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Discriminating Between Individuals with and without Musculoskeletal Disorders of the Upper Extremity by Means of Items Related to Computer Keyboard Use

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Abstract *Introduction* Identifying postures and behaviors during keyboard use that can discriminate between individuals with and without musculoskeletal disorders of the upper extremity (MSD-UE) is important for developing intervention strategies. This study explores the ability of models built from items of the Keyboard-Personal Computer Style instrument (K-PeCS) to discriminate between subjects who have MSD-UE and those who do not. *Methods* Forty-two subjects, 21 with diagnosed MSD-UE (cases) and 21 without MSD-UE (controls), were videotaped while using their keyboards at their onsite computer workstations. These video clips were rated using the K-PeCS. The K-PeCS items were used to generate models to discriminate between cases and controls using Classification and Regression Tree (CART) methods. *Results* Two CART models were generated; one that could accurately discriminate between cases and controls when the cases had any diagnosis of MSD-UE (69% accuracy) and one that could accurately discriminate between cases and controls when the cases had neck-related MSD-UE (93% accuracy). Both models had the same single item, "neck flexion angle greater than 20°". In both models, subjects who did not have a neck flexion angle of greater than 20° were accurately identified as controls. *Conclusions* The K-PeCS item "neck flexion greater than 20°" can discriminate between subjects with and without MSD-UE. Further research with a larger sample is needed to develop models that have greater accuracy.

Keywords Keyboard · Observation · Cumulative trauma disorders · Work related upper extremity disorders · Rehabilitation · Ergonomics

Introduction

Computer use has been associated with musculoskeletal disorders of the upper extremity (MSD-UE) with an incidence rate of 58 cases/100 person years [1]. There are several risk factors related to keyboard use that have been identified in the literature: long duration low force static postures such as holding the position of the hands over the keyboard [2]; non-neutral neck, shoulder, and elbow postures [3–5]; non-neutral wrist postures such as wrist ulnar deviation and extension [2, 6]; specific finger postures such as hyperextension of the 5th digits metacarpophalangeal (MCP) joint and "isolation" of the 1st and 5th digits [7, 8]; and high key activation forces [7, 9, 10].

Measuring postures and behaviors during keyboard use is important for identification of risk factors and for determining appropriate workplace interventions. Methods for measuring human motion can be broadly categorized as direct and observational methods [11]. Direct methods, such as electric goniometry, optical marker methods, and electromagnetic systems, have been successfully used to describe aspects of typing [12–14]. However, direct measures require highly technical equipment, are expensive,

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non-portable, and are often difficult to translate into real world interventions. Observational methods tend to be less precise [15] than direct measures, but are also less expensive, more portable, and provide more clinically interpretable information. While some observational methods that can be used to evaluate hand intensive work tasks are described in the literature [16–22] these instruments are limited in their applicability to keyboard use: though they assess body and wrist postures, few assess hand and finger use, if they do assess finger use, they lack enough detail to discriminate between different keyboard users' styles.

In response to the need for a valid and reliable observational instrument to measure keyboarding postures, we developed the Keyboard-Personal Computer Style instrument (K-PeCS). The K-PeCS is a 19-item criterion-based instrument which documents stereotypical postures and behaviors during computer keyboarding. The instrument was developed both to provide rehabilitation personnel with a method to document keyboarding styles as well as to identify behaviors associated with MSD-UE [23]. The K-PeCS is a reliable and valid instrument [24], and has also demonstrated the ability to discriminate different keyboarding behaviors [25]. This study explores the ability of models built from K-PeCS items to discriminate between those individuals who have MSD-UE and those who do not, and examines the interactions between K-PeCS items in those models. The questions explored in this study are: what items of the K-PeCS can accurately discriminate between subjects with and without MSD-UE; and how do those items interact to identify subjects with and with MSD-UE.

Method

This study was approved by the University of Pittsburgh Institutional Review Board.

