Computer Use Exposed

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Chapter 1

General Introduction

The pervasiveness of computer use

Increase in computer use

Ever since the introduction of the personal computer, our daily lives are influenced more and more by computers. A day in the life of a PhD-student illustrates this:

"At the breakfast table, I check my e-mail to see if the meeting later that day has been confirmed, and I check the time table of the train to Rotterdam. In the train, I might check the latest news on my mobile phone with internet access and from the moment I enter the office to the moment I leave, 95% of the work I perform involves computer work. I spend my day reading and writing articles, searching information online, keeping in contact with fellow researchers and performing data analyses. At the end of the afternoon, I check the computer data files from study participants that have automatically been sent to us by means of the university network. Back home, I buy tickets for a music festival online, and stream the TV program I missed the night before from my laptop to the television. While I'm lying in bed, I just send a quick message to a friend on MSN with my laptop, and with that, another computer-filled day has ended."

The rise of IT (information technology, which refers both to devices that have digital technology built in and to software that is implemented in those devices) has led to a massive change in the working process and working conditions since the 1960's. This impact has only been matched by the first and second industrial revolutions (Fourth European Working Conditions Survey 2005). A large IT research company stated that during the summer of 2008, the number of personal computers in use had surpassed 1 billion units, with the expectancy of another billion unit increase already in 2014 (Gartner 2008).

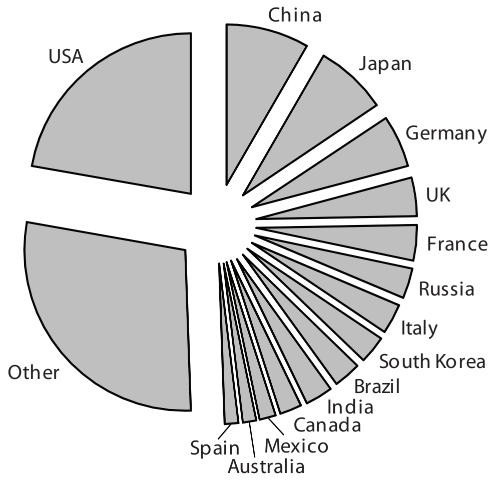

Figure 1.1: Top 15 countries of PCs in use in 2008 (Source: Computer Industry Almanac, www.c-i-a.com)

Differences between countries

In 2003, 56% of all American employees used a computer at work (Hipple and Kosanovich 2003). In 1990, around 13% of workers across Europe worked with computers (nearly) all the time, and this number even increased to 26% in 2005. In Figure 1.1, the 15 countries are shown with the highest number of PCs in use in 2008. Not surprisingly, the USA tops the list with a market share of 22%, which is more than twice as high as China (8%). The USA has led the ranks since the start of the survey in 1993, while China didn't appear in the top-15 until 2000. The Netherlands were initially in the list, but disappeared from the top-15 in 2005.

Relationship with complaints of the upper extremity

Epidemiological evidence has shown that computer-based work is an important risk factor for the development of upper body musculoskeletal symptoms and disorders (Griffiths et al. 2007, Village et al. 2006). A range of different terms, like repetitive strain injury (RSI), cumulative trauma disorder (CTD), complaints of arm, neck and/or shoulder (CANS) and musculoskeletal complaints (MSC) is used to describe these symptoms and disorders. In this dissertation, the term CANS will be used (Huisstede 2007), which is defined as 'musculoskeletal complaints of arm, neck and/or shoulder not caused by acute trauma or by any systemic disease' (Huisstede et al. 2007). Some of the related complaints include pain, stiffness, tingling or loss of strength or coordination, all of which can occur in the neck, shoulders, arms, wrists and hands (Health Council of the Netherlands 2000).

CANS are divided in specific and non-specific conditions. There are 23 specific forms of CANS, including carpal tunnel syndrome, lateral epicondylitis and rotator cuff tears (Huisstede et al. 2007). However, 73 to 87% of all musculoskeletal complaints cannot be diagnosed as one of these specific disorders, in which case the complaints are called non-specific. In this dissertation, we will only focus on non-specific CANS, which affects many people. Surprisingly, the underlying mechanisms are still poorly understood, despite a large amount of research (Burdorf and van der Beek 1999a, Visser and van Dieën 2006). Factors of physical, psychosocial and individual origin are thought to be involved in the onset of CANS, which indicates that CANS have a multi-factorial origin (Health Council of the Netherlands 2000, Staal et al. 2007). The occurrence of CANS is high, although it has remained stable over the past years (in 2000 as well as in 2007, 27% of the Dutch working population experienced CANS (Heinrich and Blatter 2005, Arbobalans 2007–2008). Episodes of CANS may be difficult to capture, since the course of CANS demonstrates a highly dynamic pattern with a high recurrence rate (Luime et al. 2005). This means that complaints may flare up or disappear within relatively short periods of time. Furthermore, CANS may require a certain induction time of exposure and a latency time before the onset of symptoms (Hakkanen et al. 2001), thus making it difficult to choose an appropriate monitoring period.

Although CANS does not only occur in professions with intensive computer use, computer work is performed by a large percentage of the total work force, and the number of employees working most of their working hours with a computer is high and still increasing (Heinrich and Blatter 2005). Therefore, the focus of this dissertation will be on office workers in the administrative sector.

The relationship between computer use and CANS has been much debated over the years. Much attention is given to which aspects of computer use might pose a threat, how to alleviate risks and which interventions are most effective in primary and secondary prevention of CANS. The biomechanical risk factors related to computer work have been well established and include prolonged periods of low-intensity work with sustained static muscle activity in the neck, shoulder and arm (Griffiths et al. 2007, IJmker et al. 2007). Furthermore, repetitive movements of the fingers and wrists when operating a keyboard or mouse, as well as high precision demands in work tasks have been suggested as computer-related risk factors (Bernard and Fine 1997, Health Council of the Netherlands 2000, Huysmans 2008, Visser and van Dieën 2006). Besides physical risk factors, psychosocial and individual risk factors have been found to be related to CANS as well, such as stress, high job demands, low job satisfaction, low task variation, non-work-related stress, female gender and higher age (Bongers et al. 2002, van den Heuvel et al. 2006, Gerr et al. 2002).

However, only few longitudinal field studies have been performed in computer users, meaning that the current knowledge of risk factors for CANS relies mainly on laboratory studies and cross-sectional field studies (IJmker et al. 2007). The main disadvantage of cross-sectional studies is that it is unknown if risk factors cause CANS, or that people with CANS sybsequently alter their behaviour in order to avoid pain or discomfort. Furthermore, laboratory studies have the advantage of a high level of control over the experimental conditions and the surroundings, but they usually have a limited amount of participants and measurements and they may involve exposure to risk that is not representative of typical exposure in workplaces. For example, lab tasks may have a simplified set-up, making extrapolation to the complex workplace setting unvalid (e.g. in lab studies, participants are often restricted in the allowed tasks or postures).

Scientists agree that the description of exposure variables should include the three principle dimensions that express exposure: (1) the exposure level, (2) the temporal pattern of exposure delivery (for instance repetitiveness) and (3) exposure duration (Winkel and Westgaard 1992). However, epidemiologic studies on computer use tend to focus on only one dimension, that is: exposure duration (review: IJmker et al. 2007). Moreover, postures, loads and their time aspects are, in general, superficially described in the investigated job (Mathiassen 2006). Finally, many sources of exposure variability exist in occupational work tasks; variability associated with the performance of each specific task in the job (within-task variability), variability due to different tasks having different exposure profiles (between-task variability) and variability caused by differences in exposure between people (between-subject variability or between groups of people (Loomis and Kromhout 2004). As an example, Figure 1.2 shows different sources of variability for the proportion of keyboard use in total computer use for four office workers. Different professions include different intensities of keyboard use, but for some job functions, between-day variability in proportion of keyboard use is higher than for other functions. Information on the level of variability of physical exposure has so far been scarce in occupational epidemiologic studies on computer use (Mathiassen 2006), while at the same time, little is known on how these sources of variability influence exposure measurements (Loomis and Kromhout 2004).

In conclusion, information on the appropriate methods and measures of quantifying physical exposure during computer use is lacking from the present literature. As a consequence, a gap exists in the knowledge on which exposure variables might play a role in CANS.

The aim of the current dissertation is to describe patterns of computer use and provide suggestions how these patterns might be related to CANS (complaints of the arm, neck and/or shoulder).

In this dissertation, analyses and results are presented from a longitudinal study on 571 office workers from the Erasmus MC in Rotterdam, the Netherlands. We studied patterns of computer use by following participants for two years and monitoring them by means of registration software and questionnaires. With custom-built registration software that registered mouse and keyboard use with high temporal resolution (10 Hz) we were able to unobtrusively capture natural computer use of office workers for an extended period of time. Furthermore, in a subgroup of the total research population, we were able to measure (variability in) muscle activity during natural office work for a whole working day.

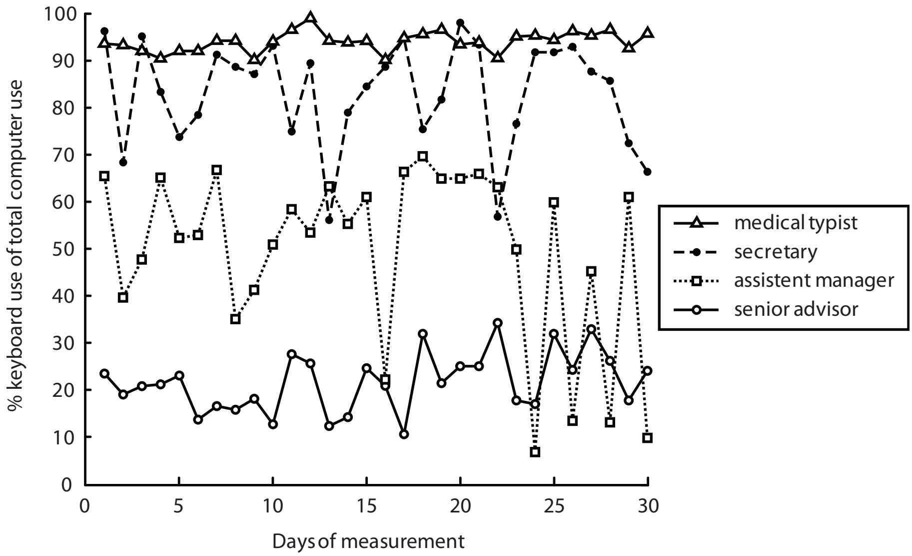

Figure 1.2: Different sources of exposure variability in office workers on consecutive work days.

Registration software as exposure measurement technique

Since about a decade, there has been incredible progress in computer processing speed, working capacity and reliability. Thanks to this improvement, the computer itself has transformed into a powerful measuring and recording tool for ergonomics-related studies (Chang et al. 2004). For these reasons, epidemiologic studies are increasingly using registration software to quantify exposure during computer use. This gives researchers a chance to quantify computer use patterns, since registration software has made it possible to collect data across a large number of computer users over an extensive period of time (e.g. Andersen et al. 2008, Chang et al. 2007, IJmker et al. 2006). Moreover, registration software runs in the background, and is therefore unlikely to influence participants' natural computer behaviour. Registration software measures input device use, such as keyboard strokes, mouse clicks, mouse movements and mouse scroll wheel use. However, although registration software gives an objective measure for input device use, software cannot tell anything about what the person was doing in the time between the moments the input devices were used, like sitting behind the screen (and looking) and other close to 'computer use'-related behaviour.

Because registration software logs input device use by registering single events (a click, a key stroke, a change in cursor coordinates), which do not have a particular duration themselves, it is impossible to calculate total computer use duration. For this reason, a non-computer threshold (NCT) is commonly used to estimate computer use duration, which tells how far two computer events can be separated in time, while the time between is still classified as uninterrupted computer use (from here on referred to as an episode of CW (computer work)). The time in between events that exceeds the NCT is called non-computer work (NCW). Figure 1.3 shows how episodes of CW and NCW are classified with this method and that the total duration of computer use (the sum of all episodes of CW) depends on the choice of the NCT.

A few validation studies combined computer use duration from registration software with duration from observation and found that using a NCT of 20 to 30 seconds showed reasonable correspondence in work duration (Heinrich et al. 2004, Homan and Armstrong 2003). However, this only indicates that the total sum of all CW episodes in registration software is equal to that of observation data, but gives no information on the computer use pattern throughout the day. Moreover, these studies only used a limited number of computer users, so which NCT is best used to describe exposure is still unknown. In the studies mentioned above, no differences in user groups were made, while differences in exposure could lead to exposure measurement error and group misclassification (Loomis and Kromhout 2004). The research questions that will be answered in Chapter 2 are: *"What is the relationship between the non-computer threshold (NCT) used and the duration of computer use? Is this relationship different for different groups of computer users?"*

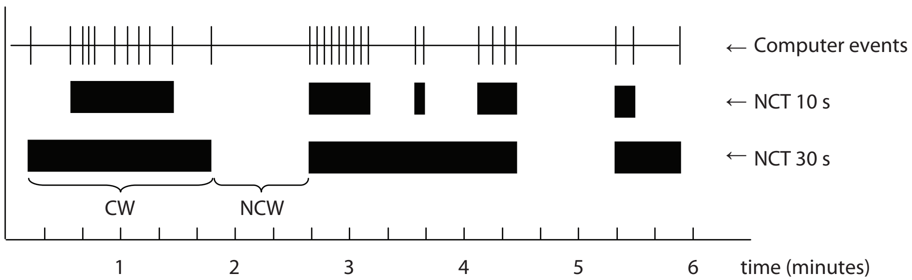

Figure 1.3: Timeline of single, discrete computer events (top line), and the resulting episodes of computer work (CW) and non-computer work (NCW) using non-computer work thresholds (NCT) of 10 s and 30 s.

Other methods for exposure assessment during computer work

Before the introduction of registration software, ergonomists mostly used (video) observation and questionnaires to assess exposure during computer use (for an overview, see Homan and Armstrong 2003). Self-reported questionnaires are easy and cheap to use in large populations, but the validity and accuracy for estimating physical exposure at work has been questioned (Burdorf and van der Beek 1999b, David 2005, IJmker et al. 2007, Stock et al. 2005). For example, studies comparing work duration estimated by self-administered questionnaires with work duration measured by external observers show that participants tend to overestimate the time they work with the computer (Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Lassen et al. 2005, Van der Beek and Frings-Dresen 1998). Furthermore, exposure assessment by means of (video) observation is prone to within- and between-observer variability (David 2005).

Measurements can be influenced by two types of measurement error: systematic error and random error. Systematic errors lead to results or readings which are consistently too high or too low, and are caused by a bias of a measurement system or estimate method. On the other hand, random errors are random fluctuations or measurement errors that are scattered around the true value. Random errors are reduced when an experiment is repeated, whereas the level of systematic error will remain constant. Therefore, in order to assess the presence of systematic bias, repeated measurements have to be conducted, and to our knowledge, no cross-validation studies have done this so far.

Some factors have been suggested to introduce systematic bias in self-reported computer use duration. In a validity study, males had lower overestimation than females (Mikkelsen et al. 2007), although other studies failed to find gender-based systematic bias (Balogh et al. 2004, Douwes et al. 2007, Hansson et al. 2001). Increased age resulted in better agreement between self-reported and observed or registered duration (Faucett and Rempel 1996, Mikkelsen et al. 2007), and higher psychosocial work load increased the level of self-reported duration (Faucett and Rempel 1996, Mikkelsen et al. 2007). However, since these factors only explained a small proportion of the overestimation (5–10%), the causes of self-reported overestimation are still far from understood.

Further understanding of the causes of overestimation is of great importance since self-reported duration seems to be related to the occurrence of upper extremity complaints (Andersen et al. 2008, Chang et al. 2007, IJmker 2008, Village et al. 2006) while this relationship with registered computer use duration seems to be smaller or even absent (IJmker 2008). Exposure during computer work thus seems to depend on the methods that are used.

The differences between self-reported and registered computer use duration will be discussed in Chapter 3, as well as the factors that might explain this difference, addressing the following research question: *"What personal or psychosocial factors influence the level of bias associated with self-reported computer use duration?"*

Interventions for CANS in computer workers

As described earlier, sustained muscle activation with little exposure variation and repetitive elements that characterizes computer use has been found to be related to CANS (see Table 1 and Flodgren et al. 2007, Jensen 2003, Tittiranonda et al. 1999, van Rijn et al. 2009). Because of this, interventions that try to increase exposure variation by introducing more rest breaks in office work are believed to be widely effective (e.g. Balci and Aghazadeh 2003, Galinsky et al. 2007, McLean et al. 2001, van den Heuvel et al. 2003).

However, three recent reviews concluded that there is limited evidence for a positive effect of more rest breaks in both primary (Brewer et al. 2006) and secondary prevention of CANS (Mathiassen 2006, Verhagen et al. 2007). One of the reasons for this lack of evidence might be that the biomechanical exposure during breaks does not differ to a substantial extent from exposure during computer work, at least not in terms of mean exposure (Arvidsson et al. 2006, Blangsted et al. 2004, Fernstrom and Åborg 1999).

In recent years, several methods have been developed to adjust break schedules to the actual work load, taking the breaks that users naturally take into account. In particular, computer work can be regulated by pause software (of which Workpace is one of the largest in the Netherlands), which can administer additional pauses depending on the actual computer use of an individual user. Pause software developers claim that their software reduces the risk of developing complaints of the upper extremity (e.g. SmartErgo 2009). No research has yet been published on how the offered pause regimes alter the total number of pauses that computer workers take spontaneously, and thus on how and to what extent pause software alters the work-pause pattern of computer users. We will discuss these issues in Chapter 4, by asking: *"What are the natural pause patterns that computer users display and how does pause software influence the work-pause pattern?"*

Physical exposure and exposure variability during computer work

Although the pathophysiological mechanisms underlying the occurrence of CANS are still unclear, several hypotheses have been put forth in recent years (e.g. (Hägg 1991, Van Galen 2001). One of the latest and leading aetiological models of CANS integrates several of these hypotheses and explores how they interact with each other. This model takes into account that the mechanisms of the different hypotheses may work at different times in the disease process (the 'Brussels Model', Johansson 2003). According to the model, continuous long-duration low-intensity work may lead to an accumulation in the muscles of metabolites and inflammatory substances like lactic acid and potassium ions. This accumulation has two consequences: on the one hand, the activity of afferent fibres from muscle spindles (which are essential for the position and movement awareness of the limbs) is increased, causing a disturbed proprioception and thus a disturbed motor control which leads to a further accumulation of inflammatory substances. On the other hand, the accumulation of metabolites can lead to increased vasoconstriction caused by increased activity of sympathetic neurons. Vasoconstriction can hinder the removal of accumulated inflammatory substances and thus increases the build-up. These two vicious cycles can ultimately lead to excessive muscle load and pain if maintained for a long period of time (Crenshaw et al. 2006, Flodgren et al. 2007, Johansson 2003). It seems likely that low variability in biomechanical exposure can lead to an accumulation of metabolites and through activation of the described feedback mechanisms could eventually lead to musculoskeletal complaints.

A solution to increase this exposure variability is often sought in adding alternative tasks or additional pauses, but so far, it is unknown whether non-computer activities can really offer a source of increased variation in computer-intensive work. Most of the studies that estimated physical exposure during computer work have used self-reports or observational techniques (Brandt et al. 2004, Juul-Kristensen et al. 2004, Lassen et al. 2004, van den Heuvel et al. 2006), while people's perception of exposure has been found to be imprecise and unreliable, and observational methods lack measurement precision (David 2005, Li and Buckle 1999).

Measuring physical exposure by direct methods involves sensors that are attached directly to the participant, measuring variables such as muscle activity or fatigue, force, position, velocity and acceleration (David 2005). Until recently, sensor systems were so large or energy-demanding that experiments had to be done in a laboratory setting, inhibiting natural, spontaneous computer work and computer behaviour. Some studies have recently begun to measure physical exposure with mobile devices (Arvidsson et al. 2006, Fernstrom and Åborg 1999, Nordander et al. 2000), but information on how registration software is able to help in estimating natural muscle activity patterns in individual office workers is still lacking. In Chapter 5, an experiment is described in which natural computer use during office work is measured, combined with a small mobile device measuring physical exposure by means of EMG (electromyography). In this chapter, we will focus on the following research questions: *"What are the differences in exposure between computer and non-computer use and how do these differences contribute to overall exposure levels and variability?"*

Mouse use kinematics

The duration of computer use, as a measure of cumulative exposure, has received much attention in the ergonomic research field. However, much less emphasis has been given to the characteristics of keyboard and mouse use separately. Compared with keyboard use, mouse use requires more complex eye-hand coordination (Sandfeld and Jensen 2005) and is hypothesized to involve less exposure variability, more repetitive movements and more constrained postures than keyboard use (Dennerlein and Johnson 2006, Lee et al. 2007). In a recent review, IJmker and colleagues found moderate evidence for a positive association between the duration of mouse use and hand-arm symptoms (IJmker et al. 2007), while for keyboard use, such a conclusion could not be drawn. In the past years, researchers have started to focus on mouse use behaviour by performing tasks in the lab (e.g. Huysmans et al. 2008, Visser et al. 2004). These studies suggest that the high level of precision during mouse use might be associated with changes in limb stiffness (through increased co-contraction), which could, through various pathways, lead to the development of CANS.

