use, percentage mouse use, and individual factors explained the largest amount of variability in left and right wrist velocities and accelerations in both the radial/ulnar and flexion/extension directions, with all of the multivariate prediction-rule models having R-squared values of 0.75 or greater and RMS errors of less than 10% of the observed range (Table VI). The models explained less overall variability in shoulder postures (R-squared from 0.21 to 0.50) with relative RMS errors between 8 to 13% and wrist muscle activity (R-squared from 0.06 to 0.46) with relative RMS errors of 8 to 13%. The lowest r-squared values were observed for shoulder muscle activity (R-squared from 0.03 to 0.10) with relative RMS errors of 10 to 12% and wrist posture (R-squared from 0.00 to 0.23) with relative RMS errors of 9 to 12%.

Keyboard use and mouse use were the main determinants of each muscle activity, posture, velocity and acceleration data set, contributing more than any of the individual factors (Table VI). Shoulder rotation was most affected by the removal of individual factors from its prediction model. A 3% decrease was seen in the R-squared for shoulder rotation when all individual factors were removed (reduced model). The RMS errors were not changed by the removal of individual factors from the models.

#### A DISCUSSION

The goal of this study was to develop models based on keyboard and mouse use in combination with individual factors that could be used to predict median upper extremity muscle activities, postures, velocities, and accelerations experienced during computer use. Percentage keyboard and/or mouse use were significant predictors of each muscle activity, posture, velocity, or acceleration except left wrist flexion. All individual factors except gender were significant predictors of at least one muscle activity, posture, velocity, or acceleration except effect of individual factors being observed on shoulder rotation. The large amounts of variability in wrist velocities and accelerations could be explained by keyboard use and/or mouse use (74–81% for "reduced models"). While more variability in wrist muscle activities was explained than in shoulder muscle activities, and more variability in shoulder postures was explained than in wrist postures, the total variability explained in any muscle activity or posture was small (0–50%). Including individual factors in addition to keyboard and mouse use did not explain more variability (changes of less than 3% from "full models" to "reduced models"). The RMS errors were similar across physcial exposures and were not affected by the removal of individual factors.

One advantage of including individual factors as predictors in this study was that it allowed for examination of how specific individual factors influence the muscle activities, postures, velocities, and accelerations during computer use when task is also taken into consideration. Shoulder rotation was the dependent variable most influenced by individual factors, with a decrease in shoulder rotation of 3.8 degrees for every 1-cm increase in shoulder width. Several other studies have also examined the association between shoulder rotation and shoulder width,<sup>(8,16)</sup> and in each study an association was reported between shoulder rotation and shoulder width. Computer users with a smaller shoulder width have a narrower

base of shoulder rotation and therefore must externally rotate out more to reach the mouse. The current study determined that shoulder width was predictive of shoulder rotation and that the association between shoulder width and shoulder rotation was robust even when controlling for the effect of percentage of keyboard use.

In some cases, the inclusion of individual factors may expose the true relationship between keyboard and/or mouse use and the muscle activity, posture, velocity, or acceleration of interest. For example, Dennerlein and Johnson<sup>(12)</sup> report decreased ECU muscle activity with increased mouse use, and in this study we observed increased ECU muscle activity with increased mouse use when hand length is included as a predictor of ECU muscle activity. In the case of these muscles, it seems that increased hand length is the factor driving the decrease in ECU muscle activity, and after controlling for this factor, the true association between muscle activity and mouse use is positive rather than negative. This observation corroborates the results of previous studies, which have shown that mouse use is associated with increased wrist extension.<sup>(6,8)</sup> Increased wrist extensor muscle activity is required to increase wrist extension.

Consideration of other factors that contribute to the variability of physical exposures may improve the predictive capabilities of the models described here, especially for muscle activities and postures. We did not include workstation setup<sup>(26)</sup> or psychosocial factors<sup>(27)</sup> as predictors in our models, which have been shown to be associated with physical exposures during computer use. However, these parameters did not vary significantly within our laboratory study – the laboratory workstation was adjusted to match each participant's anthropometry, and psychosocial stress was not expected to result from this type of study. Another factor that could have affected our results is the amount of variability in the data used. Participants may not have been moving naturally due to the unfamiliar conditions or wearing of the data collection equipment. However, in comparison with a field study, these laboratory data have similar variability as measured in computer workers performing their own work.<sup>(13)</sup> Hence, we do not expect that our ability to predict muscle activities or postures is limited by reduced variability in our datasets.