Participants

Subjects were recruited from the University of Pittsburgh faculty and staff through a direct University mailing as well as through word of mouth. Cases had to have been diagnosed by a physician with any MSD-UE that was believed to be associated with computer use [26, 27]. Cases could have any of the following diagnoses: compression neuropathies such as thoracic outlet syndrome, cubital syndrome, or carpal tunnel syndrome (including those who had had a carpal tunnel release); radiating neck complaints such as tension neck syndrome or neck strain; epicondylitis; tendinosis/tenosynovitis, including rotator cuff tendinosis, DeQuervain's syndrome, intersection syndrome, or trigger finger; and arthritis. They had to be diagnosed with the illness within the last 6 months and/or continue to have symptoms of the illness within a week of data collection. Controls were matched to the cases for age ($\pm$5 years) and gender. They could not have been diagnosed with any of the above MSD-UE within the last 5 years. Both cases and controls had to be between the ages of 18 and 65, and use a computer at least 20 h per week. Subjects with a body mass index (BMI) above 30 were excluded from the study as obesity has been associated with MSD-UE [28, 29]. We excluded subjects with a BMI of greater than 30 as we felt that BMI could confound our ability to accurately identify which K-PeCS items could predict those with MSD-UE if we found that cases had a higher mean BMI than controls.

Instrument

The Keyboard-Personal Computer Style instrument (K-PeCS) is a 19-item criterion based observational instrument (Table 1). The K-PeCS items can be divided into three general categories: static posture, dynamic posture, and force. Items of static posture are postures that remain essentially unchanged (torso angle, neck angle, shoulder angle, and elbow angle). Items of dynamic posture are postures that different keyboard users assume at different frequencies, some never assume the posture, others occasionally or frequently assume the posture, while others maintain the postures constantly (wrist/hand displacement, wrist ulnar deviation $>20°$, wrist extension $>15°$, changes in pronation, isolated fifth digit, isolated thumb, number of fingers, space bar activation, MCP hyperextension, proximal interphalangeal/distal interphalangeal (PIP/DIP) curve and DIP hypermobility). Items of force describe keyboard activation forces and the use of supports (backrest use, forearm support, wrist support, key activation force). The rating criteria are generally of four types; ordinal ratings which identify static joint postures; ordinal ratings which identify the frequency or degree to which a keyboard user exceeds a criterion posture; dichotomous ratings which identify if a keyboard user does or does not engage in a target posture; and nominal ratings which describe a posture or action (see Table 1 for specifics). The K-PeCS has demonstrated good inter-/intra-rater reliability and validity [24] as well as the ability to distinguish between individual keyboard users' behaviors [25].

Procedure

Informed consent was obtained from all subjects prior to starting the study. Subjects were interviewed and observed at their own workstation using their own keyboard. Subjects completed a questionnaire which obtained demographics and information on typical computer use. For cases, a self-reported history of their MSD-UE was documented. After

Table 1 Items on the K-PeCS, their rating criteria, and the number of cases ($N = 21$) and controls ($N = 21$) for each rating

#	Item	What the item rates	Criterion	Case (n)		Control (n)	
Ordinal—static postures							
				Single		Single	
1	Torso angle	The angle of the keyboard user's torso to the horizontal plane	>105°	2		1	
			90°–105°	14		14	
			<90°	5		6	
3	Neck flexion angle	The displacement angle & position of the head	<10°	4		9	
			11°–20°	7		10	
			21°–30°	6		2	
			>30°	4		0	
				Left	Right	Left	Right
4	Shoulder flexion angle	The flexion angle of the shoulders	0–20°	14	16	14	10
			21°–35°	6	4	5	8
			>35°	1	1	2	3
5	Elbow flexion angle	The flexion angle of the elbows	<79°	5	5	1	1
			79°–120°	15	15	17	16
			>120°	1	1	3	4
Ordinal—frequency or degree to which target posture occurs							
				Single		Single	
9	Force	The degree of force used to strike the keys	low	3		9	
			mod	11		8	
			high	7		4	
				Left	Right	Left	Right
8	Hand/wrist displace	The frequency with which keyboard users move their hands while typing	occ	10	6	12	9
			oft	6	7	5	4
			mst/time	5	8	4	8
10	Wrist ulnar angle	The frequency with which keyboard users exceed 20° of ulnar deviation	nev	6	5	9	4
			occ	2	9	4	9
			freq	3	1	2	3
			alw	10	6	6	5
11	Wrist extension angle	The frequency with which keyboard users exceed 15° of wrist extension	nev	1	1	3	2
			occ	5	3	2	3
			freq	6	10	3	7
			alw	9	7	13	9
13	Isolated 5th digit	The frequency with which keyboard users isolate the little finger	nev	2	3	3	5
			occ	5	8	8	8
			freq	13	9	8	6
			alw	1	1	2	2
14	Isolated thumb	The frequency with which keyboard users isolate the thumb	nev	12	17	11	17
			occ	0	1	0	2
			freq	2	2	3	2
			alw	7	1	7	0