However, whether mouse movements from laboratory conditions can be extrapolated to real-life computer work remains to be seen. Hardly any information is available on mouse movements in everyday, natural computer work, not even simple demographics such as how many mouse movements office workers make, how large these movements are and in which directions they occur. In Chapter 6, we will analyse mouse movements and kinematics of hand movements, and answer the questions: *"What are the characteristics of mouse movements during daily computer use and how can these patterns be explained?"*

Outline of the thesis

In this dissertation, a description is given of patterns of natural computer use and physical exposure during computer use.

Chapter 2 focuses on the methodological aspects of measuring computer use by registration software. In this chapter, an analysis is presented on how computer use duration is influenced by choosing a temporal threshold value for classifying non-computer use.

Computer use duration can be measured by other methods as well. In Chapter 3, two methods for estimating computer use duration are compared; self-reports and registration software. In this chapter, the influence of different personal and psychosocial factors on the level of error and bias associated with self-reported computer use duration is assessed.

Registration software is often used in combination with pause software, which introduces additional computer pauses and is used as an intervention against CANS. In Chapter 4, the natural work-pause pattern of office workers is examined. Furthermore, the influence of commercially available pause software on the work-pause pattern is analysed by means of data simulation.

Even though the insertion of pauses is considered a way to increase exposure variability in office work, a thorough description of exposure and exposure variability during computer work and non-computer work is still lacking. Therefore, Chapter 5 examines the physical exposure variability in office workers by analysing arm and shoulder muscle activity in computer tasks and in non-computer tasks and comparing these tasks.

Mouse use appears to pose a larger risk for CANS than keyboard use, but only scarce information is available on mouse movements in everyday computer use. In Chapter 6, computer mouse movements are described to gain insight into kinematics of natural hand and arm movements. The movement amplitude, direction, velocity are quantified, and a hypothesis is proposed to explain the curvature of computer mouse movements.

Finally, in Chapter 7, the five research questions that are answered in the Chapters 2 through 6 are summarized and discussed. In addition, practical implications of the dissertation and recommendations for further research are presented . Finally, the question whether registration software should be used to assess physical exposure during office work is answered.

Articles described in this thesis

- Chapter 2: Richter JM, Slijper HP, Over EAB, Frens MA. Computer work duration and its dependence on the used pause definition. Applied Ergonomics 2008; 39 (6): 772–8.
- Chapter 3: Richter JM, Burdorf A, Slijper HP, Frens MA. Determinants of systematic bias in self-reported computer use duration. In preparation.
- Chapter 4: Slijper HP, Richter JM, Smeets JBJ, Frens MA. The effects of pause software on the temporal characteristics of computer use. Ergonomics 2007; 50 (2): 178–91.
- Chapter 5: Richter JM, Mathiassen SE, Slijper HP, Over EAB, Frens MA. Differences in muscle load between computer and non-computer work among office workers. Ergonomics 2009. In press.
- Chapter 6: Slijper HP, Richter JM, Over EAB, Smeets JBJ, Frens MA. Statistics predict kinematics of hand movements during everyday activity. Journal of Motor Behavior 2009; 41 (1): 3–9.

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Chapter 2

Computer work duration and its dependence on the used non-computer threshold

J.M. Richter, H.P. Slijper, E.A.B. Over, M.A. Frens

Adapted from:

Richter JM, Slijper HP, Over EAB, Frens MA.

Computer work duration and its dependence on the used pause definition.

Applied Ergonomics 2008; 39 (6): 772–8.

Abstract

Several ergonomic studies have estimated computer work duration using registration software. In these studies an arbitrary non-computer threshold (NCT; the minimal time between two computer events to constitute a pause) is chosen and the resulting duration of computer work is estimated. In order to uncover the relationship between the used non-computer threshold and the computer work duration (PWT) we used registration software to record usage patterns of 571 computer users across almost 60.000 working days. For a large range of NCTs (1–120 s) we found a shallow, log-linear relationship between PWT and NCTs. For keyboard and mouse use, a second order function fitted the data best. We found that these relationships were dependent on the amount of computer work and subject characteristics. Comparison of exposure duration from studies using different non-computer thresholds should take this into account, since it could lead to misclassification. Software manufacturers and ergonomists assessing computer work duration could use the found relationships for software design and study comparison.

Introduction

Several studies have been shown a relation between musculoskeletal complaints of arm, neck and/or shoulder (i.e. CANS) and the duration of computer work (see recent reviews, e.g. IJmker et al. 2007, Village et al. 2006). From these reviews, a good indication for a dose-response relationship was found between mouse use and the incidence of CANS (odds ratios (OR's) mostly >2 to 7.3), while the evidence for a similar relationship between the hours of keyboard use and the incidence of CANS was weaker (OR's from 1.2 to 2.9). All the studies included in the reviews used questionnaires to estimate the time spent working with the computer. Other methods commonly used by ergonomic researchers are (video-based) observation and registration software, of which the latter one gained popularity this decade (for an overview see David 2005, Homan and Armstrong 2003).

From studies combining work durations estimated by self-administered questionnaires with external observers, it is known that participants tend to overestimate the time they work with the computer (Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Lassen et al. 2005, Van der Beek and Frings-Dresen 1998). Some studies have therefore investigated whether work duration as measured by monitor software corresponds to duration measured by external observers (Heinrich et al. 2004, Homan and Armstrong 2003). Results indicate that when pauses shorter than 20 to 30 seconds of the recorded time traces are not included, work times as measured through software are in reasonable correspondence with the work times reported by observers. Nonetheless, the criterion of whether a gap in computer input is of sufficient duration to constitute a pause (*non-computer threshold*) is arbitrary (Slijper et al. 2007). So far, most studies have used a non-computer threshold of 30 seconds for determining the duration of all computer use, and a different non-computer threshold (5 seconds) for assessing keyboard use and mouse use separately (Blangsted et al. 2004a, Douwes et al. 2003, Douwes et al. 2005, Heinrich et al. 2004, Homan and Armstrong 2003, Lassen et al. 2005). However, others used non-computer thresholds of 60 seconds for all computer work (Chang et al. 2007) or 2.5 seconds for keyboard use (IJmker et al. 2006). The non-computer threshold that is chosen will influence total computer work duration. However, no research has yet exactly quantified this influence.

The *goal* of this paper is therefore to objectively quantify the relationship between the non-computer threshold used and the resulting computer work duration. Besides total computer use we also investigated whether there were differences in this relationship for mouse and keyboard use separately. It is important to note that although we will compare work duration across different non-computer thresholds, this study is NOT able to provide insight into which non-computer threshold is best used. Cross-validation studies like those by Mikkelsen et al. (2007) or Heinrich et al. (2004) are suited to answer this question.

In the current paper, we investigated whether the relationship between non-computer threshold and computer work duration is modified by factors like the *amount of computer usage* or the *characteristics of the computer users*. If the relationship is indeed different for different user groups, it is possible that when results from different studies are compared, work duration can be over- or underestimated due to the fact that different non-computer thresholds were used. Results of this analysis are thus important for study comparison and the design of future studies.

Methods

Monitor software

We installed custom built registration software on the computers of 571 healthy employees of the academic hospital in Rotterdam, the Netherlands, for a period of 2 years. Participants signed informed consent before entering the study, and were all regular computer users (the inclusion criterion was working with a computer >50% of total contract hours). Before the start of the study participants filled in a small questionnaire in which they were asked about personal characteristics. The participants (mean age: 39.9 ± standard deviation (SD) 10.5 years, 140 males and 431 females) performed a variety of computer intensive work. Participants were divided in four main job functions[1]: 150 participants had an administrative job (26%), 77 participants were researchers (14%), 40 were IT-professionals (7%) and 304 participants had managerial or other job functions (53%). They reported working for 35 (± 8) hours per week on average or, taking the amount of working days into account, 8:06 hours: minutes/day. Of these working hours, they estimated working 5:30 (± 0:41) hours/ day with the computer.

During the time the participants were logged on to their computer, the software registered the position of the cursor (x, y coordinates in pixels) with a frequency of 10 Hz, whenever this position changed. Additional *computer events* that the software recorded were key presses, mouse clicks and mouse wheel use (temporal resolution 0.1 s). The software logged these data in the background in order not to interfere with the regular work of the participants. Data files were collected centrally and processed offline.

1 Job functions: The group with administrative jobs contained professions such as (medical) typists, data-entry employees, and secretaries. The 'research' group consisted of scientific employees, ranging from PhD-students to Professors. 'IT-professional' jobs included IT-specialists, data managers and statistical employees. Managerial and other jobs contained jobs such as (financial) advisors, policy makers and (communication) managers.

Data analysis

Recorded data files were included in the analysis when recorded working days contained 5.000 computer events or more. Using this criterion, we included 59.044 working days in the analyses. From these days we extracted the times at which a computer event was recorded. The work time (WT) was defined as the time from the first to the last recorded computer event on a working day. For all recorded days the file sizes were saved, reflecting the total number of events (E_{tot}) generated through input devices, making it a good indicator of the total amount of computer use.

The time series corresponding to computer events were used to calculate the percentage of the day classified as computer work (PWT, the percentage computer work of the WT) for a wide range of *non-computer thresholds* (NCT: 1, 2, 4, 8, 12, 16, 20, 25, 30, 35, 40, 45, 50, 55, 60, 70, 80, 90, 100, 110, 120 s). An analysis was performed on three different time series containing all computer events, keyboard events and mouse events, respectively. From these time series, the computer work duration (PWT), keyboard duration (PWT_k) and mouse duration (PWT_m) were calculated for every NCT.

On average we recorded from each subject 103 days (range 1–654 days). To estimate the relationship between NCTs and computer work duration (PWT), keyboard (PWT_k) and mouse duration (PWT_m) we performed a fit between the $\log_{10}$ (hereafter called 'log') of the NCT and PWT. The slope and intercept of a *linear* fit were used to characterize the relationship for PWT. For keyboard (PWT_k) and mouse duration (PWT_m) a quadratic function was used to fit the data. As a measure for the reliability of the relationship between NCT and PWT, PWT_k and PWT_m we calculated the correlation coefficient between the two variables for every day separately.

To quantify whether the variability of PWT was constant for different NCTs we calculated the standard deviation and coefficient of variation (relative error) of PWTs across all participants and days for every NCT.

In order to estimate the effects of the amount of computer work (total number of events: E_{tot}) and subject characteristics (age, main job function and gender) we performed four repeated measures ANCOVAs on the PWT values of individual days. The dependent variable was the PWT value for every subject averaged across all days. For each analysis, the variable of interest was entered in the model as a between groups factor while the other factors were entered as covariates. The following categories were used for age: 18–30, 31–40, 41–50, >50 years and for job function: administrative, research, IT-professional and managerial/other. For E_{tot} we divided all files into four equal quartiles (p0–p25, p26–p50, p51–p75, p76–p100) corresponding to an average number of 14000, 28000, 42000 and 67000 computer events per data file. In the analyses we focused on both the interaction between NCT and the between-groups factor and the main effect of the between-groups factor. While the interaction effect denotes differences in the slope of the relationship between NCT and PWT between subgroups, the main effect describes differences in intercept. Additionally, post-hoc analyses with Bonferroni corrections were performed (alpha = 0.05).

Results

Relationship between non-computer threshold and computer work duration

Inspection of data from individual days showed monotonically increasing values of computer work duration (PWT) with the log of the non-computer threshold (NCT) (see for example Figure 2.1). The correlation coefficients of the two

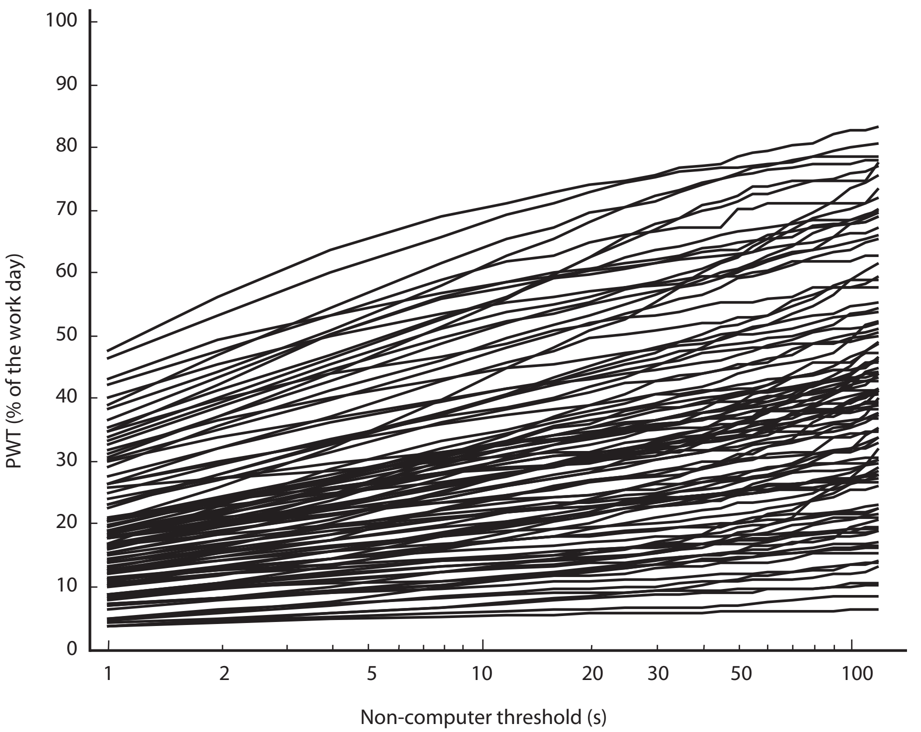

Figure 2.1: Hundred randomly selected working days from our dataset of almost 60.000 days. Shown is the relationship between the 21 non-computer thresholds (1–120 s) and the percentage of computer work time (PWT). For each day, the 21 data points are connected through a line. Note the monotonic increase in PWT with an increase of the log_{10} of the non-computer threshold.

variables for each subject-day separately were generally very high (mean r: 0.984 (SD 0.018)). We found variability across participants especially with regard to the intercept of the relationship.

When we pooled all data together, we found a near linear relationship between log of NCT and PWT. Figure 2.2 shows the mean data points for each NCT. The fit of the log of the NCTs versus the PWT is plotted as a straight line (top line).

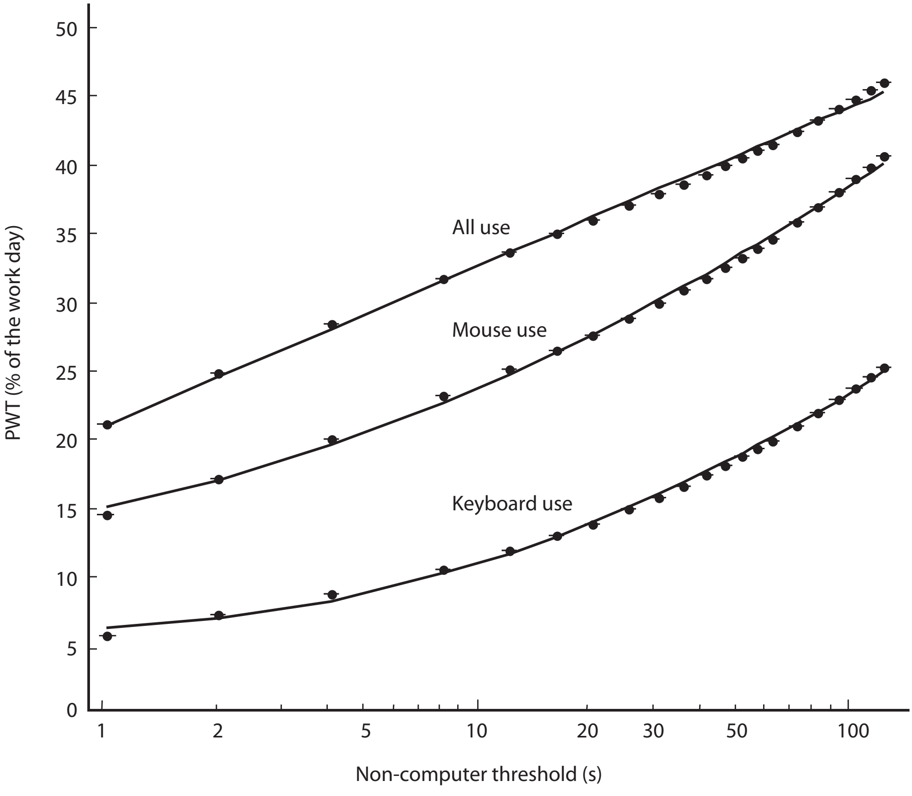

Figure 2.2: The relationship between PWT and the $\log_{10}$ of the non-computer thresholds for all computer use (top line), mouse use (middle line) and keyboard use (bottom line). Shown data are values averaged over all days and participants. The mean data points, as well as fits through the data are shown. For all computer use a linear fit was used, and for mouse and keyboard use a quadratic function. Note that mouse and keyboard durations do not add up to overall computer usage duration due to overlap of the activities in the underlying time series.

The mean fit of the data was described by the following equation:

$$PWT_k = 11.64 * \log(NCT) + 21.06$$

Equation 2.1a

For the range of NCTs that were calculated (1 to 120 seconds), the mean PWT varied from 21.15 to 46.04% of the total work time. In order to assess what *changes* in NCT lead to corresponding changes in PWT, Equation 2.1a was rewritten. Based on the original NCT used (NCT_{old}) and corresponding PWT (PWT_{old}), a new PWT (PWT_{new}) corresponding to a different NCT (NCT_{new}) can be calculated as follows:

$$PWT_{new} = PWT_{old} + 11.64 * \log\left(\frac{NCT_{new}}{NCT_{old}}\right)$$

Equation 2.1b

According to Equation 2.1b, a doubling of the non-computer threshold results in a 3.5% increase in computer use duration for the studied non-computer thresholds. The variability of PWT across days was different for different NCTs. Standard deviation of PWT increased from 10.5% (at NCT 1 s) to 18.5% (at NCT 120). Coefficient of variation showed however an opposite relationship. CV values decreased from 0.5 to 0.4 with increasing NCT, indicating the declining relative variability across days with increasing NCT.

Keyboard and mouse duration

Based on the same dataset, the percentage work time that the participants spent using their keyboard (PWT_k) or mouse (PWT_m) was calculated for the same range of NCTs. Figure 2.2 (two bottom lines) shows both variables as a function of the non-computer threshold. Note that work durations for keyboard and mouse use separately do not add up to yield overall computer use duration, due to overlap in the activities. This will be further explained in the Discussion.

Like for total computer use, correlations between the log of NCTs and keyboard or mouse duration were high for individual days (mean r keyboard: 0.953 (SD 0.040), mean r mouse: 0.973 (SD 0.028)). We found that the relationships between log(NCT) and PWT_k and PWT_m were not linear and therefore introduced a quadratic term while fitting the data. Note that the two bottom curves shown in Figure 2.2 differ substantially in intercept. Less time is thus spent using the keyboard than using the mouse. For keyboard use, the following equation was best fitted through the data points:

$$PWT_k = 6.37 + 0.68 * \log(NCT_k) + 3.96 * (\log(NCT_k))^2$$

Equation 2.2a

Depending on the NCT (1–120 seconds), keyboard use constituted 5.81 to 25.33% of WT per day in our dataset. The impact of using different NCTs on the PWT_k was calculated by rewriting Equation 2.2a to:

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$$PWT_{newk} = PWT_{oldk} + 0.68 * \log\left(\frac{NCT_{newk}}{NCT_{oldk}}\right) + 3.96 * (\log(NCT_{newk}))^2 - 3.96(\log(NCT_{oldk}))^2$$

Equation 2.2b

Since a quadratic function was used, the difference in PWT_{newk} when doubling the NCT was not constant for all NCTs, but varied from 0.56% (NCT 1→2 s) to 4.80% (NCT 60→120 s). Similar to keyboard use, a quadratic function of log-transformed non-computer thresholds versus PWT_m yielded a good fit. The corresponding equations for mouse use are as follows:

$$PWT_m = 15.04 + 5.71 * \log(NCT_m) + 3.07 * (\log(NCT_m))^2$$

Equation 2.3a

$$PWT_{newm} = PWT_{oldm} + 5.71 * \log\left(\frac{NCT_{newm}}{NCT_{oldm}}\right) + 3.07 * (\log(NCT_{newm}))^2 - 3.07(\log(NCT_{oldm}))^2$$

Equation 2.3b

From equation 2.3b, it follows that dependent on the NCT (1–120 seconds), a computer working day (WT) consisted of 14.56 to 40.72% mouse use. A doubling of NCT resulted in an increase of 2.00% (NCT 1→2 s) to 5.28% (NCT 60→120 s) of PWT_m.