Although the relationships between many upper extremity muscle activities, postures, velocities, accelerations, and MSDs has not yet been reported in epidemiologic studies, they are biologically plausible. Visser and van Dieen<sup>(28)</sup> propose several mechanisms for developing MSDs that could be influenced by physical exposures, including increased levels of muscle activity, which could be an indication of selective loading and damage of small motor units, and postural deviations, which may lead to compression of arteries and loss of blood flow to active muscles. It is possible that with improved assessment of the physical exposures associated with computer use, by means of alternative methods such as those described here, the relationship between physical exposures and MSDs will be realized in epidemiologic studies.

The results of this study must be taken with consideration of its limitations. First, the levels of significance reported here must be interpreted with caution, since all seven computer use and individual factors were allowed to be introduced into the regression models for each muscle effort, posture, velocity, and acceleration dataset. For example, the effect of age on wrist velocities and accelerations reported here has not been previously reported or hypothesized and may be due to chance. The levels of significance also cannot be compared between the computer use and individual factors because the computer use factors were repeated for each participant. However, it is possible that greater effects were observed for keyboard and mouse use than individual factors because we had a larger range of percentages of keyboard and mouse use than of any of the individual factors studied. The

ages of the participants in this study were lower than in a previous study of the effect of age on muscle activity<sup>(15)</sup>, which may explain why no effect of age on muscle activity levels was observed in the current study. Second, we only considered the median values of physical exposures. However, within this dataset the 10th, 50th, and 90th percentiles of all physical exposures were highly correlated across tasks, and therefore, we did not expect to find different results than for the median for these metrics.<sup>(12)</sup> Also, it is generally believed that an increase in median physical exposures may lead to increased musculoskeletal damage, so predictions of this metric specificially would be useful.<sup>(28)</sup> Other studies may consider whether more variability could be explained using other ways of characterizing physical exposures. Third, we were unable to separate our data into distinct keyboard and mouse tasks and, instead, used percentage keyboard use and percentage mouse use as indicators of task. Future work should confirm our results and explore a task-based approach when the physical exposures can be separated by task.

#### A CONCLUSIONS

This study determined that keyboard and mouse use explained a large amount of the variability in wrist velocities and accelerations experienced during computer use. However, keyboard and mouse use did not explain much of the variability in muscle efforts or postures experienced during computer use. The individual factors that have been previously identified in the literature as being associated with physical exposures explained very little of the variability in any of the physical exposures investigated.

The results of this study can inform alternative methods of exposure assessment, including the development of prediction models. The models were able to generate accurate predictions of median wrist velocities and accelerations and may be useful tools for epidemiologic studies. However, the models were not able to generate accurate predictions of median muscle activities or postures.

It is unlikely that the addition of the individual factors investigated in this study will improve the predictions of any physical exposures substantially, although there is a possibility that other, unexplored factors could be used to improve the predictions. Future work in this area should focus on identifying other factors that might be used to create alternative, effective prediction models or other strategies for generating muscle effort and postural data. Ultimately, once accurate predictions are developed, these can be applied to epidemiologic studies investigating the association between physical exposures and MSDs in the computer worker population.

#### Acknowledgments

The authors would like to acknowledge Dr. Peter Johnson for his contribution to the experimental and equipment design for this study, as well as the funding sources for this project: CDC/NIOSH 1-R01-0H-03997 (PI: Dennerlein) and CDC/NIOSH 1-R01-0H-08781 (PI: Dennerlein). Dr. Katz is supported in part by NIH/NIAMS P60 AR 47782.

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**TABLE I** 

\$watermark-text

	Maximum	41
	Minimum	22
	Standard Deviation	5
mmdi	Mean	28
	Median	28

22 47

16 37

З \_

18 42

18 43

Shoulder width (cm) Hand length (cm) Age (years)

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TABLE II

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Percentage Keyboard and Mouse Use for Each Task

		Median	Mean	Standard Deviation	Minimum	Maximum
E	% Keyboard Use	87	87	9	75	76
1 ype	% Mouse Use	9	9	ω	0	13
	% Keyboard Use	39	39	15	17	68
LUIII	% Mouse Use	37	37	16	7	66
1. 1 1	% Keyboard Use	18	18	4	6	66
EUL	% Mouse Use	64	26	19	17	76
dam C	% Keyboard Use	0	25	40	0	90
Utapii	% Mouse Use	06	68	37	7	66
Web	% Keyboard Use	0	0	0	0	0
M CD	% Mouse Use	LL	67	26	23	66