Table 1 continued

#	Item	What the item rates	Criterion		Case (*n*)		Control (*n*)	
					Left	Right	Left	Right
17	MCP hyperext.	The frequency with which keyboard users hyperextend their MCP joints	3rd	nev	15	18	13	15
				occ	2	1	1	5
				freq	3	2	4	1
				alw	0	0	2	0
			4th	nev	6	11	8	9
				occ	6	5	3	10
				freq	7	4	7	1
				alw	2	1	3	1
			5th	nev	6	13	5	7
				occ	2	4	7	9
				freq	12	4	6	3
				alw	1	0	3	2
Nominal—how/where the target posture occurs								
					Single		Single	
2	Back rest use	Whether keyboard users rest at least 2/3 of their back against the chair	yes		10		12	
			yes/pause		0		0	
			no		11		9	
6	Forearm support use	Whether keyboard users support their forearms/ elbows	yes		4		7	
			yes rt/no lt		1		0	
			yes lt/no rt		0		1	
			no		16		13	
16	Space bar activation	The finger used to strike the space bar	rt thmb		15		18	
			rt ind		2		0	
			other		4		3	
					Left	Right	Left	Right
7	Wrist support use	Whether keyboard users support their wrist	yes		12	12	13	8
			unsupp key supp pause		3	2	2	3
			no		6	7	6	10
15	# of fingers used to type	Number of digits used by keyboard users to strike the keys	1 dig		0	0	0	0
			2 dig		0	0	0	0
			3 dig		0	1	2	2
			4 dig		18	8	16	7
			5 dig		3	12	3	12
Dichotomous—target posture occurs or does not occur								
					Left	Right	Left	Right
12	Forearm rotation	Whether keyboard users change the rotation angle of their forearm	yes		1	4	1	3
			no		20	17	20	18
18	PIP/DIP curve	Whether keyboard user's PIP/DIP joints are curved (> 25°)	3rd	yes	20	21	21	20
				no	1	0	0	1
			4th	yes	20	20	20	18
				no	1	1	1	3
			5th	yes	17	14	16	14
				no	4	7	5	7
19	DIP Hypermobility	Whether keyboard users' DIP joints hyperextend when striking the keys	yes		2	1	3	1
			no		19	20	18	20

All items except 1; 2; 3; & 9 are measured on both the right and left sides; Items 17 & 18 are measured separately for digits 2–5; oft—often; nev—never; occ—occasionally; freq—frequently; alw—always; mst/time—most of the time; supp—supported; unsupp—unsupported, right—rt; left—lt; ind—index; thmb—thumb; key—keyboard completing the questionnaire, two digital video cameras were set up on each side of the subjects' keyboards to capture lateral views of the right and left hand while the subjects were using their keyboards. A third camera was positioned overhead to capture a dorsal view of the subjects' hands. A standardized paragraph was opened in the subjects' computer, and subjects were instructed to type this paragraph at their normal pace.

As the subjects typed the paragraph, the researcher rated them using the K-PeCS. In addition the researcher took two lateral still photographs to obtain static body postures. The entire typing process took approximately 10 min to complete.

Data Processing

Data from the questionnaires were entered into a database. The video recordings were downloaded into video clips. Each clip contained the final 1-min of typing for each of the right, left, and overhead views. Only one minute of data was required as typing has been shown to be highly stereotypical [17, 30]. We selected the last minute of typing to help minimize the potential changes in typing style that might be caused by the subjects' knowledge that they were being recorded.

A rater skilled in using the K-PeCS rated each of the clips twice, with a one-week interval between the ratings. To prevent the rater from identifying if the clip was from a case or control the clips were coded and presented in a random order. The results of the two ratings were compared and discrepancies between the first and second rating period were reviewed and agreement as to the correct rating was reached.

Data Analysis

Classification and Regression Tree (CART) analysis was performed. CART analysis provides both information on whether items can predict those with and without MSD-UE, and also provides details on how items interact. The CART methodology [31] for classification trees is a binary, recursive partitioning model which can be used to develop a decision tree model for prediction. It has become a popular data exploration alternative to regression, discriminant analysis, and other methods based on algebraic models [32].

In CART analysis, the researcher selects a dichotomous target (outcome) item. The CART program completes a brute force search through all items to find the one which best splits the cases in the "parent node" into those who have the target outcome and those who do not have the target outcome. Once this best split is found, CART repeats the process for each child node (thus, each child node becomes a parent node), continuing recursively until further splitting is impossible. All cases falling within a terminal node (one that can be split no more) are given the class assignment of the majority of that node.