Factors modifying the relationship between NCT and PWT

In order to investigate whether factors like the amount of work (E_{tot}) or subject characteristics can modify the relationship between NCT and PWT we performed multivariate analysis on subgroups of the dataset. First we looked whether the files with a different number of recorded events (E_{tot}) on a particular day influenced the relationship. We found a high correlation between E_{tot} and the average work duration across all NCTs (r = 0.7122). As is shown in Figure 2.3a, the difference in work duration for different values of E_{tot} is mostly brought about by a vertical

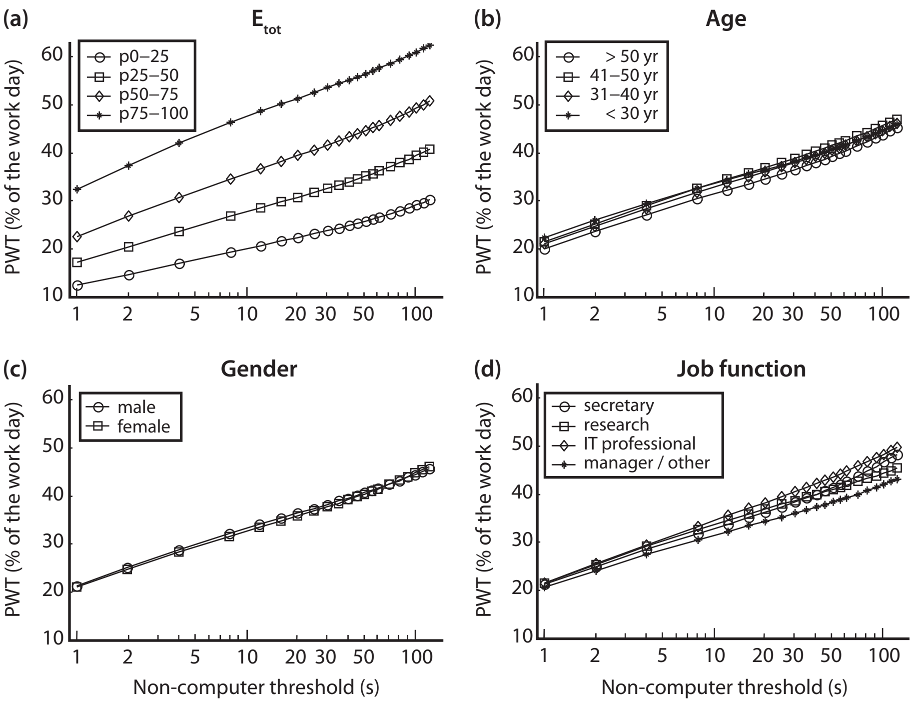

Figure 2.3: The relationship between PWT and NCT for different characteristics of the working day (2.3a) and subject characteristics (2.3b–d). Shown are the adjusted marginal means for each subgroup. 2.3a: PWT-NCT relationship where different lines represent each of the four quartiles of E_{tot} (see Methods) as a measure of overall computer work. 2.3b: Relationship for different age categories (age groups shown in legend). 2.3c: Relationship specified by gender. Note that there are large differences in intercept in the relationship due to differences in the amount of computer use. Note also that the slope of the relationship is not equal for all subject groups. 2.3d: Relationship for different job functions. Main job functions are described in the Methods.

shift of the whole curve (change in intercept). Comparing changes in slopes and intercepts for the lowest and highest quartile of E_{tot} showed that changes in intercept were on average 2.1 times larger than changes in slope. Nonetheless, statistical analysis showed that besides a large main effect of E_{tot} ($F(3,59037)=15764.8$; $P<0.001$) there was a significant interaction between NCT and E_{tot} (Pillai's Trace: $F(60,177060)=381.2$; $P<0.001$). Analysis of the adjusted slopes showed that for small E_{tot} values (p0–p25) the slope of the relationship was more shallow (0.15 %/s) than for large E_{tot} values (p75–p100; 0.24 %/s). This effect can also be seen in Figure 2.1. The values shown in Figure 2.3a–d are the predicted marginal means, in which are adjusted for the effects of covariates (see Methods).

Next, we looked at the effects of the subject characteristics of age, job function and gender on the relationship. Results are shown in Figures 2.3b–d. Significant main effects for all three factors were found (age: $F(3,59037) = 84.7$; $P<0.001$; job function: $F(3,59037) = 316.2$; $P<0.001$; gender: $F(1,59039) = 4.49$; $P<0.04$). Post hoc analyses showed that males and IT-professionals and researchers had slightly higher computer work durations across non-computer thresholds (all differences significant $P<0.001$) (see Figure 2.3). Again, also significant interactions were found between NCT and each of the factors (Pillay's trace: age: $F(60,177060) = 24.6$; $P<0.001$; job function: $F(60,177060) = 152.1$; $P<0.001$; gender: $F(20,59020) = 68.5$; $P<0.001$). Analysis showed that slopes were slightly shallower for younger participants, although this effect was ambiguous for older age categories (Figure 2.3b). Changes in intercepts for age categories were on average 0.45 times larger than the differences in slopes. The significant interaction for gender was due to slightly shallower slope for male users (0.198 vs 0.204 %/s), the two curves therefore merge for higher non-computer thresholds (see the right end of the curves in Figure 2.3c). Similar changes in the relationship were visible for the different job functions (Figure 2.3d), in which the slope of the relationship for researchers and those with managerial or other job functions was shallower (on average: 0.19 %/s) than that of the IT-professionals and secretaries (on average 0.23 %/s).

Discussion

Having measured a large and diverse group of computer users for a long period, we found a robust relationship between the non-computer threshold and the computer work duration. For the range of non-computer thresholds we looked at (covering all realistic non-computer thresholds) doubling the non-computer threshold resulted in an increase of 3.5% in computer work duration. For keyboard and mouse use separately, the resulting work duration was fitted using a second order function, meaning that an increase in non-computer threshold did not result in a constant increase in work duration. However, these differences were never larger than 6% for a doubling of the non-computer threshold.

The intercept of the fitted relationship between the non-computer threshold and the work duration gives a good indication of the amount of computer work that is being performed on a particular day. This was reflected in a high correlation (>0.7) between the intercept and the amount of computer events. The changes in intercept due to differences between subgroups of participants (based on age, job function and gender) were relatively small compared to the changes due to the amount of computer events (compare Figure 2.3a with Figures 2.3b–d).

Based on these data, we can conclude that for the range of non-computer thresholds we looked at, groups of participants shared rather similar work-pause patterns. This is an indication that the relationship between the non-computer threshold and the computer work duration that we found can be generalized to other job functions which consist of frequent computer use and could facilitate study comparison. Moreover, these robust relationships could be used by software manufacturers interested in administering pause regimes (see Slijper et al. 2007) depending on the duration of a work period and a given non-computer threshold . For the ergonomist working in the field it might not always be possible to install registration software. In this case the ergonomist could assess work duration manually with a relative large non-computer threshold (practically, this would be easier to implement) and then use the given equations to extrapolate what the work duration might be using a non-computer threshold of 30 s. It is uncertain whether the found relationships are applicable when NCTs are used that are much larger than the two minutes investigated here, so ergonomists should stay within the studied range.

Keyboard, mouse and total computer use

While the relationship between NCT and PWT was log-linear, such a relationship was not found for mouse (PWT_m) and keyboard (PWT_k) use. Furthermore, for mouse and keyboard use separately we found differences in both the intercept and the curvature of the relationship (see Figure 2.2). The differences in intercept reflect differences in the amount of time spent using the mouse and keyboard, a proportion already reported by other authors (Chang et al. 2007, Heinrich et al. 2004, Mikkelsen et al. 2007). On the other hand, the found curvature is more difficult to explain: when one uses the computer, keyboard and mouse are commonly interchangeably used. That is, episodes of keyboard use are interrupted by mouse usage and vice versa. When calculating either PWT_m or PWT_k continuous episodes of computer use are broken down into separate smaller duration episodes in which only the keyboard or mouse is used. The interruptions in input device activity that are created this way are relatively large, i.e. larger than the times between individual keystrokes or cursor changes. This would favor the occurrence of relatively larger breaks in input device activity over smaller ones. This is corroborated by the relatively shallow slope of the relationship for small NCTs and the steeper slope for larger NCTs (more breaks get now added as work).

A related issue is that adding mouse and keyboard usage does not necessarily yield overall usage duration. For instance, Figure 2.2 shows that for the smallest NCT, adding mouse and keyboard work duration yields a value smaller than the overall computer work duration, while for the highest NCT the added work duration is much larger than the overall usage. How can this pattern be explained? For example, consider using the keyboard for short periods of time, interchanged with mouse use. When calculating keyboard work duration using a NCT shorter than the episodes of mouse duration, all the mouse episodes would not be considered work time. Moreover the time it took to switch from keyboard to mouse use is also not classified as work time. Consequently, for small NCTs the summed work durations of mouse and keyboard use can be smaller than the overall use.

For the same time series, using a NCT that is larger than the episodes of mouse use duration would however consider the whole time between keyboard usage to be classified as work. This is of course also true when calculating the duration of mouse usage; keyboard episodes will also be classified as work. So for larger NCTs the amount of time classified as both keyboard *and* mouse use increases. In other words, when calculating mouse and keyboard use separately the amount of overlap between the two activities increases with larger non-computer thresholds. As a result the summed worked duration ($PWT_m + PWT_k$) can become much larger (up to two times) than overall work duration (PWT). The duration of mouse and keyboard work can thus not be added to get an estimate of overall computer use duration. Studies assessing keyboard and mouse use separately should take this into consideration.

Misclassification of work duration

In the Introduction we asked the question whether the relationship between non-computer threshold and computer work duration was modified by *characteristics of the computer users*. As the results show this is indeed the case. In our statistical model differences due to other factors like the amount of computer use were entered in the model as covariates. The found effects can thus solely be attributed to differences in subject characteristics (age, job function, gender). Differences between groups were mostly reflected in differences in intercept, however significant interactions were found between subject characteristics. These interactions showed that for some subject groups the slope of the relationship was slightly steeper or shallower than for others. It is therefore important to notice that this could lead to misclassification of the exposure level if (in different studies) different non-computer thresholds are used to estimate work duration. For example, looking at Figure 2.3, using a NCT of 8 s researchers and IT-professionals work an equal duration, while using a NCT of 120 s IT-professionals work longer. It is thus important to take this into consideration when comparing results from different studies or when designing a new study. It is fortunate that most studies so far have used similar non-computer thresholds (around 30 s).

In conclusion, the current study has shown a robust log-linear relationship between non-computer threshold and the work duration. Equations 2.1b, 2.2b and 2.3b can be used as benchmarks for comparing work duration estimates in existing studies. Hopefully future studies, using the described equations, will allow for better comparisons of work load between different workers, branches, companies and even countries.

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Chapter 3

Determinants of systematic bias in self-reported computer use duration

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Adapted from:

Richter JM, Burdorf A, Slijper HP, Frens MA.

Determinants of systematic bias in self-reported computer use duration.

In preparation.

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Abstract

Computer use duration as measured by self-reports is different from duration measured by registration software. Since the relationship between computer use duration and CANS (complaints of the arm, neck and/or shoulder) is apparent for self-reported duration but much weaker or even absent for registered duration, this indicates that different duration estimates measure different constructs of physical exposure. In the current study, the influence of personal and psychosocial factors on the level of disagreement between self-reported and registered duration (aRB; absolute relative bias) was assessed. Female gender and higher psychosocial job demands were found to have a higher average aRB, and the influence of these factors on the model indicates the presence of systematic bias. However, these two factors only slightly altered the within- and between-worker variance, which was suggesting a large amount of variability in aRB is present in both factors. This suggests that comparing these two estimates of computer use duration introduce a large amount of random error, which indicates that self-reported and registered computer use duration measure a different construct of computer use duration.

Introduction

Extensive computer work is often associated with complaints of the upper extremity, and is mediated by repetitive motion of the fingers and sustained muscle activation of the arm and shoulder with little exposure variation (Flodgren et al. 2007, Jensen 2003, Tittiranonda et al. 1999). However, assessing the duration of computer use has proven to be a challenge for ergonomists and epidemiologic research. (Video) observation and self-reports are the most widely used methods for assessing computer use duration, but since about a decade, registration software has increasingly been used in ergonomic studies (e.g. Andersen et al. 2008, Chang et al. 2007, IJmker et al. 2006, Richter et al. 2008).

Two recent reviews have found a positive relationship between the duration of computer use and the occurrence of complaints of arm, neck and/or shoulder (CANS) (Wahlström 2005, IJmker et al. 2007). In these reviews, computer use duration was estimated with self-reports or observational techniques. However, the validity of self-reported exposures has recently been found to be low to moderate, which is most likely caused by the lack of specificity in the methods of validity assessment (Barrero et al. 2009, Stock et al. 2005). Moreover, three recent studies measuring computer use duration by registration software did *not* find a positive relationship between computer use duration and the prevalence or incidence of chronic CANS (Andersen et al. 2008, IJmker et al. 2008). The reason for this discrepancy might be that different computer use duration estimates measure different constructs of physical exposure, or the fact that both the outcome measure (CANS) and the risk factors are measured with self-reports (common method bias) (Podsakoff et al. 2003). In order to prevent CANS, it is vital to understand the relationship with different measures of computer use duration.

Most cross-validation studies that have compared self-reports with observation or direct measurements have found that participants tend to *overestimate* the time they work with the computer (Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Lassen et al. 2005, Van der Beek and Frings-Dresen

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1998). This consistent finding indicates the presence of systematic bias, which can be caused by a bias of a measurement system or estimate method and causes results which are consistently too low or too high. One possibility might be the presence of response bias; for example, participants with CANS might feel that the reason for their complaints originates in using the computer, and therefore - unintentionally or intentionally - report working longer with the computer than participants without CANS. Apart from systematic bias, overestimation can also result from random errors, which arise from random fluctuations in the measurements. These errors increase the variance of a variable and therefore decrease the magnitude of correlations with other variables, an effect known as *attenuation of risk* (Armstrong 1998). In order to assess the presence of systematic bias with some level of certainty, repeated measures have to be performed. To our knowledge, no cross-validation studies have done this so far.

Furthermore, other factors seem to influence the level of self-reported measures of computer use exposure. In some validity studies, males had lower overestimation than females (Mikkelsen et al. 2007), although other studies failed to find gender-based systematic bias (Balogh et al. 2004, Douwes et al. 2007, Hansson et al. 2001). Older age has been found to agreement better between self-reported and observed or registered duration than younger age (Faucett and Rempel 1996, Mikkelsen et al. 2007), and higher psychosocial work load increased the level of self-reported duration (Faucett and Rempel 1996, Mikkelsen et al. 2007). However, since these factors did not explain a large proportion of the overestimation (5–10%), the (variability of the) magnitude of this overestimation is far from understood.

We performed a longitudinal study in which we repeatedly (up to 3 times) asked computer users in a questionnaire to estimate the duration of their computer use while software registered their computer use based on their input device use. Furthermore, we collected personal and psychosocial characteristics from the self-reported questionnaires. The aims of the study were to estimate the level of random error and systematic bias in self-reported computer use duration, and to determine individual and psychosocial determinants of random error and systematic bias.

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Methods

Study population

A longitudinal study was conducted among 221 office workers from the Erasmus MC in Rotterdam, the Netherlands. They were all frequent computer users; before the onset of the study, they all estimated working at least 50% of their contract hours with a computer. They had a mean age of 37.7 years (±9.9, range 20–60 years) and 29% was male. On average, they had 11.4 years of computer experience (±4.7, range 2–34 years). Educational level ranged from junior vocational education to university level. 25% did secretarial work, 26% were researchers, 12% were IT-specialists and 37% had managerial or other jobs (for more information on the main job function categories, see Richter et al. 2008). Before the study onset, participants signed an informed consent.

Materials

We installed custom built registration software on participants' computers, which stayed on the computer until the end of the study (18 months). This software recorded all *computer events* (mouse cursor position changes, key presses, mouse clicks and mouse wheel use) while participants were logged on to their occupational computer. Data for every participant and every day were stored in a personally identified file on participant's computer and were automatically sent to the researchers and processed offline. Furthermore, participants filled in a questionnaire on work-related, personal and psychosocial characteristics approximately every six months, starting with the installation of the software, up to a total of four questionnaires. Since no software data was available with the first questionnaire, we used this questionnaire only to compare work and personal factors with the second questionnaire. From here on, the second questionnaire will be called the first questionnaire, the third the second and so on.

Computer use duration estimates

Computer use duration in all three questionnaires was derived from the following question: 'In the period between the last questionnaire and the current one, on average how many hours per day did you work with a computer at work on a regular workday?' The time between two questionnaires was on average six months. Possible answer categories were '2 to 4 hours', '4 to 6 hours', or 'more than 6 hours'.

Computer use duration from registration software was measured as follows. The time between two computer events (i.e. keyboard strokes, mouse clicks, mouse movement or mouse scroll wheel use) was not allowed to exceed 30 seconds (*non-computer threshold, NCT*) for the events to be considered as uninterrupted computer work (see also Richter et al. 2008). For each participant and each day, the computer work duration was calculated by taking the sum of all the periods of uninterrupted computer work on a working day.

Available dataset

Since participants had to estimate their work duration in the previous six months, we selected all recorded work days up to six months before participants filled in each questionnaire for the dataset. In order to be included, a recorded work day had to consist of 5000 computer events or more. When participants worked at more than one computer during one working day, we used the data from the computer that had the longest work duration. The 221 participants described above all filled in at least one questionnaire and had at least one day of registered computer use. Since from some participants we recorded only a small number of days in the half year periods prior to a questionnaire we applied empirical resampling of data to assess whether the daily exposure measures were reliable estimates of the average exposures across the previous six months. Resampling for each subject and every questionnaire period separately was performed ten thousand times using different sample sizes (from 2 up to 60 measured days of computer use) (Hoozemans et al. 2001).

In order to compare results across participants and questionnaire periods, the standard deviation of these individual responses were normalized by dividing through the mean of the sample responses (Coefficient of variation; CV_d). The CV_d values were interpreted as relative errors in estimating the six month exposure level for particular sample sizes. In order to select only those questionnaire periods which had enough days to reliably estimate the six month exposure period, we set the CV_d threshold at a maximum of 10% of the average duration measured over all days, including 90% of all participants. In Figure 3.1, the result of this procedure is shown. In the current study, we found a minimum of 44 measured days per participant per six months (see arrow at thick horizontal line), so for the analyses, we included only those participants with at least this number of days measured.

Measurements

At baseline, participants were asked about the following personal characteristics: gender, age, job function, working hours and educational level. Psychosocial work characteristics were assessed with the Dutch version of the Job Content Questionnaire (Karasek et al. 1998, Landsbergis et al. 2002). The items were scored on a Likert scale of 1 to 4, and value labels are “strongly agree”, “agree”, “disagree” and “strongly disagree”. Questions were combined to form dimensions of psychosocial job demands (5 items) and decision latitude (9 items). These questions were only asked in the first and third questionnaire. For further details on the subscales, see (Landsbergis et al. 2002). Furthermore, we used the subscale ‘worrying’ (4 items) from the questionnaire on perception and judgement of work, with four value labels ranging from “always” to “never” (in Dutch: VBBA, van Veldhoven and Meijman 1994). This subscale appeared in every questionnaire. Age was divided

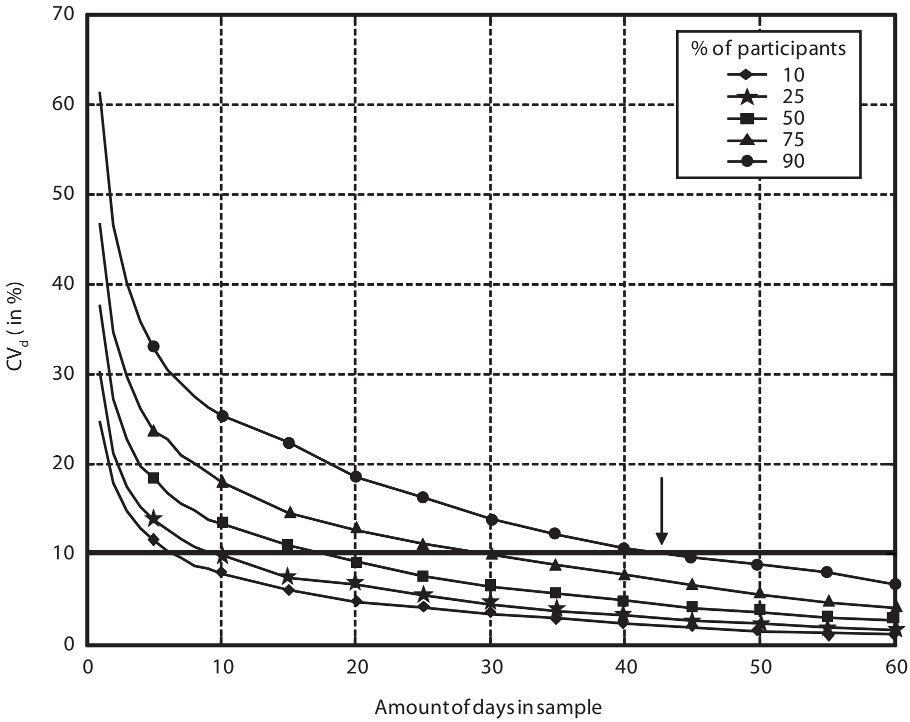

Figure 3.1: Amount of days (x-axis) that is needed to reliably estimate the six-month exposure period with a corresponding coefficient of variation (CV_d, y-axis), including 10–90% of all participants (different lines). In the current study, setting the CV_d threshold at a maximum of 10% of the average duration measured over all days (thick horizontal line) including 90% of participants (top line with circles) resulted in a minimum of 44 measured days per participant per six months (see arrow at thick line).

in the following categories: 18–30, 31–40 and >40 years. Computer experience was dichotomized (≤ 10 years (1) and >10 years (2)), since a continuous scale resulted in too much correlation with age category. Job demand, decision latitude and worrying were analysed on a continuous scale.

Complaints of arm, neck and/or shoulder (CANS) were identified with questions of an adapted and translated version of the DASH (Disabilities of the Arm, Shoulder and Hand, Hudak et al. 1996). We used the DASH subscale "severity of complaints", that had 7 items. Instead of recalling complaints in the past week, as used in the original version, we asked participants to recall complaints in

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the preceding 6 months, with five value labels ranging from "no complaints" to "very serious complaints". Participants answering "moderate complaints" to "very severe complaints" to at least one of the DASH questions were classified as having CANS.CANS was tested on an ordinal scale; no (0), acute (1) or chronic (2) CANS. In acute CANS, participants reported CANS in the current questionnaire, but no CANS in the previous questionnaire. Participants with chronic CANS reported CANS in both questionnaires.