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Results of Prediction Modeling for Median Muscle Activity

	% Keyboard		%Mouse		Hand Length		Age		Shoulder Width	
Description	β <sup>A</sup> (CI)	d	$\boldsymbol{\beta}^{A}$ (CI)	d	β <sup>B</sup> (CI)	d	β(CI)	d	β <sup>C</sup> (CI)	d
Shoulder EMG (%MVC)										
Anterior deltoid	0.02 (0.01,0.03)	<0.01								
Medial deltoid	[		0.01 (0.00,0.02)	<0.01					[	
Trapezius	0.02 (0.00,0.03)	0.03								
Forearm EMG (% MVC)										
ECR	0.10 (0.03,0.16)	<0.01							-1.6 (-2.8, -0.3)	0.02
ECU			$0.09\ (0.03,\ 0.04)$	<0.01	-3.0 (-5.0, -0.9)	$<\!0.01$				
FCR	0.01 (0.00,0.02)	<0.01			-1.2 (-2.0, -0.4)	$<\!0.01$				
FCU	0.06 (0.04,0.09)	<0.01	$0.05\ (0.03, 0.08)$	<0.01						
$A_{\rm Beta\ coefficients\ for\ keybc}$	oard or mouse use co	orrespond	I to the change in %I	MVC wit	h a 1% change in key	/board or	mouse us	e.		
$B_{ m Beta}$ coefficients for hand ]	length correspond to	the char	nge in %MVC with a	a 1-cm ch	ange in hand length.					
$C_{ m Beta}$ coefficients for should	der width correspon	d to the c	hange in cm/sec for	velocity	%MVC with a 1-cm	change in	shoulder	· widtł	ť	

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Wrist Postures
and
Shoulder
Median
for
Modeling
f Prediction
Results of

	% Keyboard		% Mouse		Hand Length		Age		Shoulder Width	
Description	$\boldsymbol{\beta}^A$ (CI)	d	$\beta^A$ (CI)	d	$\beta^B$ (CI)	d	β (CI)	d	β <sup>C</sup> (CI)	b
Shoulder Posture (°)										
Abduction			$0.08\ (0.05, 0.10)$	<0.01						
Flexion	-0.10 (-0.13, -0.06)	<0.01								
External rotation	-0.48 (-0.59, -0.36)	<0.01							-3.8 (-5.8, -1.8)	<0.01
Wrist Posture (°)										
Left ulnar deviation			-0.10 (-0.13, -0.06)	<0.01				I		
Right ulnar deviation	0.12 (0.07,0.17)	<0.01	0.07 (0.02,0.12)	0.01						
Left extension								Ι		
Right extension			0.08 (0.04,0.12)	<0.01	2.6 (0.1,5.1)	0.04				
${}^{A}_{ m Beta}$ coefficients for key	oard or mouse use corre	spond to	the change in degrees w	ith a 1%	change in keybo	ard or me	ouse use.			
$B_{ m Beta}$ coefficients for han	l length correspond to th	e change	in degrees with a 1-cm c	change in	hand length.					
$C_{ m Beta}$ coefficients for shor	lder width correspond to	the char	ige in degrees with a 1-ci	m change	e in shoulder wid	th.				

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# TABLE V

Results of Prediction Modeling for Median Wrist Velocities and Accelerations

	% Keyboard		% Mouse		Hand Length		Age		Shoulder Width	
Description	$\beta^A$ (CI)	d	β <sup>A</sup> (CI)	d	β (CI)	d	$\beta^B$ (CI)	d	β (CI)	d
Wrist Velocity (°/sec)										
Left ulnar deviation	$0.04 \ [0.04, 0.04]$	$<\!0.01$					$0.04 \ [0.01, 0.07]$	< 0.01		
Right ulnar deviation	$0.06 \ [0.05, 0.07]$	<0.01	$0.00 \ [0.00, 0.03]$	<0.01			$-0.06 \left[-1.33, -0.01\right]$	0.02		
Left flexion	0.11 [0.10,0.12]	$<\!0.01$								
Right flexion	0.16 [0.14,0.19]	<0.01	0.03 [0.01,0.06]	0.02						
Wrist Acceleration(°/sec <sup>2</sup> )										
Left ulnar deviation	0.50 [0.46, 0.54]	$<\!0.01$					$0.53 \ [0.16, 0.91]$	0.01		
Right ulnar deviation	0.79 [0.65,0.93]	$<\!0.01$	$0.24 \ [0.10, 0.38]$	<0.01			-0.71 $[-1.33, -0.09]$	0.03		
Left flexion	1.37 [1.26,1.47]	$<\!0.01$								
Right flexion	2.20 [1.84,2.56]	<0.01	$0.49 \ [0.12, 0.86]$	0.01						
$^A$ Beta coefficients for keybc	oard or mouse use co	hrespond	to the change in cm	Nsec for	velocity, or in cm/	'sec <sup>2</sup> f	or acceleration, with a 1	% change	e in keyboard or mo	ouse use.
$^{B}_{ m Beta}$ coefficients for age co	prespond to the char	nge in cm	//sec for velocity, or	in cm/se	sc <sup>2</sup> for acceleratio	n, witl	h a 1-year change in age.			