For each CART tree model it is possible to estimate the accuracy of that model. Accuracy is the probability that the model correctly identifies the status of the subject on the target outcome item. Accuracy can be further divided into the sensitivity and specificity of the model. Sensitivity is the conditional probability of the ability of the model to identify a case as being a case and specificity is the conditional probability of the ability of the model to identify a control as being a control. These measurements are estimated using the relative percentages from the individual observations from the study sample. The error rate of the model is equal to *1-accuracy*. CART provides two types of error rate, the "apparent" error rate which is the error rate associated with the ability of the model to correctly identify the status of subjects used to fit the model, and the "true" error rate which is the error rate associated with the ability of the model to correctly identify the status of subjects not used to fit the model, a novel sample of subjects [33].

In CART, unlike other decision tress methods (such as AID and CHAID), the tree is first grown to the point where no further splitting can occur (a maximal tree). Since the ultimate goal of model building is to be able to extrapolate or generalize the ability of the model items to predict the status of a sample from a novel sample, CART examines smaller trees by "pruning" branches of the maximal tree, a process of systematically removing terminal splits and the resulting terminal nodes from the maximal tree to create smaller subtrees. CART estimates each subtree's "true" error rate using cross validation methods. There are several different methods to accomplish cross validation, the process of testing a model on a "novel" sample of subjects. As this study had a small sample an *n*-fold cross validation method was used. CART randomly partitioned the sample into *n* sub-samples (10 for this study), each of which acted in turn as a test set for the cross-validation. Trees were grown for each of the whole sample, minus one test set. At each subtree the estimated accuracy of the model was tested on the omitted test set. This was repeated for all subsets, and the estimated error rate for each iteration was averaged to obtain the "true" error rate of the subtree model. The subtree model with the smallest "true" error rate estimate (i.e., the smallest probability of making an incorrect prediction) was chosen.

For our study, CART had several advantages over other discriminate analyses such as multivariate logistic regressions. CART analyses, unlike logistic regressions, are inherently non-parametric, and can handle data with any type or mixture of measuring scales [34–36]. CART can, therefore, easily handle the K-PeCS data which is categorical, not equally distributed, and has many different scales. As CART uses very efficient and exhaustive algorithms to identify each "splitting" variable, a large number of predictive variables can be reduced to a few important ones [35, 37]. In addition, CART allows for the exploration of complex interactions between variables without a priori specification [34, 38]. Finally, interpretation is relatively straight forward. Outcomes are presented as "simple" trees, with cutoff points clearly defined. For this reason, CART is increasingly being used in clinical studies, particularly to develop decision rules for clinical situations [35, 38].

As this was a small sample, we were most interested in whether K-PeCS items could distinguish between those with MSD-UE (MSD) and those without MSD-UE (NOMSD) for any type of MSD-UE diagnosis. However, we also completed secondary analyses in which the sample was divided by the part of the body which was injured; the neck/shoulder, arm, and wrist/hand. Diagnoses related to neck and shoulder use were classified as "neck" diagnoses, diagnoses related to the upper arm, elbow and forearm above the wrist were classified as "arm" diagnoses, and diagnoses related to the wrist and hand were classified as "wrist/hand" diagnoses. For these body part models, all those without MSD-UE were included as NOMSD, but only those with a diagnosed MSD-UE in the body part examined in the analysis were included as MSD.

For all models we estimated the sensitivity, specificity and accuracy. The sensitivity and specificity assist in interpreting the ability of a tree to distinguish those with MSD-UE (sensitivity) compared to the ability of the tree to identify those without MSD-UE (specificity).

Results

Subjects

Forty-three subjects [21 cases (MSD) and 22 controls (NOMSD)] were recruited. One person who was recruited as a control developed numbness and pain in her wrists and hands during the 10-min typing task. We concluded that she had an undiagnosed case of MSD-UE, instructed her to contact a physician, and excluded her data from the control analysis. We recruited another matched control to replace that control, and used her data, which gave us 21 controls. Subjects were primarily older women. The self-reported hours of computer use were essentially the same between MSD and NOMSD, as were the number of subjects trained in touch typing. MSD had a variety of different MSD-UE, although the majority of them were for the wrist and hand (Table 2). The K-PeCS item distributions for cases and controls are displayed in Table 1.