The answer categories of the question on computer work duration (2–4h, 4–6h, >6h) were replaced with values of 2, 4 and 6 hours, respectively, as a conservative measure of self-reported work duration. In order to quantify the accuracy of participants estimating computer use duration, we calculated the relative bias (RB) as follows: (self-reported duration - registered duration) / (registered duration).

Statistics

For each participant, registered work duration from the software was averaged across all working days of the six months preceding a filled-in questionnaire. We tested whether participants' relative bias (RB) in self-reported computer use duration could be explained by personal or psychosocial characteristics. We found that relative bias (RB) did not follow a normal distribution. Therefore, we tested two derivatives of RB for normality, namely the natural logarithm (ln) of RB and the absolute value of RB. Although these values were both not normally distributed either, the distribution of the absolute values of RB approached normality, and all values were valid, contrary to ln(RB), in which the negative values of RB (13%) were discarded. We therefore decided to use the absolute value of relative bias (aRB) in the analyses.

A linear mixed model (LMM) was used to find possible determinants of the level of aRB. We chose this analysis because it is designed to handle correlated data, and it uses all available data during follow-up, regardless of the number of measurements per subject (Krueger and Tian 2004). The seven possible determinants of aRB were gender, age, years of computer experience, CANS, worrying, psychological job demands and decision latitude. These factors were entered as fixed effect variables, while the repeated measurements (up to three per participant) were the random part of the model. Akaike information criterion (AIC) was used as measure of the overall fit of the model, since it attempts to find the model with the least parameters possible to best explain the data. The model with the smallest AIC was retained. For the covariance structure, we used the compound symmetry covariance structure, which assumes equal within-worker variance (correlations between repeated measurements are the same, regardless of the time lag between individuals) as well as between-worker variance (variance between workers is equal across all fixed determinants of exposure) (Burdorf 2005). The LMM was conducted using the procedure Proc Mixed in SAS software version 8 (SAS Institute Inc., Cary, NC, USA).

Results

Response

Of our total set of 221 participants, 180 participants met the above criterion of at least 44 days of registered computer use in a measurement period of six months, and their recorded work days and questionnaires were included in the final dataset. On average, we recorded 79 (±19) days per participant per measurement period. Characteristics of the participants are shown in Table 3.1. No significant differences in the used variables were found between the initial dataset (N=221) and the selected participants (N=180).

Accuracy of estimation

In Figure 3.2, both the registered (black crosses) and self-reported (grey rectangles) work duration are shown for all three answer categories. Note that there is significant variability in registered duration across participants for all three answer categories (wide distribution of the data points in Figure 3.2 and large standard deviation in Table 3.1). Relative bias (RB) was on average 0.55 (± 0.56 SD), meaning that self-reported duration across all three answer categories was on average 55% higher than the registered duration. Note that there were participants who correctly estimated their computer use duration, while in 13% of all measurements RB was negative (i.e. computer use duration was underestimated). The level of relative bias was dependent on the self-reported category; RB (2–4 hrs) = 0.13 (± 0.40), RB (4–6 hrs) = 0.52 (± 0.56), RB (>6 hrs) = 0.82 (±0.47). For every extra hour that participants reported to work longer, their relative bias increased by 17%. The absolute level of RB (aRB) was on average 0.62 (± 0.487, range 0 to 2.80). Furthermore, aRB had a large variance (0.237).

Determinant	Categories	n	Mean (± SD)	Range
Gender	male	54	-	-
	female	126		
Age (year)	20–30	55	37.5 (± 10.0)	20–60
	30–40	54		
	>40	71		
Computer experience (years)	0–10	78	11.2 (± 4.7)	feb-34
	>10	94		
MSC	no MSC	105	-	-
	acute MSC	71		
	chronic MSC	142		
JCQ psychological job demands	low (≥0 & <11)	88	11.9 (± 2.3)	5–18.75
(range: 0 – 20)	middle (≥11 & <13)	131		
	high (≥13 & ≤20)	90		
JCQ decision latitude (range: 12 – 48)		308	26.3 (± 2.8)	dec-35
VBBA worrying (range: 0 – 100)		318	39.3 (± 11.1)	0–83.3
Computer duration (registrated average hours:minutes/day)	2–4 hours	57	2:00 (0:42)	0:53–3:49
	4–6 hours	148	3:00 (1:18)	1:07–11:25
	> 6 hours	113	3:33 (1:11)	1:35–10:45

Table 3.1: Description of all potential contributing factors to absolute relative bias (aRB). Discrepancies in amount of measurements (n) arise from the fact that the factors gender, age and computer experience all had one data point per subject (n_{max}=180), while the other variables had up to three data points per subject (n_{max}=318).

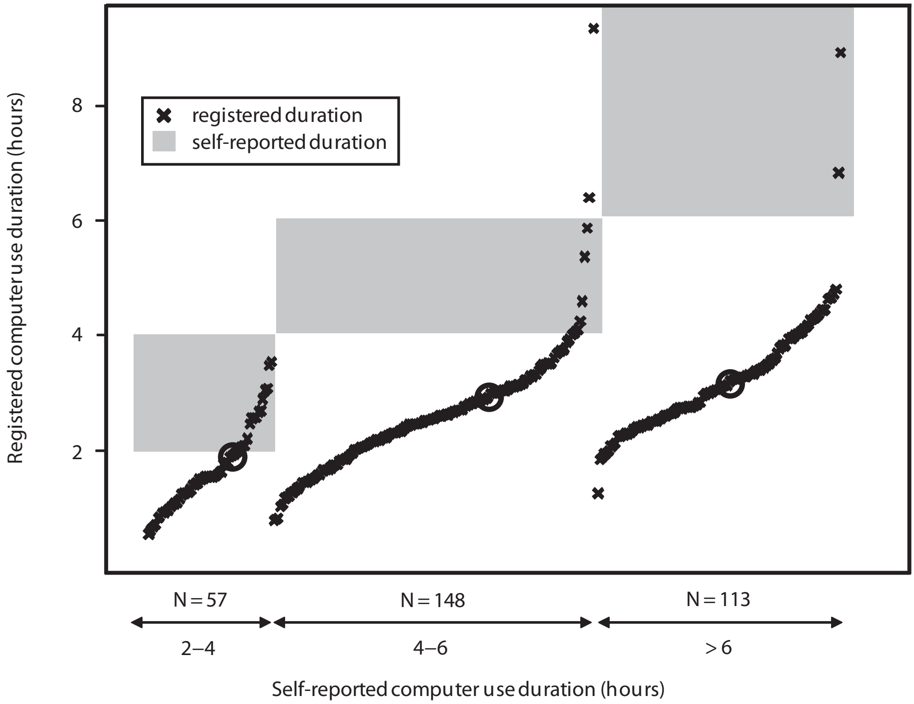

Figure 3.2: The relationship between self-reported and registered computer use duration for every participant and questionnaire. The three grey blocks indicate the range of self-reported categories (2–4 h, 4–6 h and >6 h).The registered duration of every measurement is indicated by a black cross, and black open circles indicate the mean registered duration for every self-reported duration category.

Relative bias for different subgroups of participants

Table 3.2 presents the results of the mixed-effect model, demonstrating that female gender and higher psychological job demands had a significant effect on the absolute level of relative bias (aRB). Males were found to have a lower aRB than females, and aRB increased with increasing psychological job demands. On average, females had a 0.22 larger aRB than men (Table 3.2), meaning that ((0.22/0.62)*100=) 35% of the level of aRB was attributable to gender. Secondly, the effect of JCQ job demands was calculated by the multiplying the estimate by one SD, which is (0.025*2.3=) 0.058 for every unit increase, meaning that every increment of one standard deviation in job demands explained the level of aRB by 10%. Or, put differently, including the factors gender and psychological job demands to the model decreased the systematic bias in aRB with 45%. However, these two factors only slightly altered the within-worker component of variance (σ^2_w) (6.5% reduction from 0.114 to 0.107), and left between-worker variance (σ^2_b) virtually unchanged (1.9% reduction from 0.124 to 0.121). Also, a large confidence interval surrounded the mean estimates for gender and job demands (Table 3.2).

Factors that didn't contribute to the explanation of aRB were age, years of computer experience, CANS, worrying, decision latitude and measurement. The fact that measurement (questionnaire 1, 2 or 3) did not contribute to the model indicates that the level of relative bias was stable over questionnaires, and thus that participants were relatively consistent in their level of estimation.

Determinant	Estimates (±SE)	σ^2_w	σ^2_b	95% CI
Intercept only	0.60	0.114	0.124	0.54 to 0.67
Intercept	0.37	0.107	0.121	0.07 to 0.68
Female gender	0.22 (±0.071)			0.08 to 0.36
Job demands	0.025 (±0.013)			0.00009 to 0.050

Table 3.2: Coefficients for factors contributing significantly ($p<0.05$) to the explanation of relative bias (aRB), analysed by a linear mixed model (LMM). 95% CI is the 95% confidence interval, SE is the standard error, σ^2_w is within-worker variance, σ^2_b is between-worker variance.

3

Discussion

As compared to registration software, participants overestimated their computer work duration on average by 55% (RB 0.55), which is roughly 1.5 hours per day. In the current study, the absolute relative bias, which was used as outcome measure, was on average 0.62. Higher psychosocial job demands and female gender were significantly associated with deviation from measured computer use duration. An increase in job demands of one standard deviation accounted for about 10% of this overestimation, whereas female gender explained about 35% of the overestimation. However, these two factors only slightly reduced the within-worker (σ^2_w) and between-worker variance (σ^2_b) components of variance (with 7 and 1.9%, respectively). Moreover, the outcome measure aRB had a large variance (0.237), and the determinants of aRB (gender and job demands) had large confidence intervals (see Table 3.2).

Factors influencing relative bias

The systematic bias in aRB could be reduced by 45% by the factors gender and psychosocial job demands. The other tested factors (age, years of computer experience, CANS, worrying, decision latitude and measurement) did not significantly contribute to the model. Below, we will discuss some of these factors and possible explanations for the (lack of) influence on the aRB.

Gender

In our study as well as the study from Mikkelsen (2007), females were found to report computer use duration less accurately than men. However, other studies did not find a difference in overestimation between genders (Balogh et al. 2004, Douwes et al. 2007, Faucett and Rempel 1996). In the studies measuring estimation in duration, gender was often not equally distributed among participants (100%, 74% and 79%, (Lassen et al. 2005, Mikkelsen et al. 2007, Unge et al.

2005, respectively). Through the LMM we performed, we were able to quantify the effect of gender on the systematic bias in aRB (β was 0.22, see Table 3.2). The fact that he studies described above did not find any effect of gender on RB is probably explained by the lack of discriminative capacity to show the small influence of gender on RB. It is of interest to note that the overestimation among women was presented in all three categories of self-reported duration of computer use (data not shown).

Psychosocial characteristics

Apart from psychosocial job demands, the other two measures of psychosocial work characteristics (worrying and decision latitude) did not significantly influence the level of aRB. Similar to the results of the current study, Mikkelsen et al. and Faucett and Rempel analysed the influence of several psychosocial variables and only found a small significant influence of psychosocial job demands in the level of overestimation (Faucett and Rempel 1996, Mikkelsen et al. 2007). Furthermore, Hooftman et al. found that women reported both higher job demands than men and higher exposure to physical risk factors, which corresponds to our model (Hooftman et al. 2005). Similar to the effect of gender, the overestimation due to higher psychosocial job demands was very similar across the three categories of self-reported computer use duration.

Musculoskeletal complaints (CANS)

In the current study, CANS did not influence the level of aRB. However, IJmker et al. found a better agreement between self-reported and registered duration in participants with arm, wrist and hand symptoms compared to participants without symptoms (2008). Mikkelsen et al. (2007) found a positive effect of arm pain on the level of computer and mouse duration estimation, but did not find an effect of neck-shoulder pain, and even found a negative effect of arm pain on keyboard duration estimation. In these studies, the differences in methods of the studies could have influenced the relationship. The measurement period and recall period differed between studies, and the definition of CANS in questionnaires was not standardized. The fact that we didn't find an effect of CANS on the level of aRB indicates that response bias of participants with CANS did not influence the level of aRB. Another reason that we did not find an influence of CANS on the level of aRB might be because of the long measurement period (six months); with this method, we are not sure whether participants with CANS experienced CANS throughout the whole measurement period and therefore whether they estimated their computer use differently during an episode of complaints. A shorter measurement period or more frequent questionnaires might be necessary in order to analyse the influence of CANS on aRB.

Physical exposure

Prolonged duration of physical exposure is an important risk factor for the development of musculoskeletal disorders according to one of the leading etiological models of CANS ('Brussels Model', Johansson 2003). Therefore, in quantifying computer use duration that is representative for duration over a longer period of time, it is vital to measure computer use reliably, and thus to account for variability in duration between days. In previous studies, duration of computer use was only measured with software for a short period of time (Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Unge et al. 2005). This short period of measurement may not represent natural, everyday duration, especially since we found a high variability in duration between days in the current study (steepness of lines, representing CV, in Figure 3.1). Especially with less than about five days of measurement, between-day variability in duration is too large to represent average duration over six months. Even though the office workers on the current study all had computer work as their main task, computer use duration is thus more variable than previously thought.

Definition

Furthermore, although in the questionnaire we stressed the fact that all questions applied to participants' work situation in the past six months, we did not emphasize this again in the question concerning computer use duration. The exact question that was asked each time was: 'On average how many hours per day do you work with a computer at work?' Therefore, it was possible that participants had a much shorter recall period in mind than the six months we measured duration with software. Although we did not test this, aRB might have been smaller with either an unambiguous question on computer use duration or with a shorter measurement period. In previous studies, the measurement period of the above described studies ranged from one day to one year. However, in the only studies that measured computer use duration for more than a few days, the amount of days that computer use was actually registered within the total measurement period was not described (Lassen et al. 2005, Mikkelsen et al. 2007, IJmker 2008). This hampers a solid comparison between methods of duration estimation across studies, since it does not provide information on the between-day variability in duration.

This study used RB as measure of disagreement between self-report and registration measurements. About 13% of all measures had a negative value of RB, implying an underestimation of computer use. The negative values were primarily observed in the self-reported category 2–4 hrs/day and had relatively small magnitude (see Figure 3.2). In the statistical analysis, the absolute bias (aRB) was used in order to comply with normality assumption in the regression analysis. This may have resulted in some underestimation of the within-worker variance, but most likely has only had a small effect on the systematic overestimation.

Conclusion

When comparing computer use duration between self-reports and registration software, self-reported duration deviated on average 62% from registered duration (aRB 0.62). Gender and psychosocial job demands accounted for 45% of the systematic difference in aRB, but self-reports hardly explained any of the variance. However, since the outcome measure aRB had a large amount of variation between participants, and a large variation was also present within categories of gender and job demands, the predictive value of the two factors was low. This suggests that comparing these two measures introduces a large amount of random variation and indicates that self-reported and registered computer use duration measure a different construct of computer use duration.

4

Chapter 4

The effects of pause software on the temporal characteristics of computer use

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Adapted from:

Slijper HP, Richter JM, Smeets JBJ, Frens MA.

The effects of pause software on the temporal characteristics of computer use.

Ergonomics 2007; 50 (2): 178–91.

Abstract

The study investigated the natural work-pause pattern of computer users and the possible effects of imposing pause regimes on this pattern. Hereto, the precise timing of computer events was recorded across a large number of days. It was found that the distribution of the pause durations was extremely skewed and that pauses with twice the duration are twice less likely to occur. The effects of imposing pause regimes were studied by performing a simulation of commercially available pause software. It was found that depending on the duration of the introduced pause, the software added 25–57% of the pauses taken naturally. Analysis of the timing of the introduced pauses revealed that a large number of spontaneous pauses were taken close to the inserted pause. Considering the disappointing results of studies investigating the effects of introducing (active) pauses during computer work, this study has cast doubt on the usefulness of introducing short duration pauses.

Introduction

It is commonly acknowledged that physical load factors such as excessive force, frequent bending and twisting, repetitive motions and static posture contribute to the occurrence of musculoskeletal complaints of arm, neck and/or shoulder (CANS). Consequently, guidelines (CEN 1995, Fallentin et al. 2001), standards (CEN 1995) and national legislation (European Communities 1990, Swedish National Board 1998) have been implemented to promote variation in loading patterns.

However, recent reviews of the literature by Burdorf et al. (2003) and Mathiassen and Christmansson (2003) indicate that the effects of increasing variation are only supported by vague or indirect empirical evidence. These authors argue that there are only few studies explicitly addressing variation and CANS and that there are insufficient methods for quantifying variation.

For example, one of the most frequently recommended interventions against CANS is the introduction of more rest breaks (Dababneh et al. 2001, Galinsky et al. 2000, Genaidy et al. 1995, Henning et al. 1997, Kopardekar and Mital 1994, Mathiassen and Winkel 1996, McLean et al. 2001, Sundelin and Hagberg 1989). A reason why the effects of short organized rest breaks on fatigue and discomfort have been shown to be only weak might be that the additional rest breaks are not sufficient to significantly alter the work-pause pattern. That is, the additional breaks might not contribute significantly compared to the large amount of variation already obtained through natural and regulatory breaks present in the job, and through exposure variability associated with the task(s).

In recent years several innovations have been developed to adjust break schedules to the actual work load, taking into account the breaks that users take naturally. In particular, during computer use, work can be regulated by pause software, which can administer additional pauses depending on the actual computer use of an individual user. Such pause software works by administering a pause of a particular length when a period of continuous computer use (without pauses) has been exceeded (computer use limit). A threshold (non-computer threshold or

NCT) is used to define how far two recorded computer events are allowed to be separated in time to be classified as continuous work. For instance, a NCT of 30 seconds would mean that the time between all recorded computer events larger than 30 s is classified as a pause. When a particular pause regime is implemented, several computer use limits are often used simultaneously, after each continuous period of use a corresponding pause of a particular duration is administered (pause duration). So, computer users receive both micro pauses (5–30 s) after a relatively short period of computer use and macro pauses (5–30 min.) after longer periods of use.

From studies using both self-administered questionnaires and external observers, it is known that users tend to overestimate the time they work behind the computer (Burdorf and van der Beek 1999a, Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Van der Beek and Frings-Dresen 1998). Some studies (Heinrich et al. 2004, Homan and Armstrong 2003) have therefore investigated whether work times, as measured by pause software or by external observers, correspond. Results indicate that a NCT between 20 and 30 s yields work times in reasonable correspondence with the work times reported by observers.

The choice for the specific values of pause duration, computer use limit and NCT that make up the pause regimes seem arbitrarily chosen. That is, no research has been published on how these regimes alter the total number of pauses that computer workers take. This is surprising since this software is used by over a million computer users worldwide (i.e. www.workpace.com), forms an important method for regulating the amount of time spent behind the computer, and is used to guide (inter)national legislation (European Communities 1998, 1990) regarding workload during computer use.

Since pause software developers claim that their software reduces the risk of developing CANS, the authors were interested as to what extent the implementation of additional breaks can alter the work-pause pattern of computer users.

Whether the administration of additional pauses has possible health benefits is beyond the scope of the current study.

In order to precisely determine the time-pattern of computer use during a working day, a new software tool was developed. This software records, during normal computer use, the times at which the mouse and the keyboard are used. This enables the authors to reconstruct time traces over extensive periods of time for a variety of computer users.

In order to determine the computer user's natural working behaviour, a detailed analysis on the recorded time traces was performed. To study the effect of different pause regimes on worker's pattern of computer use, this study performed a simulation of how this pattern, as measured by the registration software, would be altered under the influence of different pause regimes. That is, based on the criteria and thresholds that make up a pause regime, pauses of specific durations were inserted in the recorded time traces. Using a simulation, instead of administering different pause regimes to different users in a controlled trial, made it possible to estimate the potential effects of a whole range of changes in the work-pause schedule without being influenced by non-compliance of the users, compensation for non-work periods (speeding-up) and other confounding factors that might influence users' working behaviour.

The current study posed the following specific questions regarding the temporal variability of computer use and the influence of imposing different pause regimes:

1. What are the natural pause patterns that users display?
2. How many pauses would pause software administer to the users and how do these numbers compare to the number of pauses taken spontaneously?
3. Is the timing of the inserted pauses appropriate, that is, how long would it take before a computer user would take a similar pause spontaneously?

Methods

Custom-built registration software was installed on the computers that were used by 20 healthy employees of the academic hospital in Rotterdam, the Netherlands. Participants signed informed consent before entering the study. Before the start of the study participants filled in a small questionnaire in which they were asked about their computer use. The participants (mean age: 33.9 (SD 8.7) years) performed a variety of computer-intensive tasks; eight had an administrative job, six were researchers and six had managerial or other functions. The male (n = 9) and female (n = 11) participants estimated that they worked for 5.5 (± 1.1) h/d behind the computer and spent 22.4 % (± 15.9) of their time doing other work. They also reported taking on average 1.5 (± 1.3) scheduled rest breaks (lunch, coffee etc.) during a working day. Of the participants, 14 worked behind a single computer while six worked with two computers. According to the participants, they worked on average for 36.4 (± 7.7) h per week.

The software registered with a frequency of 10 Hz the position of the cursor (x, y coordinates in pixels), whenever this position changed. Additional events that the software recorded were key presses, mouse clicks and mouse wheel use (temporal resolution 0.1 s).