**TABLE VI** 

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Goodness of Fit of All Models

				Fu	ll <sup>A</sup>		Redu	cedB
Description	Min Median <sup>C</sup>	Max Median <sup>C</sup>	${f R}^2$	$RMS^D$	Relative RMS	${f R}^2$	$RMS^D$	Relative RMS
Shoulder EMG (%MVC)								
Anterior deltoid	0.15	15.51	0.10	1.78	12%			
Medial deltoid	0.33	90.6	0.11	0.89	10%			
Trapezius	0.57	27.13	0.03	2.54	10%			
Forearm EMG(%MVC)								
Extensor carpi radialis	0.51	103.57	0.26	4.72	5%	0.26	4.72	5%
Extensor carpi ulnaris	1.39	81.58	0.46	4.13	5%	0.46	4.13	5%
Flexor carpi radialis	0.83	27.26	0.06	1.48	6%	0.06	1.48	6%
Flexor carpi ulnaris	0.23	23.66	0.20	1.92	8%			
Shoulder Posture (°)								
Right Abduction	-8.47	23.62	0.50	4.15	13%			
Right Flexion	-26.94	42.64	0.21	6.24	9%			
Right Rotation	-98.42	166.79	0.38	21.90	8%	0.35	21.70	8%
Wrist Posture (°)								
Left radial/ulnar deviation	-19.20	36.00	0.23	5.85	11%			
Right radial/ulnar deviation	-13.60	28.00	0.22	4.02	10%	I		
Left flexion/extension	-24.80	107.20	0.00	16.19	12%			
Right flexion/extension	-4.80	64.80	0.13	6.39	9%	0.13	6.41	6%
Wrist Velocity (°/sec)								
Left radial/ulnar deviation	0.00	7.12	0.80	0.65	%6	0.79	0.64	%6
Right radial/ulnar deviation	0.07	96.9	0.75	0.91	%6	0.74	0.91	9%
Left flexion/extension	0.01	19.69	0.84	1.60	8%			
Right flexion/extension	0.36	23.30	0.80	2.16	%6			
Wrist Acceleration (°/sec <sup>2</sup> )								
Left radial/ulnar deviation	0.00	95.95	0.81	8.03	8%	0.81	7.99	8%
Right radial/ulnar deviation	1.15	124.54	0.76	11.09	6%	0.76	11.09	9%
Left flexion/extension	0.10	269.13	0.83	20.27	8%			

				Ful	A		Reduce	$d^B$
Description	Min Median <sup>C</sup>	Max Median <sup>C</sup>	${f R}^2$	$RMS^D$	Relative RMS	R <sup>2</sup> RN	AS <sup>D</sup> 1	<b>telative RMS</b>
Right flexion/extension	6.69	330.23	0.79	31.17	10% -	1		

"--" indicates those physical exposures where individual factors were not included in the full prediction model. In most cases, addition of individual factors from the prediction rule did not improve the Rvariance.

squared value or RMS error.

 $^{A}$ The "full model" included all significant computer use and individual factor predictors.

 ${}^{B}_{}$  The "reduced model" did not include individual factors.

 $C_{
m In}$  %MVC for EMG, in degrees for shoulder and wrist postures, in degrees/sec for shoulder and wrist velocities, and in degrees/sec<sup>2</sup> for shoulder and wrist accelerations.

 $^D$ RMS error, in %MVC for EMG, in degrees for shoulder and wrist postures, in degrees/sec for shoulder and wrist velocities, and in degrees/sec<sup>2</sup> for shoulder and wrist accelerations.