Tree Model for Overall MSD

Although several trees with multiple K-PeCS items were generated during the CART analysis, the tree which best predicted those who had MSD contained only a single item, neck flexion angle greater than or equal to 20° (Fig. 1a). Model sensitivity was low (0.48) but specificity was very high; 90% of subjects who did not have MSD were correctly classified as NOMSD if neck flexion was 20° or less. Thus, only two NOMSD subjects out of 21 had neck flexion greater than 20°.

Table 2 Demographic and computer use variables

Item	Case ($n = 21$)	Control ($n = 21$)	All ($n = 42$)
Demographic			
Age	47.8 ± 9.7	45.5 ± 8.5	46.7 ± 9.1
Sex (Female)	18 (86%)	18 (86%)	36 (86%)
Computer use			
Hours computer use (day)	6.5 ± 1.6	6.2 ± 2.5	6.3 ± 2.1
Touch typing (Yes)	13 (62%)	12 (57%)	25 (59%)
Diagnoses[a]			
Radiating neck syndrome	3 (14%)	–	–
Carpal tunnel syndrome	5 (24%)	–	–
Epicondylitis	3 (14%)	–	–
Tendonitis	6 (29%)	–	–
Tenosynovitis	3 (14%)	–	–
Arthritis	3 (14%)	–	–
Body area of diagnoses[a]			
Neck	6 (29%)		
Arm	7 (33%)		
Wrist/hand	15 (71%)		

[a] Several cases had more than one diagnosis and/or more than one affected body part

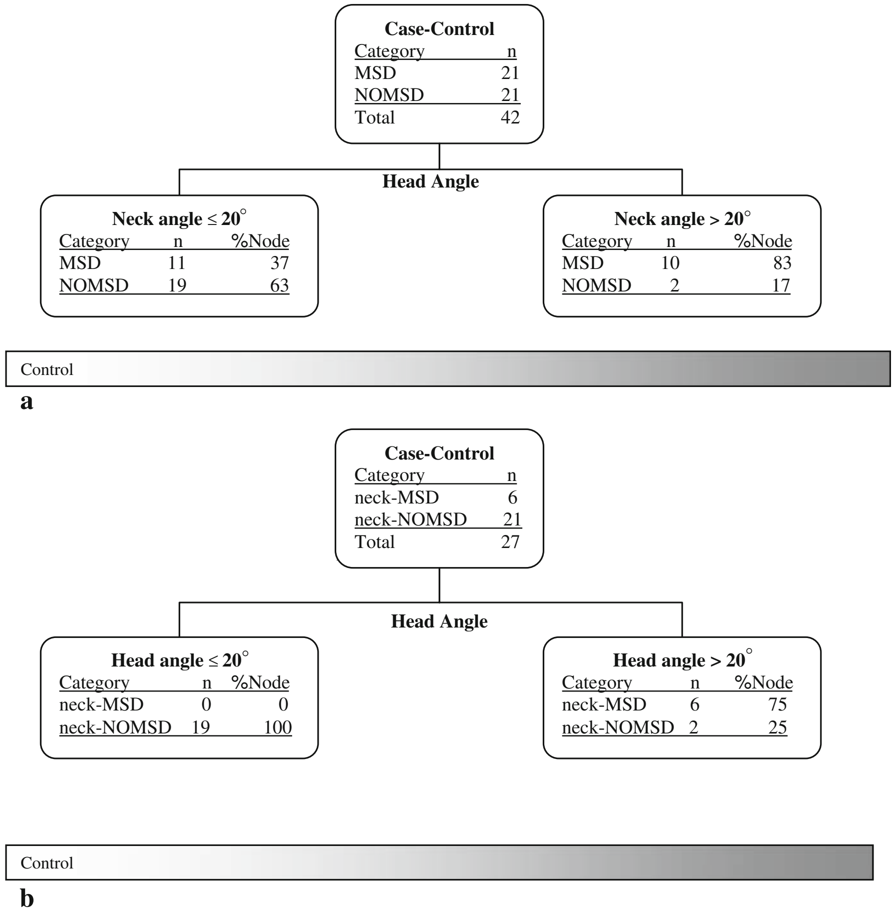

Fig. 1 CART subtree models which discriminate between cases and controls. (**a**) CART subtree model which discriminates between subjects diagnosed with any MSD-UE (MSD) and subjects without any MSD-UE (NOMSD). (**b**) CART subtree model which discriminates between subjects diagnosed with neck-related MSD-UE (neck-MSD) and subjects without any MSD-UE (neck-NOMSD)

Table 3 CART tree models: trees sensitivity, specificity, and percent accuracy

	Model	
	Best subtree MSD	Best subtree neck-MSD
Sensitivity	0.48	1.00
Specificity	0.90	0.90
Percent accuracy	69%	93%

Tree Model for MSD by body part

Neck MSD—Six subjects had a diagnosis related to neck-MSD. Only one tree was generated for this CART analysis; this tree contained the same neck flexion angle item as for the overall MSD model (Fig. 1b). This model had perfect sensitivity (1.00) and excellent specificity (0.90) (Table 3). All neck-MSD had a neck flexion angle of greater than 20°, and 90% of neck-NOMSD had a neck flexion angle 20° or less.