The software logged these data in the background in order not to interfere with the regular work of the participants. Participants could view daily statistics on their computer use, such as number of keyboard strokes, mouse clicks, mouse moves, etc. Participants were made aware that their computer usage was monitored as part of a study investigating computer usage patterns. Participants were not told that their pause behaviour would be studied. The unobtrusive nature of the installed monitoring software ensured that they quickly forgot that they were being monitored. It is therefore highly unlikely that participants altered their working behaviour as a consequence of participating in the study.

Data were collected centrally and processed offline. A sample of 50 workdays of each participant was selected to ensure the data files (for each participant for every day) contained sufficient data. Data files containing less than 15000 events were not selected.

Data processing

For each of the 1000 recorded files, the times were extracted at which an event (a mouse movement, mouse click, mouse wheel use or keyboard stroke) was recorded. These time series, in which no distinction was made between the different types of events, were used to calculate the distributions of pause durations for each participant and day. In order to compare these distributions across participants and days, coefficients of variation (CV) were calculated, across participants and days, for a range of pause durations.

Additionally, the obtained time traces were used to simulate the effects of pause software. To this end, the standard regimes administered by the most commonly used (approximately 800000 user-licences) pause software in the Netherlands were implemented; Workpace (Wellnomics Ltd., Christchurch, New Zealand).

These pause regimes vary in the level of altering the natural pause behaviour of computer users. Table 4.1 shows the settings for all the regimes. The regimes consist of implementing micro pauses (durations varying from 5 to 30 s) and macro pauses (5 to 30 min pause) after a specific duration of computer use has been exceeded (computer use limit). On top of this, a daily limit on the total amount of computer use could be imposed (Table 4.1). In accordance with the Workpace software, a NCT (non-computer threshold) of 30 seconds was used. During the simulation the appropriate pause was inserted after the computer use limit was reached (see Table 4.1). Since the duration of the micro pauses was always smaller than the NCT, the insertion of macro and micro pauses could be done in subsequent steps. This yielded simulated time series of days with pauses imposed according to each of the regimes. As can be seen in Table 4.1, the last seven regimes are only used for people recovering after CANS and have extreme limitations on the computer work that can be performed during a day. As all the participants were without CANS during the period of recording and worked considerable hours behind the computer, simulation of the data for these last regimes would therefore yield results beyond what is normally expected from a working person (i.e. working hours >12 h). The results from the simulations of these regimes are therefore not reported.

Pause Regime	Non-computer threshold (s)	Computer use limit micro pause (min)	Inserted micro pause (s)	Computer use limit macro pause (min)	Inserted macro pause (min)	Day limit (h)
1 (normal prevention)	30	8	5	60	5	-
2 (normal prevention)	30	7.5	8	50	5	7
3 (normal prevention)	30	6	8	45	6	6.5
4 (past complaints)	30	5	9	45	7	6
5 (past complaints)	30	4.5	10	45	6	6
6 (past complaints)	30	4	10	40	8	5.5
7 (recovery complaints)	30	3.25	12	30	10	4.5
8 (recovery complaints)	30	3	15	20	10	4
9 (recovery complaints)	30	2.5	20	18	15	3
10 (recovery complaints)	30	2	30	10	20	2
11 (recovery complaints)	30	2	30	10	25	1.5
12 (recovery complaints)	30	1.75	30	10	25	1
13 (recovery complaints)	30	1.5	30	10	30	0.5

Table 4.1: The pause regimes used by the Workpace software. Regime 1 administers a 5 s pause after 8 min of consecutive computer use (i.e. without pauses larger than 30 s) and a 5 min pause after 1 h of computer use. No limit on the amount of computer hours per day is imposed for this regime. Regimes 7 to 13 are recommended when computer users are recovering from CANS. Since our participants were healthy volunteers, only regimes 1 to 6 were used in our simulation analysis.

Results

Natural computer pauses

On average 50618 events were recorded for each participant every day (range 17772–97000, SD between participants averaged across days: 14742; mean SD over days, within participants: 9430). Considering that these events could be as close as 0.1 second apart, the total number of the events corresponds to less than 85 minutes of continuous computer use each day. In contrast, the total time

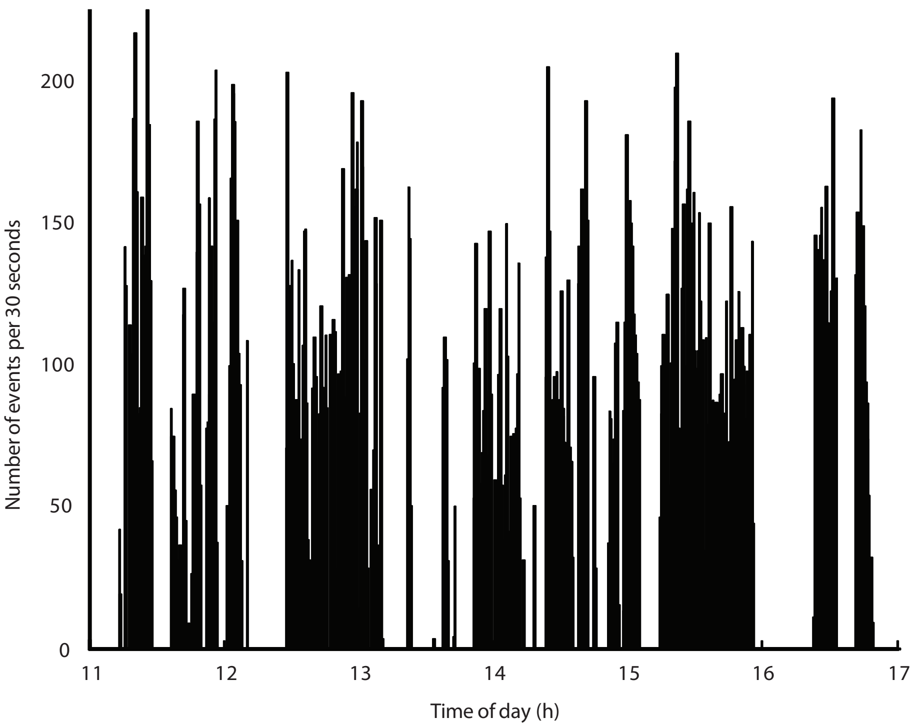

Figure 4.1: Histogram of the number of events per 30 s for a participant during one particular day. The empty bins (white) show the distribution of pauses over the day. This participant, a research scientist, started working behind the computer at 11.10 a.m. and stopped just before 5 p.m. on 2 March 2005.

participants worked with the computer, that is, the time from the first recorded event until the last one for a particular day was on average 8 h and 33 min (SD 1.19 h).

Participants exhibited a great number of natural computer pauses of different duration during the day. Figure 4.1 shows the number of events for every 30 s interval during a working day of one of the participants. As can be seen, both the duration and timing of the (natural) pauses taken by a participant can vary considerably.

To gain insight into the distributions of pause durations, the number of pauses per hour was counted for a range of pause durations. The short duration pauses occur more frequently than the longer duration pauses. For instance, the

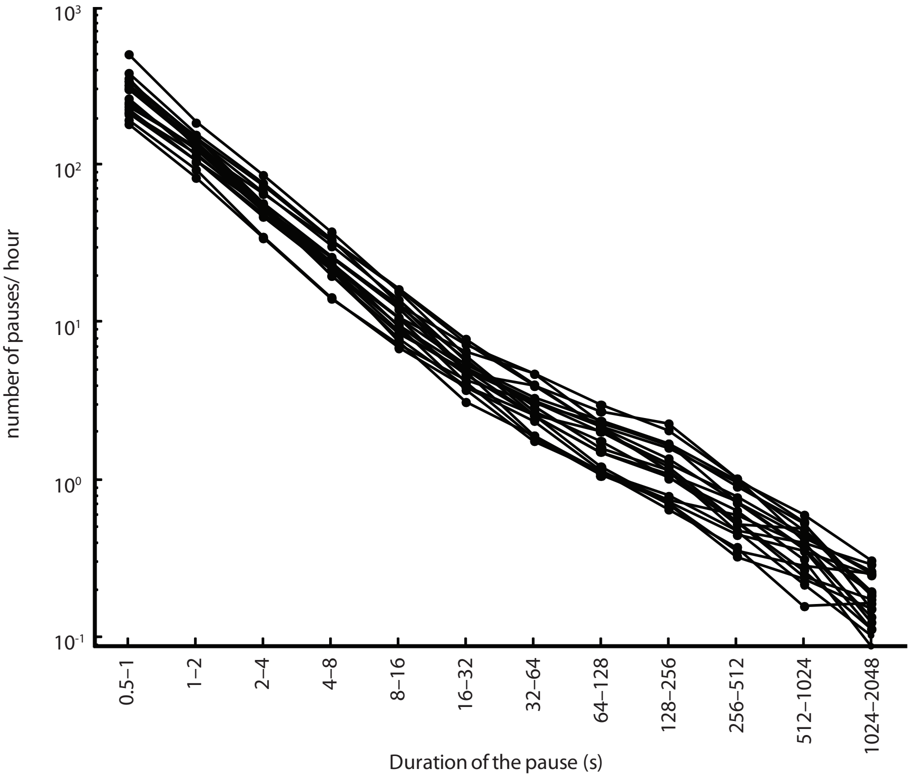

Figure 4.2: Histogram of pause durations for the different participants (the different lines), across all days. Both axes are on a log scale. 512 to 1024 s is approximately 8.5 to 17 min.

majority (96.2%) of all pauses are shorter than 1 s. For pauses larger than 0.5 s, as can be seen in Figure 4.2, a two-fold increase in pause duration leads to a decrease in the number of pauses by a factor of approximately two. The straightness of the curves in the log-log plot of Figure 4.2 indicates that the pause distribution follows a power law.

The variability between participants, as shown in the spread of the different lines in Figure 4.2, can partially be explained by the intensity with which participants worked during each of the 50 days of recording. That is, the more intensely a user works, the more events are recorded each hour, thereby increasing the number of pauses between those events. The lines of the different participants run in a band. This was reflected in CV across participants that were independent of the pause duration (0.29 ± 0.06). The CV for variability across days (within participants) for the different pause durations was somewhat lower (0.22 ± 0.03).

When a NCT of 30 s was applied, it was found that on average (across days and participants) a working day consisted of 64 working periods, with a mean duration of 4 min (see Table 4.2). The longest period of continuous computer use (mean over all participants and days) lasted almost 0.5 h. The average duration of the pauses in between the working periods was somewhat longer, with the longest

Non-computer threshold (s)	1	10	30	100
% workday classified as 'computer work'	26.7 (7.1)	40.4 (8.9)	45.6 (9.2)	52.7 (9.2)
Number of work periods	1839 (424)	158 (37)	64 (16)	26 (7)
Pause duration (min)	0.2 (2.3)	2.2 (7.8)	5.1 (12.1)	11.2 (17.3)
Longest pause (min)	74.0 (42.0)	74.0 (42.0)	74.0 (42.0)	74.0 (42.0)
Work time duration (min)	0.1 (0.1)	1.4 (2.1)	4.0 (5.7)	11.1 (13.6)
Longest work time (min)	1.3 (0.4)	13.2 (4.5)	27.5 (9.1)	50.8 (13.4)

Table 4.2: Characteristics of the working day averaged across participants and days. How many events are classified as work, depends on the NCT used. Calculated here is the number and duration of the (longest) working periods and pauses under four different NCTs (1, 10, 30 and 100 s).

pause lasting on average 1 h and 14 min. Note that the pause duration is much more variable than the duration of the working periods. This was reflected in a 42% smaller CV for the working periods.

Artificial computer pauses

During the simulation, pauses were inserted every time the computer use limit was exceeded. In Figure 4.3 the number of inserted pauses is shown for the first six pause regimes across all participants and days. It should be noted that the majority (89%) of pauses that are administered are micro pauses and that the more

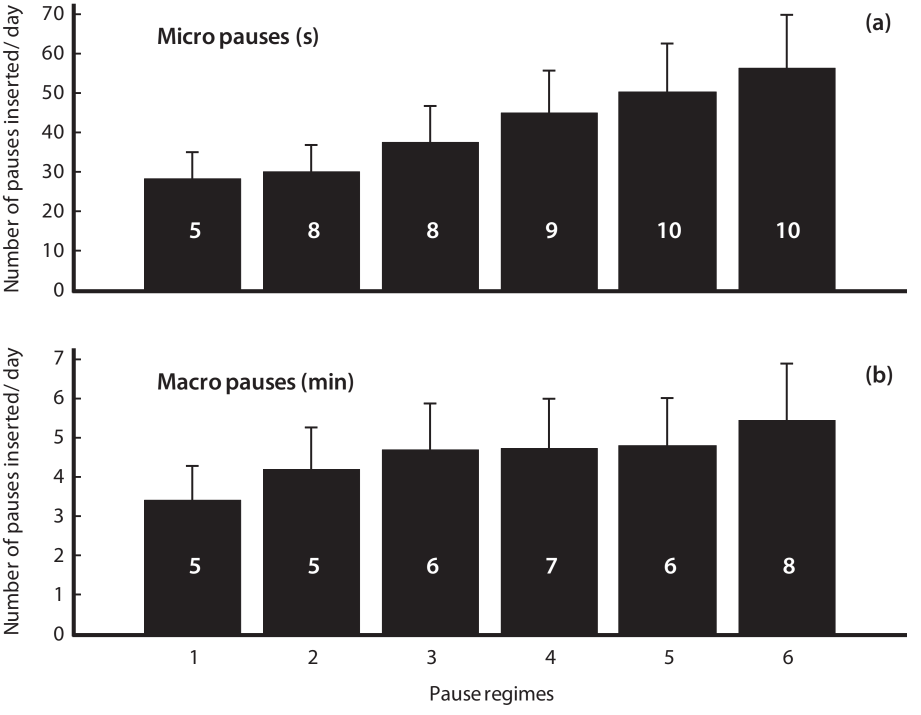

Figure 4.3: Mean number of micro (a) and macro pauses (b) per day inserted for all pause regimes across participants and days. Error bars are standard deviations for variability across participants. The numbers in the bars are the durations of the pauses for that regime. Note the different scales on the y-axis.

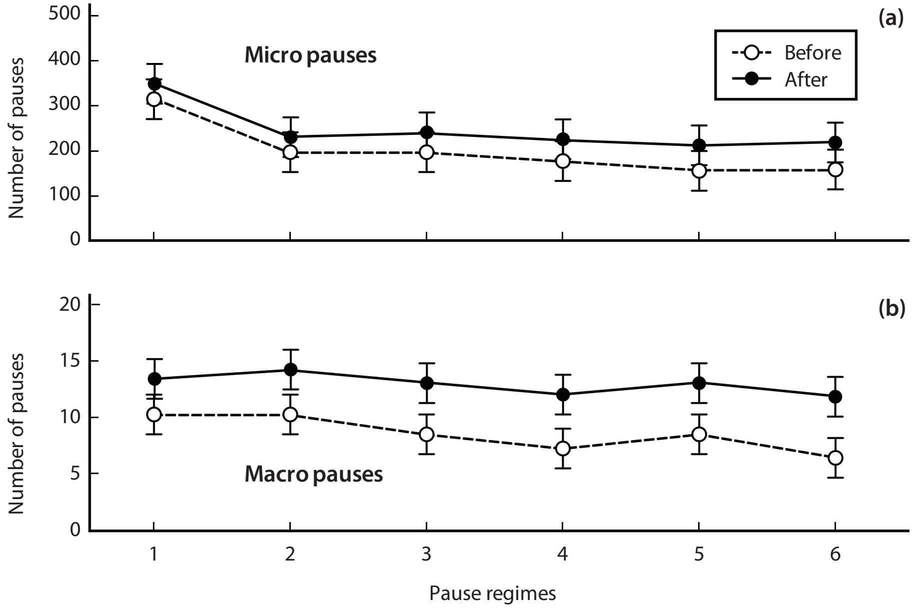

Figure 4.4: Number of micro (a) and macro pauses (b) before and after pause insertion for six pause regimes across participants and days. Error bars are standard deviations for variability across participants. Note the different scales on the y-axis.

stringent the regime becomes, the more pauses are administered. The daily limit of computer use is not taken into consideration in the analyses.

In addition to the additional pauses introduced by the simulation, participants took a great number of natural pauses of similar duration as the introduced pauses during each workday (as already shown in Figure 4.2). Using Figure 4.4, the number of pauses before and after the implementation of the pause regime can be compared. For each pause regime, the number of pauses with a length corresponding to the duration of the inserted pause or larger is shown. It should be noted that the number of pauses given on top of the ones that occur naturally is rather small, especially for the micro pauses. For the micro pauses, on average 25% more pauses are inserted across the six pause regimes. This percentage increases with the stringency of the pause regime (from 9 to 39%). For the macro pauses, the number of additional pauses is larger; for regime 1 there are 32% more pauses added while for the last regime, 83% more pauses are administered than occur naturally. On average 57% more macro pauses were inserted.

Changes in the duration of the working day

The inserted pauses in the simulation lengthened the working day by an amount equal to the summed duration of all inserted pauses. For the six pause regimes studied, the working day increased on average by 37 min (7.2%). If the workers had been working with pause software on their computer, they would most likely reduce the number of spontaneous pauses, having a pause already administered by the software. The above increase in working day should therefore be seen as an upper limit. Based on an NCT of 30 s, on average 46% of the total time the computer was on was classified as 'computer work', this would come down to approximately 4 h of computer use per day. Since this amount of time was far below the daily limit of computer use, only in 3% (range 0 to 11.7%) of the days this limit was reached during simulation of the six pause regimes. The total amount of time classified as 'computer work' hardly increased for the six pause regimes studied (maximally 8 min for regime 6). Because 'computer work' is defined by an NCT of 30 s, pauses smaller than 30 s will lead to an increase of the total amount of 'computer work' performed. Counter intuitively, this means that by adding micro pauses, work time is increased.

Pause software intervention

For each of the pause regimes, a certain amount of computer use needs to be exceeded (computer use limit) before a pause is administered. The time differences were calculated between the moments an artificial pause would have been administered and the subsequent moment a natural pause of equal or greater length occurred. This time difference is a measure of the amount of time participants would be stopped using the computer earlier than they would naturally do (or

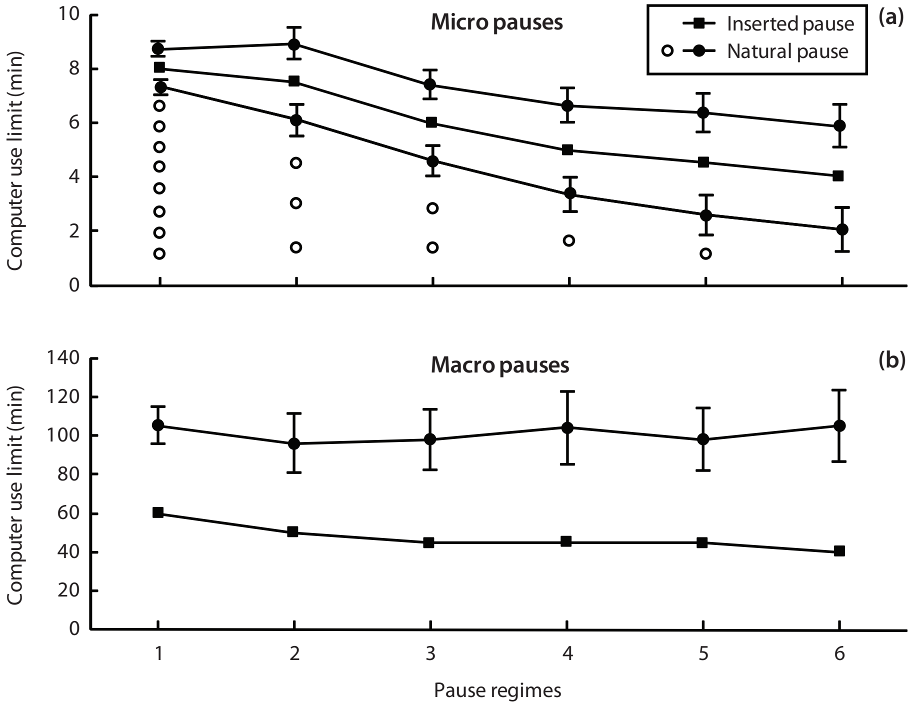

Figure 4.5: The amount of time after a pause of 30 s or more before the software would notify the user to take a micro (4.5a) or a macro (4.5b) pause is shown in the lines with the square markers. The top lines show the time it took participants to spontaneously take a pause of a length equal or greater than the one just administered. Since the NCT is larger than the administered micro pauses, participants also showed micro pauses preceding the inserted pause. The lower line in (a) shows the time at which the previous pause of equal or greater length was spontaneously taken. The open circles indicate the number of pauses of these durations taken in the period up to administration of the pause. Timing of these pauses is not taken into consideration and numbers are rounded off to integers (for actual values see text).

the amount of time participants continue to use the computer while the software would have stopped them). These data, averaged across all participants and days and for the six pause regimes, are shown in Figure 4.5. Figure 4.5a (compare the top two lines) shows that for short duration pauses the software administered the pause only shortly (45 s (=8%)) before the natural pause would occur and that this time increases with the stringency of the imposed pause regime (up to 2 min or 32% earlier). In contrast, Figure 4.5b shows that this time difference is much larger for the macro pauses. Participants are stopped much earlier (on average 53 min (=52%)) than they would naturally do. Dependent on the stringency of the regime this effect becomes even larger (from 45 to 64 min earlier (= 43 to 61%)).

Since the administered micro pauses have a duration which is shorter than that of the NCT, micro pauses of the same length could also have occurred in the 'computer work period' prior to the administration of the micro pause. It was calculated at what time before the insertion of the micro pause the last spontaneous micro pause occurred. These time points, averaged across participants and days, are shown in Figure 4.5a in the bottom line. As can be seen in this graph the time difference between the spontaneous pauses before and after the inserted micro pause are quite similar (due to the random distribution of the pauses).

Additionally, the number of micro pauses, with a length larger than the administered pause, was calculated in the computer use period prior to the administration of the pause.These numbers are indicated in Figure 4.5a by the number (rounded off to integers) of open circles below the line of inserted pauses. The actual values for the six regimes were: 8.76; 4.15; 3.27; 2.22; 1.65; 1.44 pauses. The timing of these pauses was not calculated.

Discussion

In the Introduction, three questions were asked regarding the possible effects of pause software on computer use. The answers to these questions and the generality of the results will shortly be addressed. Subsequently, the following section will discuss how the current results should be interpreted in the light of possible health benefits of pause software.

What are the natural pause patterns that computer users display? The results show that the distribution of pauses, the time between two computer events, is extremely skewed. That is, the vast majority (96%) of pauses are shorter than 1 s and only a small number of pauses are of long duration. The distribution of pause durations follows a power law with a slope of approximately - 2, meaning pauses with twice the duration are twice less likely to occur. Such distributions of waiting times have been found in the distribution of a large number of human activities, such as the times between sending emails, between telephone conversations, between words during speech production and other forms of communication (Barabasi 2005). The variability of the pause distributions, as expressed in the CV, was somewhat larger across participants than over days (0.29 vs. 0.22), which means that participants apparently show some personal trends (intensity of work) in how their pause durations are distributed. This indicates that it might be possible to identify computer users by their work-pause patterns.

When a NCT of 30 seconds was applied, the work-pause pattern consisted of on average 64 short duration (4 min) work periods, interlaced with slightly longer pause periods (5 min). The duration of the work periods was less variable (a 42% smaller CV compared to that of the pauses; see Table 4.2). Moreover, the longest pause lasted on average more than twice as long as the longest working period. The work-pause pattern of computer users can thus be described as a highly intermittent behaviour with short duration work periods being followed by slightly longer, and very variable, pauses.

How many pauses does pause software administer and how do these pauses compare to the number of pauses taken spontaneously? When the simulation of the pause software was applied, pauses of different durations were inserted when a computer use limit was exceeded. For an average working day of 8.5 h, 38 micro pauses (5 to 10 s) and 4 macro pauses (5 to 8 min) were administered, a nine-fold difference. Compared to the number of pauses taken spontaneously, an additional 25% micro pauses were inserted. For the macro pauses, an additional 57% pauses were inserted compared to the number of natural pauses with the same or longer duration. The inserted pauses add on average only 7.2 % extra pause time to a working day. Only in a very small percentage (3%) of the days a day limit would be imposed.

Is the timing of the inserted pauses appropriate? The number of pauses that the software would administer seems to be quite significant when compared to the number of pauses taken spontaneously. However, upon further examination into when these pauses were inserted, it was found that, specifically for the micro pauses, a large number of spontaneous pauses was taken just before and after the inserted pause (see Figure 4.5). The spontaneous pauses just before and after the inserted micro pause occurred on average within 90 s. This means that pause software, through the administration of micro pauses, does not seem to alter the work-pause pattern of computer users to a large extent. For longer duration pauses (5–8 min), the software would administer a pause long before the computer user would take a pause of equal or a longer length, spontaneously. The administration of longer duration pauses, although they compromise only 11% of the total amount of pauses, seems therefore to be a method for altering the work-pause pattern.

Sensitivity analysis

Because of our choice of simulating the effects of pause software, instead of comparing groups working with and without the software, we ensured that the study was not hampered by non-compliance of participants, nor influenced by compensatory strategies that participants might use in response to an imposed pause, such as speeding up computer use. This means that the presented data are most likely an overestimation of the possible effects of pause software on the temporal characteristics of computer users. Since participants were not informed about the nature of our analysis and the monitor software was running unobtrusively in the background, participants were only minimally aware that they were being monitored. The authors are therefore convinced that the recorded time traces are representative of the natural working pattern of the participants.

In order to study the generality and robustness of our simulation results two sensitivity analyses were performed. First was the analysis of whether the choice of data, only selecting files with a large amount of recorded events, could have influenced the results. Therefore, the results were compared for analyses done on the 100 smallest files and on the 100 largest files of the dataset, which differed by a factor 3.44 in size (bytes). The results from this comparison showed that there were neither differences in the pause distributions nor differences in the ratio of spontaneous and administered pauses between the two groups of data files. This shows that although the total number of administered pauses might increase, there was no fundamental difference in work-pause patterns for short or long working days, nor would pause software have different effects.

Second, an analysis was performed to determine whether the results would be dependent on the NCT used. The analysis calculated how much time would be classified as computer work when NCTs of 1, 10, 30 and a 100 s were used (Table 4.2). These results were obtained for both the natural pauses as well for the six simulated pause regimes. As can be seen in Table 4.2, the number of work periods decreases 70-fold when the NCT was increased. The duration of the working periods increases more than 100 times, resulting in a two-fold increase in the time being classified as computer work. Note also that for all NCTs the duration of the work period is consistently shorter than that of the pauses and that the variability of the pause durations is higher than the variability of each of the working durations.

When the effects of the pause software were simulated, it was found that working times were similarly affected under the different pause regimes, independent of NCT used (results not shown). This means that, although the amount of computer activity classified as computer work might be higher or lower, depending on the specific NCT used, the way pause software affects the work-pause pattern is similar.

Possible health benefits of pause software

Variation in physical exposure is the result of the variation within and between all of the tasks performed in the job, including non-work activities. The recorded time traces that were used in the simulation of pause software therefore give only a rough approximation of the possible physical exposure during the working day. For example, similar computer activities can be performed using a variety of working postures and with different amounts of task variability (variability in movement repetitions). Also, the amount and the variability of muscle activity associated with the execution of computer work can vary considerably due to the mechanical redundancy of the muscles, for instance, by co-contracting muscles around a joint. Additionally, the time traces provide no insight into the exposure during pauses of longer duration, when the computer user is most likely engaged in non-computer work. For these reasons, it is important to be cautious when drawing conclusions whether alterations in work-pause pattern, as imposed by pause software, can lead to possible health benefits. Nevertheless, the recording of the timing of computer events forms the basis for pause software to impose pause regimes, which, according to the manufactures, has health benefits.

In the literature, two possible mechanisms are described that explain how additional rest breaks could influence computer user's health (e.g. reduce fatigue, discomfort and other CANS; Kumar 2001). First, rest breaks might lower the cumulative loading during a workday, which might in turn give muscles the chance to recover from fatigue, promote blood circulation or promote some other form of recovery (Galinsky et al. 2000, Helliwell et al. 1992). Second, rest breaks might introduce an increase in the variation of the physical exposure. By increasing variation, i.e. reducing stereotypy of the work, selective exhaustion of muscles, tendons and nerve tissue could be alleviated (Hägg 1992, Hägg 2000).

As stated in the Introduction, the benefits of additional rest breaks on fatigue and discomfort have found only marginal support in the scientific literature. One of the reasons for this modest effect might be that the additional breaks do not contribute to the decrease in cumulative loading. A review by Lötters and Burdorf (2002) concluded that substantial (14%) reduction in physical load is needed to result in a corresponding decline in CANS. In the current study, it was found that the additional rest breaks added only 7.2% extra 'pause time' to the working day. This seems to suggest that, regardless of whether a changed work-pause pattern might influence workers' health, it is very unlikely that pause software contributes to reducing cumulative load.

For long-lasting work at low load levels, such as computer work, increases in exposure variation are thought to be better met by introducing more activity than by introducing more rest. Studies on active breaks, such as specific exercises or stretching, have shown, however, very disappointing results (van den Heuvel et al. 2003). The results of the current study suggest that with regard to introducing additional variability the effect of micro pauses is probably quite low considering the large number of spontaneous micro pauses taken just prior and after the administration of the pause (see Figure 4.5). In all the analyses the authors did their best to verify possible effects of pause software on temporal characteristics of computer use. Despite this, it seems very unlikely that the introduction of micro pauses (those below 10 s) has a possible benefit. It therefore seems a logical step for computer users to switch off this functionality in their pause software.

5

Chapter 5

Differences in muscle load between computer and non-computer work among office workers

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Ergonomics 2009. In press.

Abstract

Introduction of more non-computer tasks has been suggested to increase exposure variation and thus reduce complaints of arm, neck and/or shoulder (CANS) in computer-intensive office work. This study investigated whether muscle activity did, indeed, differ between computer and non-computer activities. Whole-day logs of input device use in 30 office workers were used to identify computer and non-computer work, using a range of classification thresholds (Non-Computer Thresholds or NCTs). Exposure during these activities was assessed by bilateral electromyography recordings from the upper trapezius and lower arm. Contrasts in muscle activity between computer and non-computer work were distinct but small, even at the individualized, optimal NCT. Using an average group-based NCT resulted in less contrast, even in smaller subgroups defined by job function or CANS. Thus, computer activity logs should be used cautiously as proxies of biomechanical exposure. Conventional non-computer tasks may have a limited potential to increase variation in muscle activity during computer-intensive office work.

Introduction

Several studies have established an association between extensive computer work and complaints or disorders in the arms, neck and/or shoulders (recent reviews include Griffiths et al. 2007, Village et al. 2006). The generic risk factor for these complaints has been suggested to be prolonged periods of sustained muscle activation with little variation in exposure (Mathiassen 2006, Wahlström 2005), which would lead to local accumulation of metabolites, and eventual damage to certain muscle fibres (Visser and van Dieën 2006).

Because of this low exposure variability during computer work, interventions that manipulate the temporal exposure pattern are widely believed to be effective against complaints of arm, neck and/or shoulder (CANS) (Mathiassen 2006, van den Heuvel et al. 2003, Wells et al. 2007). Many interventions have for instance focused on introducing more rest breaks in office work (e.g Balci and Aghazadeh 2003, Galinsky et al. 2007, Galinsky et al. 2000, McLean et al. 2001, van den Heuvel et al. 2003). However, three recent reviews concluded that there is limited evidence for a positive effect of more rest breaks in both primary (Brewer et al. 2006) and secondary prevention of CANS (Mathiassen 2006, Verhagen et al. 2007).

An important reason that additional breaks seem to have a limited effect among computer workers could be that the biomechanical exposure during breaks does not differ to any substantial extent from exposure during computer work, at least not in terms of mean exposure (Arvidsson et al. 2006, Blangsted et al. 2004b, Fernstrom and Åborg 1999). Thus, it has been suggested that "non-computer work" activities in general (i.e. all work activities that do not involve computer work, including other desk work and breaks) do not contribute to any major extent to increasing exposure variation (McLean et al. 2001, Slijper et al. 2007). A few studies (Fernstrom and Åborg 1999, Mathiassen et al. 2003a, Nordander et al. 2000) comparing the muscle loads of several office tasks suggest that differences between computer and non-computer tasks might, indeed, be limited.

In order to compare exposure and exposure variability between computer work (CW) and non-computer work (NCW), an operational definition is needed, according to which the work day can be divided into separate episodes of CW and NCW. A classification method that has gained considerable attention in recent years relies on software installed on a subject's computer, which records all use of input devices by logging single *computer events* (i.e. a mouse click or a keyboard stroke). The software tracks computer use in a fast, unobtrusive and inexpensive manner and is suited for monitoring large groups of computer users for extended periods of time (Chang et al. 2007, Mikkelsen et al. 2007).

In order to decide whether the time between two recorded consecutive events should be classified as a CW episode or a NCW episode, an arbitrary threshold (*Non-Computer Threshold, NCT*) is needed. The NCT defines how far two computer events can be apart with the time in between still being classified as (uninterrupted) computer work. A short NCT will only classify activities closely related to the actual use of input devices as "computer work", while for a large NCT, "computer work" might also include other desk-related activities like paper-based desk work, or even short periods off the workplace, for instance when walking to the copier.

Some evidence suggests that with a NCT of about 30 s, total computer work duration as obtained from registration software corresponds roughly to the duration according to observations by an ergonomist (Blangsted et al. 2004a, Heinrich et al. 2004). To which extent "computer" and "non-computer" work differ in biomechanical exposure is, however, unknown, while essential to the significance of the information obtained by the registration software.

Thus, a primary goal of the present study was to examine exposure contrasts between CW and NCW episodes. A particularly interesting issue concerns the optimal magnitude of the NCT, i.e. the NCT at which exposures during CW and NCW show the largest possible contrast, and the corresponding maximal ability of the registration software to discriminate between CW and NCW exposures. Since working habits differ between subgroups of office workers, e.g. according to gender, main job function or CANS status (Hipple and Kosanovich 2003, Richter et al. 2008), the size of exposures, contrasts and optimal NCTs might even differ between groups. So far, studies using only software registrations have assigned a "standard" optimal NCT to all participants, since personal optimal NCTs based on biomechanical exposure recordings have not usually been available (e.g. Blangsted et al. 2004a, Chang et al. 2007, Mikkelsen et al. 2007). This could imply that the exposure contrast is less than optimal for each particular individual, but the size of this possible effect is not known at present.

In the present study, computer events were recorded using registration software during a regular working day from participants that performed their normal office work at their own computer, and these registrations were synchronized with continuous electromyography (EMG) measurements of arm and shoulder muscle activity. EMG has been used as a measure of biomechanical exposure in numerous studies of computer work in laboratory settings (e.g. Crenshaw et al. 2006, Huysmans et al. 2008, Szeto et al. 2005) as well as in the field (Arvidsson et al. 2006, Larsman et al. 2009, Mork and Westgaard 2007), based on the notion that the magnitude and variation of arm and shoulder muscle activity are important determinants of the risk of developing CANS. By systematically varying the NCT in the obtained dataset we were able to address the following questions:

1a. How does the mean and variability of muscle activity during CW and NCW change with NCT?

1b. Which NCT (NCT_{opt}) leads to the highest contrast (C_{max}) in muscle activity between CW and NCW episodes and what is the size of this contrast?

2. Does the mean and variability of muscle activity and the values of NCT_{opt} and C_{max} differ between subgroups of office workers?

3a. What is lost in exposure contrast between CW and NCW when applying an averaged, group-based NCT_{opt} to individuals, rather than their personal NCT_{opt}?

3b. Can the discriminative ability of a group-based NCT_{opt} be improved by using values specific to each subgroup?

Methods

Subject population

At the Erasmus MC in Rotterdam, the Netherlands, about 5000 employees are engaged in office work tasks on a regular basis, using computers to different extents. Out of these, 571 participants volunteered to participate in the present research, all of which reported to spend more than 50 percent of their work time at computer-related activities (for more details, see Richter et al. 2008, Slijper et al. 2007). Among these extensive computer users, 70 participants were identified who reported in a self-administered questionnaire to have had moderate to severe non-specific complaints of arm, neck and/or shoulder (CANS) for several months prior to the study. From this CANS population, 15 participants were randomly selected into the present study. For each of the 15 CANS participants, a matched (gender, job function, age and working hours) control subject who had no history of CANS in the past year was selected from the population of extensive computer users. Matching was successful, since no significant differences were found on the matching criteria between the CANS group and the control group.

On the basis of previous experience of the size of within- and between-subject variability in EMG from the upper trapezius and the lower arm (Jackson et al. 2009, Mathiassen et al. 2002, Mathiassen et al. 2003a, Mathiassen et al. 2003b, Nordander et al. 2004), a total sample size of 30 participants, with 15 in either group with and without CANS, was considered to provide a sufficiently sensitive basis for detecting biologically significant differences in EMG levels and variabilities between these groups, and between CW and NCW within participants. Also, a sample this size would offer ample information to give credible estimates of the sizes of optimal discrimination thresholds and their associated exposure contrasts. The total group consisted of 24 females and 6 males. 14 had secretarial jobs, 9 were researchers, 5 had managerial jobs and 2 were IT-specialist (for more details on classification of main job function, see Richter et al. 2008). Twelve worked part-time (20–35 hours/week), 11 worked full-time (35–40 h/w) and 7 worked more than full-time. Twenty-nine participants were right-handed, although two of them, both in the CANS group, used the mouse with the left hand. One subject without CANS was left-handed, but used the mouse with the right hand. The mouse-handling side was defined as the dominant (D) body side, and the other side was defined as non-dominant (ND). In order to screen for 11 forms of specific CANS as defined in the SALTSA report by Sluiter et al. (2000), the participants in the CANS group completed an extensive, standardized physical examination by a rehabilitation doctor. All CANS participants were classified by this examination as having non-specific CANS in the upper extremity.

Protocol

Participants were monitored during a normal working day at their own workplace for approximately 6 hours without being interrupted or controlled by the researchers. For these participants, a normal working day included working with an office suite (e.g. Microsoft Office), e-mail and internet, having about 30 minutes of lunch break in an in-house restaurant and two coffee breaks of approximately 15 minutes each during the day. None of the participants left the office building during the measurement. Together with the participants, a working day was selected where computer work was expected to comprise at least 50% of the work time. Throughout the day, participants wore a hip bag containing the measurement device (see below), which allowed participants to move freely. Participants signed an informed consent but were not further informed about the exact variables being assessed during the day.

Measurements

Electromyography (EMG)

Electromyography (EMG) signals were collected from six muscles using bipolar surface electrodes (30 mm diameter, Nutrode Mini-P10m0 pre-gelled EMG-electrodes, Technomed Europe). Bilateral recordings were made from the extensor carpi radialis (ECR) and the flexor carpi radialis (FCR) muscles in the lower arm, and from the trapezius pars descendens (Trap) muscle. We chose these muscles because they are common sites for computer-related complaints (Goudy and McLean 2006, Juul-Kristensen et al. 2004, Laursen and Jensen 2000, Laursen et al. 2001). The skin was cleaned with alcohol prior to applying the electrodes. The electrode pair was placed according to SENIAM recommendations (Hermens et al. 1999) on the centre of the muscle belly, parallel to the muscle fiber direction.

Signals were collected at 1024 Hz to a portable logger (Porti-17TM, TMS, Enschede, The Netherlands, CMRR >90 dB), offline high-pass filtered at 5 Hz, rectified and low-pass filtered using a gauss filter with a cut-off of 32 Hz. Data were further downsampled to 8 Hz using a moving average filter (Nordander et al. 2004). The rectified and filtered signals obtained during work were normalized by the signal obtained during a voluntary reference contraction before the onset of the workplace measurement. Normalization was performed to control for within- and between-subject variability due to e.g. skin impedance, exact electrode placement and muscle fibre composition (Mathiassen et al. 1995). The reference contraction consisted in sitting with straight arms in 90° abduction with the palm of the hand facing forward, while holding a vertically oriented load of 2 kg for 5 to 10 seconds (Hansson et al. 2000). The reference EMG (%RVE) was obtained for each muscle separately as the highest average EMG value in a 2 second moving window during the reference contraction. The RVE test was organized by the same researcher (JR) for all participants, and she was also responsible for the placement of EMG electrodes.

Software registrations

Custom built registration software was installed on each subject's computer months prior to the EMG measurement day for other purposes (see Richter et al. 2008, Slijper et al. 2007). The software checked the position of the cursor (screen x and y coordinates in pixels) at a frequency of 10 Hz, and noted whenever this position had changed. Also, the software recorded key presses on the keyboard, mouse clicks and mouse wheel use (temporal resolution 10 Hz). All of these actions were defined as *computer events*. The software logged the data without notifying the computer user in order not to interfere with his regular work. Data were collected on a central server, downloaded by the researchers and processed offline.

Signal synchronization

In order to align the EMG signal with the computer registration file we performed a synchronization procedure. A button attached to the EMG recorder produced a sharp pulse when pressed. At the beginning of the working day, the experimenter repeatedly tapped a key of the keyboard using that button, thus stamping a simultaneous signal in both the registration software and the EMG file. These event marks were used to align the signals from the EMG recorder and the registration software.

Analyses

From the normalized and synchronized files, we excluded the first 10 minutes containing synchronization and the briefing of the subject, and the last 10 minutes with preparations for dismantling. Analyses of the remaining data were performed using MATLAB (version 7.0, The MathWorks, Inc.).

Definition of computer and non-computer work

In order to discriminate periods of computer work from non-computer work, a *Non-Computer Threshold* (NCT) was introduced, which specified the maximal period of time that two subsequent computer events were allowed to be separated for the time in between them to still be regarded as computer work (see also Richter et al. 2008, Slijper et al. 2007). Each uninterrupted period of computer work according to a particular NCT was classified as an *episode* of computer work (CW), while periods where the time span between events exceeded the NCT were classified as episodes of non-computer work (NCW). Thresholds (NCTs) of 2, 5, 7, 10, 20, 30, 40, 60, 120, 240, 480 and 960 seconds were applied to investigate the consequences of NCT definition. This procedure is illustrated in Figure 5.1a, showing that with increasing NCT, the time classified as CW increases, while the number of CW episodes decreases.

Because the software registration file had a different sample frequency (10 Hz) than the filtered EMG file (8 Hz), we selected the nearest points in the EMG recording file to each onset and offset of computer episodes in the registration file.

Exposure parameters

Mean exposure

Mean levels of EMG were assessed on the basis of the adjusted EMG signal. First, the overall mean EMG level for each subject was determined by averaging the whole EMG signal throughout the working day. Second, by applying each of the twelve NCTs to the EMG signal and concatenating the resulting EMG of all episodes classified as CW and NCW, twelve NCT-specific datasets were obtained on CW and NCW exposure for each subject. The mean EMG level during CW and NCW was calculated for each of these datasets. The median value across all participants was used as a measure of central tendency across the group. Variability between participants was expressed by the interquartile range (IQR) across participants, i.e. the range between the 25^{th} and 75^{th} percentile of the population distribution.