Arm and Wrist/hand MSD Trees—Seven subjects had a diagnosis related to arm-MSD and 15 subjects had a diagnosis related wrist/hand-MSD. Although CART analyses were able to develop several trees for each of these outcomes, no tree had a low "true" error rate on cross-validation, suggesting that the trees were sample specific. We therefore do not report the results.

Discussion

The CART analyses suggest that items on the K-PeCS can distinguish between those with and without MSD-UE. Despite the very small sample size, the best MSD model (accuracy = 69%) and the best neck-MSD model (accuracy = 93%) demonstrated good predictive ability. A neck flexion angle of 20° or less was a very specific predictor of subjects who did not have MSD-UE in the overall tree, and an even stronger predictor of subjects with and without neck-MSD. Although the ability of neck flexion to discriminate between those with and without neck-MSD does not indicate this criterion is a causal factor for developing MSD-UE, indeed subjects could have adapted their neck postures after they developed MSD-UE, there is evidence in the literature to support that this may be a risk factor for MSD-UE. Neck flexion greater than 20° has been reported in several studies as a significant risk factor for neck disorders [6, 39, 40]. Researchers hypothesize that neck flexion can cause static muscle contractions of the cervical extensor muscles, that can, over time, lead to neck-MSD [41–43]. Additionally, some animal evidence suggests that maintaining a constant low level stretch of the muscles of the neck can modulate the nocioceptive responses so that a muscle is more susceptible to damage or pain [44].

That CART could develop reasonably accurate predictive models with such a small sample of subjects suggests that the K-PeCS instrument with a larger sample will be able to develop a better model. We completed several exploratory analyses in which subtree models were developed which incorporated several K-PeCS items. Although these tree models demonstrated a relationship with MSD-UE, they did not add to the accuracy of the models discussed in this study, probably due to the small sample size. With a larger sample we anticipate that further models could be developed to identify those with and without MSD-UE with greater accuracy. Models for the body parts designated "arm" and "wrist/hand" were not significant in this analysis, potentially due to the small sample size, and the heterogeneous diagnoses, such as carpal tunnel syndrome and trigger finger for the wrist/hand. Particular diagnoses may be needed when evaluating the risk factors for MSD-UE rather than relying on the area of the body in which the diagnoses exist.

This study has several limitations. The subjects were aware that their typing would be analyzed and this may have affected their posture during the task. The effect of this change would probably have been to reduce abnormal postures, as subjects would have positioned themselves in the "best" posture. Reduced abnormal postures would tend to reduce the sensitivity of the K-PeCS analysis, thus reducing the chances of discriminating between cases and controls. We attempted to reduce the effect of this knowledge by having subjects type for 10-min and then using only the last minute of video for analysis. We hoped that subjects would settle into their typical typing style after having typed for that period of time. Another limitation is that subjects were typing from a standardized paragraph. Having the subjects perform more routine tasks over a longer period might have allowed them to demonstrate more typical postures. Finally, the small sample size, particularly for the neck model, limits the applicability of these results to the general population. Although the models had good rates of "true" error on cross validation, they may still represent a sample specific result. Additional models using a larger sample should be developed to see if the results of this study replicate.

The K-PeCS is the first observational instrument that can be used by personnel quickly and easily at the work-site. Even with the very small, heterogeneous sample the model developed from the K-PeCS item neck flexion proved to have excellent discriminate ability. This research suggests that the K-PeCS could eventually be used in prospective studies to develop a predictive model which could identify those individuals with keyboarding styles that put them at risk for MSD-UE. While this study cannot identify which behaviors actually place people at risk for MSD-E, it does provide insight into behaviors that are associated with MSD-UE. With additional study the K-PeCS should be a useful tool to identify the behaviors associated with the development of MSD-UE. Once these behaviors have been identified they can be addressed through equipment set-up and training. With further study, this instrument can be refined to identify the items that are the greatest risk factors, so that personnel can intervene more efficiently and effectively.

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