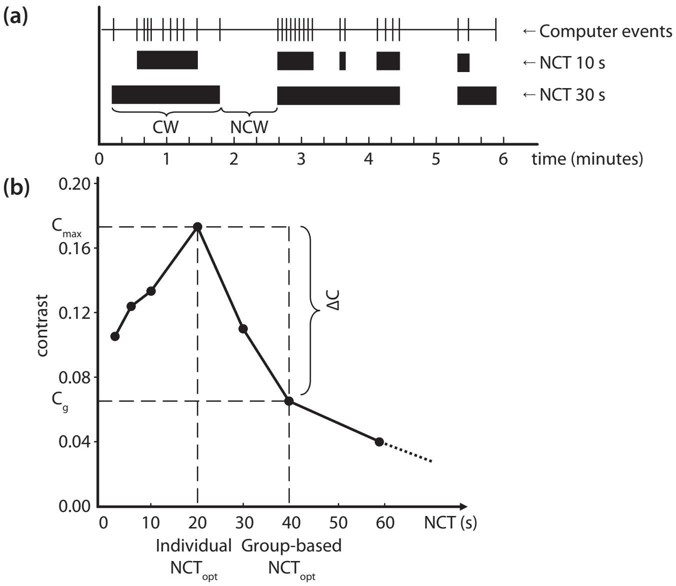

Figure 5.1 (a) Timeline of single, discrete computer events (top line), and the resulting episodes of computer work (CW) and non-computer work (NCW) using non-computer work thresholds (NCT) of 10 s and 30 s. Figure 5.1(b) Example of the influence of NCT on the contrast between CW and NCW. The optimal NCT (Individual NCT_{opt} , 20 s in this example) is illustrated together with the corresponding maximal individual-specific contrast, C_{max}, as well at the contrast C_g resulting from using a group-based NCT_{opt} of 40 s. ΔC is the loss of contrast.

Exposure variability

In order to assess the variability of EMG within day and subject, the overall EMG signal as well as the concatenated EMG signals for CW and NCW were binned in consecutive periods of 1 minute (Arvidsson et al. 2006, Mathiassen et al. 2003a, Nordander et al. 2000). The mean level of EMG was determined for each of these bins, and the standard deviation of these mean values across the bins was calculated across the entire signal and for CW and NCW separately, termed s_{CW} and s_{NCW}, respectively. Additionally, coefficients of variation (CV, i.e. s_{CW}/mean and s_{NCW}/mean, respectively) were calculated for the CW and NCW EMG as relative measures of variability. These calculations were performed for each muscle separately.

Exposure contrast

The contrast in exposure between CW and NCW was assessed for each NCT value, muscle and subject according to the equation:

$$C_t = \frac{MSE_t}{\left(MSE_t + s_t^2\right)}$$

Equation 5.1

In Equation 5.1, MSE_t expresses the difference between mean exposures during CW and NCW for a particular NCT (as defined by its threshold value t) in terms of a Mean Squared Error, and s_t^2 is the average variance within CW and NCW at that NCT, i.e. $(s_{CW}^2+s_{NCW}^2)/2$. Thus, on a scale between 0 and 1, C_t takes into consideration both the difference in mean exposure between CW and NCW and the exposure variability within either category. Equation 5.1 is an individual-based modification of the contrast formula given by Mathiassen et al. (2005) for assessing diversity between tasks at the level of groups.

For every subject and muscle, that NCT (NCT_{opt}) was identified at which the contrast was largest (C_{max}), cf. Figure 5.1b. For each muscle, the median of the subject-specific (n=30) values of C_{max} and NCT_{opt} were determined to express the central tendency of the group. The IQR was used as measure of dispersion in the group. Medians of C_{max} and NCT_{opt} were also obtained for subgroups stratified according to CANS (15 participants with CANS vs. 15 without CANS) and main job function (14 participants with secretarial jobs, nine researchers and five with managerial jobs). Only two participants in our dataset were IT-professionals, and were therefore excluded from the job function analysis. Considering that only six participants were males, stratification by gender was not warranted.

Loss of contrast when using a group-based NCT_{opt}

The magnitude of loss of exposure contrast between CW and NCW when using the group-based NCT_{opt} rather than the personal NCT_{opt} was assessed for each individual by subtracting the contrast C_g obtained when applying the group-based NCT_{opt} to that individual from the individual's personal C_{max} (see Figure 5.1b) and express the difference, i.e. $\Delta C = C_{max} - C_g$, in percent of C_{max}. Similarly, loss of contrast within subgroups was assessed by the difference, ΔC_s, between the contrast, C_s, obtained by using a subgroup-based NCT_{opt}, and the optimal, individual-based C_{max}.

Statistics

Visual inspection of the outcome parameters showed that some of the data were non-normally distributed (not shown). Formal tests (Kolmogorow-Smirnov, $p<0.05$) indicated that statistically significant non-normality was present in 7% of the investigated distributions. We therefore performed non-parametrical tests on all data. Suspected non-normality was also a reason for choosing medians instead of means as measures of central tendencies in groups.

Differences in mean EMG, s_{CW}, s_{NCW} and coefficient of variation (CV) between CW and NCW were addressed for every NCT using the Wilcoxon matched-pairs test. Differences in NCT_{opt}, C_{max}, C_g, ΔC and ΔC_s between muscles were tested using the Friedman test for multiple dependent samples and, when significant ($p<0.05$), post-hoc tests were performed using the Wilcoxon signed-rank test, with an adjusted significance threshold of 0.01 to compensate the effect of repeated multiple testing. Differences in mean EMG, CV, NCT_{opt} and C_{max} between subgroups of participants were tested using the Mann-Whitney U test for two independent samples (CANS) and the Kruskal-Wallis test for multiple independent samples (job function). Differences between ΔC and ΔC_s in subgroups were tested with the Wilcoxon matched-pairs test.

Results

Characteristics of computer and non-computer work episodes

Participants were on average monitored for 21281 s (5:55 hours:minutes) with a range of 4:10 – 6:40 hours. The number of CW episodes decreased from 648 (SD between participants 263) to 3 (SD 1) when NCT changed from 2 s to 960 s (Figure 5.2). A linear fit of the number of episodes by the log-transformed NCT revealed that doubling the NCT resulted in an approximate decrease of 40% in the number of episodes.

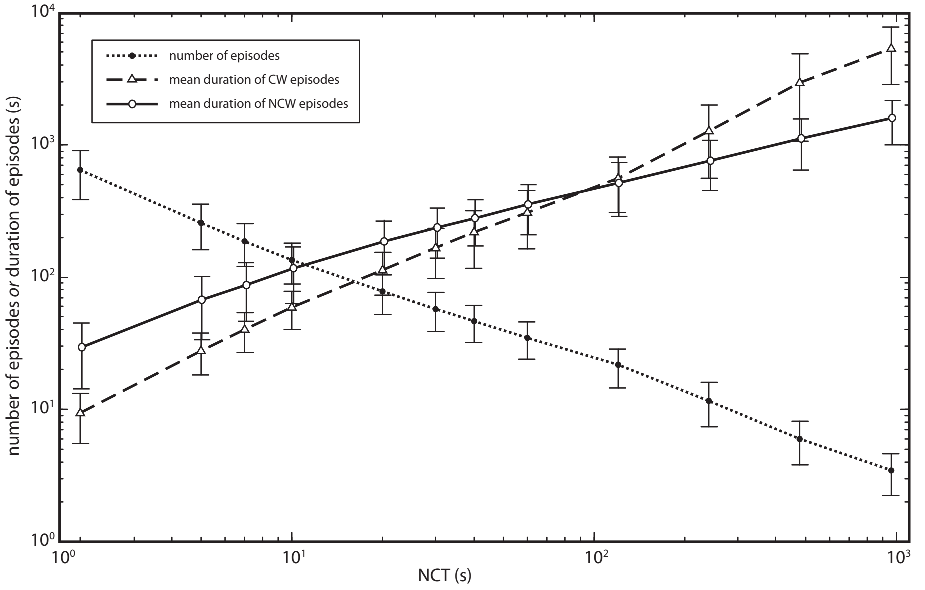

Figure 5.2: Relationship between the log_{10}-transformation of the Non-Computer Threshold (NCT) and the number of computer work (CW) episodes (dashed line with dots), the mean duration of CW episodes (dashed line with triangles), and the mean duration of NCW episodes (line with open dots). Error bars illustrate one standard deviation between participants.

With a NCT of 2 s, the average duration of CW episodes was 9.3 s (SD 3.8 s) (Figure 5.2). This duration increased to 5337 s (SD 2493 s), i.e. about 89 minutes, at a NCT of 960 s. A linear regression fit revealed an increase in CW duration by 90% when doubling the NCT. For NCW episodes, the averaged duration increased from 29.7 s (SD 15.6 s) to 1591 s (SD 597 s) across the range of investigated NCTs (Figure 5.2), corresponding to an approximate 50% increase when doubling the NCT. For a NCT of 30 seconds the mean number of episodes was 57 and the mean duration of these episodes was 165 s (SD 67 s) for CW and 236 s (SD 96 s) for NCW. This summed up to an average of 2:36 hours of computer work per subject, corresponding to 44% of the total measurement period.

For subgroups of participants with and without complaints of arm, neck and/or shoulder (CANS) and participants with different job functions, no significant differences were found in the mean number of episodes and in the mean duration of CW and NCW episodes (data not shown, p>0.3).

EMG levels during computer and non-computer work

The overall mean EMG levels in ECR were 3.8% RVE (group median ND (non-dominant side)) and 4.8% RVE (D (dominant side)); Figure 5.3, dotted lines), in the FCR, these values were 17.8% RVE and 18.1% RVE, and the mean EMG levels in Trap on non-dominant and dominant side were 25.9% RVE and 26.3% RVE, respectively.

The mean EMG levels during CW and NCW were significantly different for NCTs up to 240–960 seconds, dependent on the muscles (a Chi-square of, on average, 18: average p-value 0.004, Figure 5.3, arrows). In all muscles, the largest difference in EMG between CW and NCW was found at rather short NCTs (2 to approximately 30 s). For these NCTs, the CW EMG level was on average 45%, 70% and 65% (ND) and 57%, 75% and 56% (D) of the level during NCW (order of muscles from left to right as in Figure 5.3)

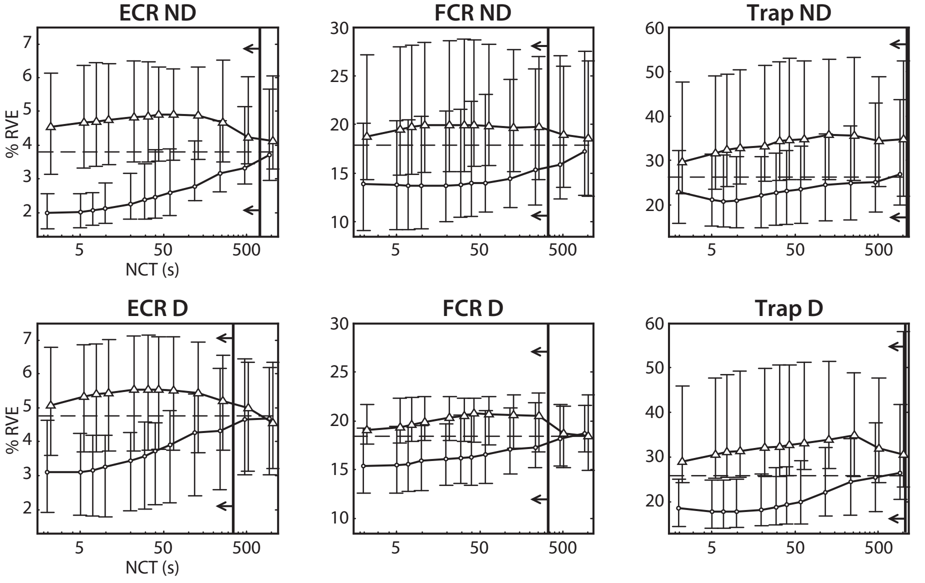

Figure 5.3: Mean EMG during computer work (CW, dots) and non-computer work (NCW, triangles) in relation to the NCT. Median values across participants are shown separately for each muscle (ECR, extensor carpi radialis; FCR, flexor carpi radialis; Trap, trapezius; ND, non-dominant side; D, dominant side). Error bars show IQR across participants. Overall mean exposure of the group is indicated by the horizontal dashed line. EMG during CW differed significantly from that during NCW at NCT values to the left of the arrows. X and y labels in all plots are similar to the two left-most plots.

EMG levels during CW and NCW changed with increasing NCT in a similar fashion across muscles and body sides (Figure 5.3). For NCW, mean EMG increased for low NCTs, followed by a decrease for higher NCTs. Mean EMG level during CW decreased in half of the muscles for low NCTs, and increased in all muscles for higher NCTs. Furthermore, with increasing NCT, mean EMG levels of CW and NCW converged towards the overall mean EMG level (horizontal dotted lines in Figure 5.3).

EMG variability during computer and non-computer work

The overall standard deviations between 1-minute bins of mean EMG in the ECR were 3.0% RVE (group median for ND) and 3.8% RVE (D); Figure 5.4, horizontal lines). For the FCR, corresponding values were 9.3% RVE and 8.7% RVE, and the EMG variability in Trap on non-dominant and dominant side was 19.8% RVE and 19.5% RVE, respectively.

The EMG variability in CW, i.e. the s_{CW}, was significantly smaller (average z=-4.41, p=0.003) than that during NCW, i.e. s_{NCW}, for all muscles and NCTs, except for an NCT of 960 s in ECR ND and ECR D. For these discriminating NCTs, the s_{CW} was on average 50%, 62%, 44% (ND) and 51%, 63% and 47% (D) of the s_{NCW} (full lines in Figure 5.4). The coefficient of variation (CV) changed

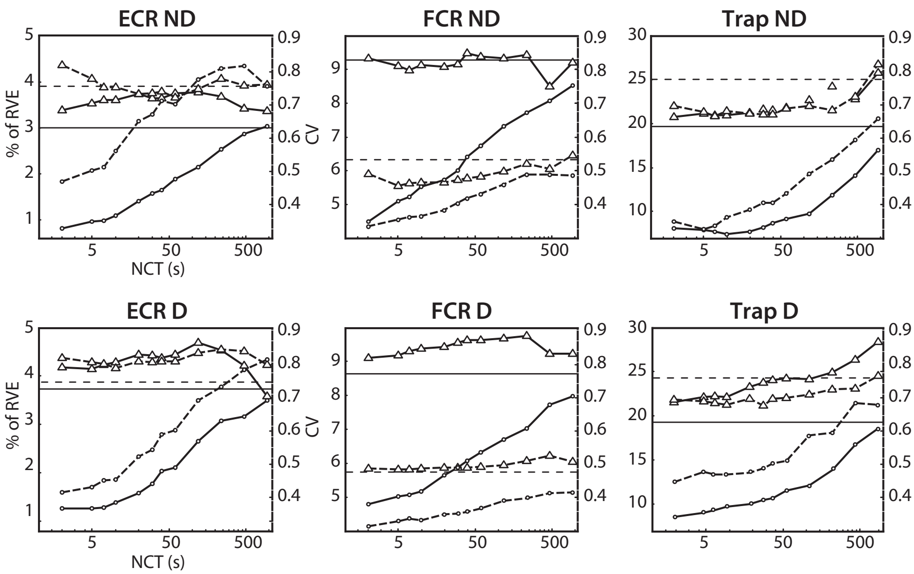

Figure 5.4: Standard deviation (full lines, left y-axis) and CV value (dashed lines, right dashed y-axis) of EMG amplitudes across one-minute bins of CW (dots) and NCW (triangles) for all NCTs; median values across participants. The standard deviation and CV of the entire EMG recording are indicated by the full-drawn and dashed horizontal lines, respectively. Muscle abbreviations, see Figure 5.3.

across NCTs in a similar fashion as the standard deviation (dotted lines in Figure 5.4) and was significantly smaller during CW than during NCW for all NCTs in some muscles (Trap ND and D, FCR D, average Wilcoxon, z= -4.41, -3.88 and -3.24, p<0.001, p=0.002 and p=0.004) and for some NCTs in the others (2–30 s in ECR ND, 2–20 s in FCR ND and 2–240 s in ECR D: average Wilcoxon, z over significant NCTs equal to -3.68, -2.77 and -4.17, p=0.007, p=0.01 and p<0.001).

Exposure contrast between computer and non-computer work

The value of NCT_{opt}, i.e. the NCT-value resulting in the largest contrast, C_{max}, between CW and NCW for a particular individual, differed considerably among participants (open circles in Figure 5.5). Group-based NCT_{opt} values between 7 and 20 s were found (vertical lines in Figure 5.5; Table 5.1), and they were significantly related to muscle (Chi-square=22, p<0.001). Post-hoc tests showed that ECR ND had a lower NCT_{opt} than all other muscles except FCR ND (average z=3.06, p=0.003: Table 5.1).

The corresponding median values of C_{max} ranged between 0.13 and 0.21 among the muscles (Figure 5.5, horizontal lines and Table 5.1), and this difference was significant (Chi-square=16.5, p=0.006). C_{max} for the dominant ECR muscles was significantly lower than ECR ND, FCR ND and FCR D (z=3.02, p= 0.003, Table 5.1).

Exposure characteristics in subgroups

The mean EMG level in participants with CANS was about 25% larger in the FCR muscle on the dominant side during both CW and NCW than in participants without CANS (z for CW and NCW between -2.71 and -2.00, depending on NCT, p between 0.007 and 0.045). None of the other muscles exhibited significant differences between participants with and without CANS.

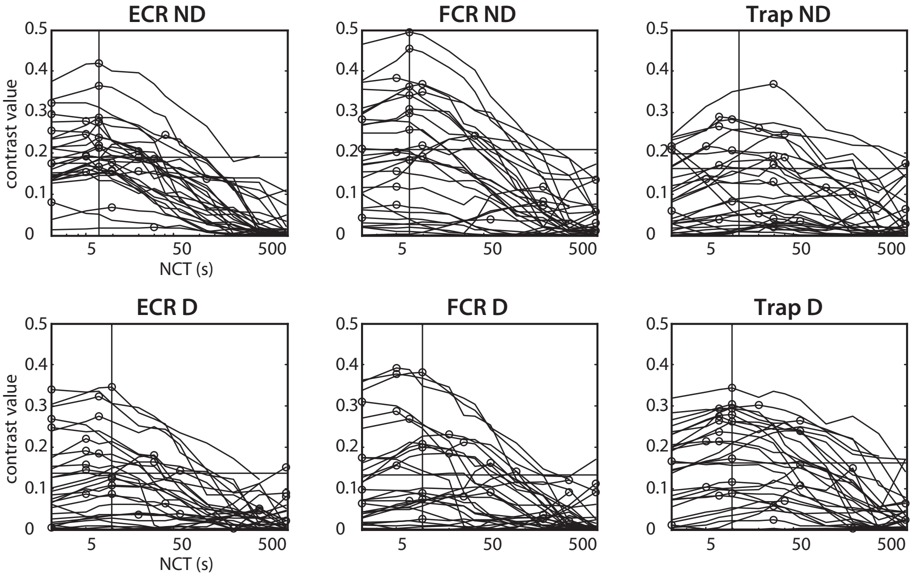

Figure 5.5: Individual lines (n=30) of the contrast in mean EMG between CW and NCW obtained at the investigated NCTs. Open circles mark the maximal contrast, C_{max}, for every subject. The horizontal line shows the median C_{max} across participants. The vertical line indicates the median NCT_{opt} across participants.

EMG variability in CW was similar for groups with and without CANS except in Trap D for most of the NCTs, for which participants with CANS had lower CV values for all NCTs between 2 and 240 s (average z=-2.47, p=0.02). Variability in NCW was only significantly different between participants with and without CANS for FCR D, where participants with CANS had lower CV values for NCTs between 2 and 120 s (average z=-2.19, p=0.03). Similarly, NCT_{opt} values were not statistically different for participants with and without CANS (Table 1). For some muscles, this lack of significance was probably due to large dispersions between participants, and hence a limited power of the study to detect even considerable differences. For Trap on the non-dominant side, the CANS group showed higher contrast values (C_{max}) than the group without CANS (z=-2.1, p=0.036, Table 5.1).

Job function significantly influenced the mean EMG in ECR ND during CW and NCW except at an NCT of 2 s during CW (mean Chi-square=8.98, p=0.016). Also, mean EMG in ECR D differed according to job function, but only for CW and not for all NCTs (mean Chi-square=6.62, p=0.037 for NCTs from 10 to 480 s). In the above cases, researchers had lower mean EMG values than secretaries and managers. EMG variability (CV) during CW did not differ between job functions. In contrast, job function had a substantial influence on EMG variability during NCW. In all muscles except FCR and Trap on the dominant side, significant differences were found for almost all NCTs (Chi-square=10.74, 8.70, 10.28 and 8.67; p=0.006, 0.015, 0.007 and 0.015 for ECR ND, FCR ND, Trap ND and ECR D, respectively). For ECR ND, FCR ND and ECR D, researchers had higher CV values than secretaries and managers, and for Trap ND, secretaries had lower CV values than researchers and managers. NCT_{opt} values did not differ significantly between job functions, and C_{max} values were also similar except for FCR ND, where secretaries had a higher C_{max} than researchers and managers (Chi-square=7.5, p=0.024).

Loss of contrast when using a group-based NCT_{opt}

As expected, applying the group-based median NCT_{opt} instead of the subject-specific NCT_{opt} led to a loss of contrast between CW and NCW for most individuals. The contrasts, C_g, obtained when using group medians of NCT_{opt}, ranged between 0.09 and 0.19 among the muscles (Table 5.1), which was between 0.005 and 0.07 lower than the individual-specific C_{max} (Table 5.1). This loss of contrast,

▸ *Table 5.1: Group median values with between-subject IQR (interquartile range) in brackets for the optimal NCT (NCT_{opt}), the corresponding maximal contrast C_{max}, the contrast C_g obtained when using the overall group-based NCT_{opt} on each subject, and the loss of contrast when using either the group-based or subgroup-based NCT_{opt} instead of individual-specific values of NCT_{opt} (ΔC and $ΔC_s$, respectively). For each muscle (columns), data are shown for the whole population as well as for subgroups with and without complaints of arm, neck and/or shoulder (CANS) and subgroups with different main job functions.*

	Subgroups	ECR ND	FCR ND	Trap ND	ECR D	FCR D	Trap D
NCT_{opt} (s)	all subjects	7 (5)[b]	7 (55)	20 (33)	10 (55)	10 (115)	10 (53)
	MSC	7 (13)	7 (33)	10 (25)	20 (365)	30 (415)	10 (31)
	no MSC	7 (5)	7 (190)	30 (47)	10 (55)	10 (45)	10 (53)
	Secretaries	7 (2)	7 (3)	10 (23)	10 (473)	10 (113)	10 (3)
	Researchers	20 (18)	40 (411)	30 (39)	30 (159)	30 (291)	60 (411)
	Managers	7 (33)	7 (415)	10 (28)	5 (4)	5 (6)	10 (31)
C_{max}	all subjects	0.19 (0.10)	0.21 (0.22)	0.17 (0.16)	0.14 (0.13)[b]	0.13 (0.13)	0.17 (0.18)
	MSC	0.22 (0.09)	0.24 (0.15)	0.20 (0.05)[a]	0.09 (0.16)	0.09 (0.13)	0.24 (0.15)
	no MSC	0.18 (0.09)	0.16 (0.30)	0.06 (0.14)	0.14 (0.09)	0.16 (0.13)	0.11 (0.18)
	Secretaries	0.23 (0.08)	0.29 (0.14)[a]	0.17 (0.19)	0.13 (0.17)	0.15 (0.15)	0.26 (0.18)
	Researchers	0.19 (0.06)	0.08 (0.18)	0.14 (0.18)	0.16 (0.11)	0.10 (0.13)	0.10 (0.17)
	Managers	0.25 (0.18)	0.13 (0.06)	0.17 (0.16)	0.15 (0.20)	0.18 (0.25)	0.17 (0.15)
C_g	all subjects	0.19 (0.09)	0.19 (0.27)	0.10 (0.17)	0.12 (0.15)	0.09 (0.16)	0.16 (0.21)
ΔC (%)	all subjects	4.7 (9.9)	2.9 (30.4)	7.8 (34.9)	9.7 (30.8)	13.2 (41.8)[b]	3.8 (29.0)
ΔC_s (%)	MSC	3.3 (6.0)	2.7 (28.7)	11.5 (53.9)	15.1 (53.3)	22.1 (55.7)	2.3 (21.4)
	no MSC	6.2 (12.1)	4.7 (32.0)	11.6 (44.0)	5.2 (22.6)	5.4 (35.2)	6.4 (42.1)
	Secretaries	0.8 (5.1)	2.1 (2.9)[a]	5.2 (8.4)	10.3 (79.7)	12.5 (58.0)	0.2 (3.2)
	Researchers	4.7 (33.3)	31.0 (65.5)	4.9 (26.6)	9.2 (31.9)	14.8 (56.7)	30.1 (52.6)[a]
	Managers	5.3 (34.2)	6.4 (57.4)	16.6 (67.4)	1.8 (8.6)	3.2 (4.8)	4.3 (25.2)

[a] p<0.05 for the difference between subgroups
[b] p<0.01 for the difference between muscles

ΔC, corresponded to, on average, 7.0% of C_{max} (4.7%, 2.9%, 7.8%, 9.7%, 13.2% and 3.8% for the separate muscles, order as in Table 5.1). While this loss of contrast was significant when tested across all muscles together (Chi-square=13.6, p=0.019), post-hoc testing did not reveal any significant differences between individual muscles except for the difference between FCR D and ECR ND, which was only borderline significant (p=0.011) when using the stricter significance limit for post-hoc testing.

When using subgroup-specific values of NCT_{opt}, loss of contrast was similar among participants with and without complaints of arm, neck and/or shoulder (p at least 0.08 across muscles, Table 5.1). Likewise, ΔC_s was similar across job functions for most muscles except for FCR on the non-dominant side and Trap on the dominant side. For FCR ND, secretaries had a lower ΔC_s than researchers and managers, and for Trap D, researchers had a higher ΔC_s than secretaries and managers (Table 5.1; Chi-square=6.6 and 7.9, p=0.038 and 0.02, respectively). Finally, using a subgroup- instead of a group-based NCT_{opt} did not result in any significant improvement of the loss of contrast (not shown).

Discussion

In the present study we used a temporal discrimination threshold (Non-Computer Threshold or NCT) to divide a time line of computer input events into CW (computer work) and NCW (non-computer work) episodes. The differences in biomechanical exposure, as assessed through EMG, between CW and NCW were investigated. We decided to use EMG as our target measure of exposure because it has been widely used in studies of computer work (e.g. Huysmans et al. 2008, Larsman et al. 2009, Mork and Westgaard 2007) to reflect what is believed to be important determinants of risk for contracting CANS, i.e. the level and time pattern of muscle activity in the upper extremity (Griffiths et al. 2007, Village et al. 2006).

In the Introduction we asked three questions regarding the relationship between EMG activity during CW and NCW episodes and the NCT used to identify these episodes. Answers to these questions are necessary to appreciate the ability of registration software to help in estimating muscle activity patterns in individual office workers, and to address whether non-computer activities are likely to offer a source of increased variation in computer-intensive work. Similar studies are needed of other important exposure measures, such as upper arm postures or movement velocities of the hand, to determine the discriminative ability of computer activity logs and the opportunities for increasing variation in these cases. Since our study population was deliberately selected to represent extensive computer users in an academic setting, results related to the time line of CW and NCW episodes and the muscle activity patterns at the overall job level may not be directly applicable to academic staff in general, let alone computer users in other occupations. Results concerning exposure within CW and NCW, however, including contrasts between CW and NCW and the ability of registration software to identify these contrasts, may be more consistent between jobs with different proportions of computer work.

Effects of the NCT on occurrence and muscle activity of CW and NCW (cf. question 1a)

Duration and number of CW and NCW episodes

The duration and number of CW and NCW episodes changed markedly and regularly with increasing NCT in a log-linear fashion. As a rule of thumb we found that when the NCT was doubled, CW and NCW episode durations increased by 90% and 50%, respectively, while the number of episodes decreased by 40%. These results add to previous findings of ours suggesting a log-linear relationship between the total duration of what is classified as computer work and the chosen NCT (Richter et al. 2008).

Mean EMG during CW and NCW

We found that the mean EMG during CW episodes increased with NCT, preceded by an initial decrease for some muscles (Figure 5.3). Mean EMG during NCW also increased with the NCT, up to values of NCT between 30 and 240 s, after which NCW EMG decreased again (Figure 5.3). The counter-intuitive increase in both CW and NCW EMG activity for NCTs between about 5 and 30 s can be explained if one assumes that NCW is associated with EMG levels that are generally higher than those seen during CW. If the lower part of the NCW EMG is then re-classified to be CW when the NCT changes, that change will lead to an increase in average EMG during both CW and NCW. The convergence of the EMG activity during CW and NCW at high NCT values is reasonable, because at these time scales more and more 'other' desk-related activities get classified as computer work, and computer and non-computer work exposures will tend to get more similar.

Independent of the discrimination threshold, the mean levels of EMG in the ECR, FCR and Trap muscles were significantly higher during NCW than during CW on both body sides (Figure 5.3). Higher EMG in NCW as compared to CW has also been reported in other studies. For instance, Fernström and Åborg (1999) found higher trapezius activity during general desk work (9.0% MVC) than during data entry work (6.0%), and Arvidsson et al. (2006) found higher muscular activities in trapezius and lower arm extensors during breaks than during computer-based work in air traffic controllers. Other studies have, however, reported a lack of difference or even a higher EMG activity during computer work. For instance, Nordander et al. (2000) found no differences in muscular "rest" between keyboard work (11% of time) and general desk work (12% of time) among office workers, while in a laboratory experiment, Blangsted et al. (2004b) found that a typing task was associated with larger EMG levels than controlled rest breaks between work bouts. The conflicting results of the above studies might be explained by large differences in study design. In the experiment reported by Blangsted et al. (2004b), participants were required to perform a controlled computer task, with non-computer work consisting only of rest breaks, while several other studies have allowed participants to perform their daily computer work including a whole range of desk-related activities (Arvidsson et al. 2006, Fernstrom and Åborg 1999, Nordander et al. 2000), which might or might not be directly related to active computer usage. In an experimental setting, the external exposure during both breaks (e.g. controlled rest in a seated position) as well as computer work (e.g. typing a particular text piece) is deliberately controlled, which probably results in a higher exposure during computer work than during non-computer work. Further studies will be needed to gain a better understanding of the contents and exposure time-line of computer-related tasks and other tasks performed by office workers, and how the exposure pattern may influence relevant outcomes such as fatigue and performance.

EMG variability in CW and NCW

Similar to the mean EMG levels, EMG variability was higher in NCW than in CW for all muscles and most NCTs (Figure 5.4). At small NCT values (2 and 5 s), variability during CW was on average 64% of the value during NCW when expressed in terms of the coefficient of variation. These results confirm the impression that at small NCT values, when computer use is closely related to input device use, computer work is characterized by low muscle activity with little variability. While sometimes difficult to compare because of various definitions and assessment methods, the magnitude of EMG variability (CV) in the current study (range 0.32–0.85) seemed somewhat higher than that reported in previous studies of EMG in assembly work (Jackson et al. 2009, Mathiassen et al. 2003b, Möller et al. 2004) and during surgery (Luttmann et al. 1996), in which CV ranged between 0.04 for trapezius and 0.20 for lower arm extensors. This difference is probably caused partly by the explicit and isolated tasks studied in the above mentioned papers, leading to less variability between episodes than in the present case of more mixed work, and partly by the fact that some of these studies report variability between "bins" (or work cycles) which are longer than the 1 min. applied by us, and hence prone to be more stable (Mathiassen et al. 2003b). In general, descriptive measures of exposure variability within participants have been explored only little as candidates for important ergonomics information (Mathiassen 2006, Mathiassen et al. 2003b).

Effects of the NCT on exposure contrasts between CW and NCW (cf. question 1b)

The maximal contrast C_{max} between CW and NCW EMG was reached at a NCT between 7 s and 20 s, depending on the muscle (Figure 5, vertical lines, and Table 5.1). At this NCT value, NCT_{opt}, the registration software discriminated best between CW and NCW exposures.

At the NCT_{opt} specific to each muscle and individual, C_{max} values of 0.13–0.21 were reached (Table 5.1), with a considerable dispersion between participants. Given that the differences in mean EMG level between computer work and non-computer work were distinct (Figure 5.3) and significant for most muscles, it follows from Equation 5.1 that the dominant cause of these low C_{max} values was substantial within-subject variability in CW and NCW EMG. As illustrated in Figure 5.4, NCW EMG exhibited a particularly large variability.

Reference data for comparison with the contrast values observed in our study are scarce in the literature. This is due to a general paucity of data on within-subject variability in muscle activity – some studies are cited above – and a specific lack of studies reporting such data from two or more tasks. However, in a study of trapezius EMG in several office tasks, Mathiassen et al. (2003a) reported the mean and within-subject variability, using 1-minute bins, of two trapezius EMG parameters describing the occurrence of muscle "rest" and the frequency of changes in EMG. Entering these data in equation 1 yield contrasts between computer work and other office tasks, which are, in general, less than 0.05 and thus considerably smaller than those obtained in the present study. The same paper also reports data from cleaning tasks, and the EMG contrast between computer work and cleaning rises to about 0.50 for the frequency parameter, but only to 0.10 for muscle "rest". The study by Möller et al. (2004) compared bilateral trapezius and lower arm EMG from three assembly tasks with a cycle time between 3 and 4 minutes. Within-subject variability was expressed by the cycle-to-cycle variance. For the right trapezius EMG level, contrasts between the tasks ranged from 0.10 to 0.29, while contrasts up to 0.56 were observed for the left trapezius. In a study of repeated 4 s cycles of nut running using a pneumatic torque wrench, Mathiassen et al. (2003b) reported data on median EMG from the trapezius muscle and the lower arm during work in three different body postures. The maximal EMG contrasts between working postures were 0.72 and 0.81 for the right and left trapezius, respectively, while lower arm EMG contrasts never exceeded 0.16. With proper caution due to different task definitions, EMG variables and measures of within-subject variability, the contrasts observed by us do not seem to be exceptionally small as compared to previous reports from office work, but probably smaller than contrasts between tasks that differ substantially in working postures and external loads. This suggests that ordinary non-computer tasks may have some potential to increase overall variation in computer-intensive office work, but that more vigorous physical activity would have a substantially larger effect.

C_{max} values differed substantially between participants, and for several subject, C_{max} was even below 0.05 (Figure 5.5). Thus, at the level of individual office workers, software registrations of computer events may provide limited information on muscle activity patterns during daily computer use. Too small exposure contrasts between computer work and non-computer work, specifically rest breaks, have been suggested in previous studies to be an explanation that introducing more non-computer activities had little effect on fatigue and discomfort (McLean et al. 2001). Based on similar considerations, Fernström and Åborg (1999) concluded that job rotation between different office tasks, including computer work, had limited effects as compared to performing only one of those tasks. Indeed, too little contrast between conventional, habitual office tasks may seriously limit the potential for creating an office job with adequate variation by combining those tasks (Mathiassen 2006), which, in turn, may call for more radical initiatives, such as introducing physical exercise at work. While some studies have been devoted to physiologic effects of combining standard office work with more vigorous activities (Henning et al. 1997, van den Heuvel et al. 2003), more research is still needed to document appropriate exposure contrasts between candidate tasks for interventions aiming at more variation. These studies should also explore the feasibility of using different task combinations (Mathiassen 2006). The design of the present study did not allow any deeper analysis of whether specific tasks or activities occurred during "non-computer work" that had particular pronounced exposure contrast as compared to computer work, and hence a greater potential to increase variation than "non-computer work" in general.

Definition of computer work

In the present study, the optimal exposure contrast between "computer work" and "non-computer work" was obtained using an entirely data-driven procedure based on the recorded time-line of interactions with the keyboard and mouse. Previous studies using event registration software have not defined the NCT using this optimization approach. In some of these studies, the NCT has been chosen on the basis of some generic idea of the time span that events can be apart for the time in-between still to be regarded as "computer work", but the resulting NCT has ranged from 2.5 to 60 s, and consensus has not been reached yet (Richter et al. 2008). In some other studies using registration software, the NCT has been selected so as to produce an overall occurrence of "computer work" that corresponded to that judged by a trained observer (Heinrich et al. 2004, Homan and Armstrong 2003). The definition of "computer work" is then essentially based on expert observation and might include both active use of the keyboard and mouse and reading from the computer screen. Notably, though, the observer and the software may not necessarily agree on the occurrence of "computer work" in real-time, even though the overall duration of "computer work" is the same.

In some research using questionnaires to estimate computer use duration, merely the use of input devices has been classified as computer work (e.g. Homan and Armstrong 2003, Menendez et al. 2008) while in other questionnaire studies, computer work was also meant to include looking at the screen as well as short periods of thinking in front of the computer (e.g. Blangsted et al. 2004a, Korhonen et al. 2003). Moreover, computer users tend to largely overestimate the duration of their computer work (for an overview, see Richter et al. 2008), and more severely so with increasing time actually spent working with the computer. What a subject considers to be "computer work" thus seems to differ from definitions based on more objective criteria. This general ambiguity regarding the definition and registration of "computer work" obstructs comparisons and combinations of studies. In the current study, the detailed records of EMG activity and computer input use throughout a whole working day in a substantial amount of participants allowed us to assess exposure and exposure contrasts during computer work and non-computer work using objective methods, which is an advantage compared to most previous studies.

Differences in exposure and contrasts between subgroups of office workers (cf. question 2)

Although we did not find differences in the number and duration of computer work episodes between CANS and control participants or between participants with different job functions, some of the EMG variables differed significantly between subgroups. A significantly larger muscle activity in the dominant FCR, and a higher contrast value in the non-dominant trapezius were found in participants with CANS as compared to controls, but the numerical differences were small. Previous studies investigating EMG activity in office workers with and without CANS showed a similar tendency with either no differences in muscle activity between participants with and without CANS (Roe et al. 2001, Thorn et al. 2007, Voerman et al. 2006) or slightly higher trapezius and forearm extensor muscle activity in participants with CANS (Szeto et al. 2005).

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Participants with different job functions showed some small but significant differences in both the mean and variability of muscle load, most notable in ECR on both body sides. The differences between job functions could be expected, given the different job contents and time schedules of the employees. Some differences between subgroups in the investigated EMG parameters may have been missed due to insufficient power.

Loss of contrast when using group-based NCTs (cf. questions 3a and 3b)

When the median NCT_{opt} across all 30 participants was used on each individual instead of their personal optimum, contrast values decreased to, in median, between 0.09 and 0.19 depending on the muscle, as compared to 0.13 to 0.21 using the subject-specific NCT_{opt}. This corresponded to a loss of contrast of on average 7%.

This further corroborates the notion that event registration software is of limited informative value with respect to muscle activity, in particular if used together with a "standard" NCT_{opt}. Notably, choosing a standard NCT_{opt} will be the preferred choice in large-scale studies, due to the extensive resource demands associated with determining a personal NCT_{opt} for each individual. The prospects of using registration software may be better for other biomechanical exposures than EMG, but this remains to be investigated.

Only small differences in loss of contrast were found between subgroups of participants (Table 5.1). Moreover, using a subgroup-based NCT_{opt} value did not lead to a smaller loss of contrast as compared to using the overall group-based NCT_{opt}. These results suggest that a stratification of participants into subgroups based on complaints of arm, neck and/or shoulder or job functions will not, to any notable extent, improve the ability of registration software to discriminate exposure.

Conclusion

In conclusion, registration software could give some, but not much, information that was useful for discriminating muscle activity patterns during computer and non-computer work. Performance was limited even in the optimal case of using an individual-based, data-driven time threshold for distinguishing computer work episodes from non-computer work, and it decreased by a further 7% when applying a standard group-based discrimination threshold to all participants. This calls for caution when using registration software results as proxies of biomechanical exposure, in particular together with standard discrimination thresholds. A more strict definition of "computer work" and "non-computer tasks" during office work than that offered by the software is necessary to arrive at better prospects for comparing and combining studies of computer-related activities, and thus to come to a better understanding of the associated biomechanical exposures and their relation to complaints of arm, neck and/or shoulder. Furthermore, our study suggests that the potential of conventional non-computer tasks to increase variation in muscle activity during computer-intensive office work is limited, at least in occupational settings similar to the one studied by us. In this case, more radical initiatives may be necessary, such as organized physical exercise at work.

6

Chapter 6

Statistics predict kinematics of hand movements during everyday activity

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Adapted from:

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Abstract

Bayesian decision theory suggests that the statistics of an individual's actions (prior experience) play an important role in motor control and execution. To elucidate this relation, we recorded 7 million mouse movements made by a group of 20 computer users across a 50-day work period, allowing us to estimate the prior distribution of spontaneous hand movements. We found that the most frequent movements were in cardinal directions. The shape of this distribution was participant-specific but constant over time and independent of the computer that the participant used. This non-uniform directional distribution allowed us to predict systematic errors in initial movement directions, which matched well with the actual data. This shows how movement statistics can influence hand kinematics.

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Introduction

The body of literature focusing on the kinematics of target-directed arm movements is vast — a search of PubMed using kinematics and arm movement as keywords yielded more than 1,500 relevant hits. Among others, general characteristics of movement times and amplitudes (Fitts 1966), curvature (Flash and Hogan 1985, Wolpert et al. 1994), movement variability (Haggard and Richardson 1996, van Beers et al. 2004), movement directions (Baud-Bovy and Viviani 2004, de Graaf et al. 1991) and relations among these descriptors (Gottlieb et al. 1997, Smeets and Brenner 1999) have been extensively described.

Recent theories of human perception and motor behaviour have hypothesized that the found regularities are caused by the statistics of the visual world (like the distribution of fixation locations) and our motor repertoire (Purves et al. 2001, Wolpert 2007). This Bayesian approach (Kording and Wolpert 2006, Kording 2007) requires a thorough knowledge of the statistics of sensory input and motor output. For visual perception, measurements of specific parameters of images and scenes can be used to obtain reliable statistics (Foster et al. 2006, Motoyoshi et al. 2007, Simoncelli 2003).

There is, however, no easy way to determine the statistics of human motor performance. If studies are limited to short-term changes in instructed movements in a laboratory situation, the relevant statistics can not be determined (e.g. Krakauer et al. 2006). Therefore, studies (Kording and Wolpert 2006, Wolpert 2007) have only been able to infer the statistics of motor actions (referred to as priors) on the basis of observed movement variability within a very limited set of circumstances. Studies of natural, spontaneous arm movements over an extensive period of time are described have not been described (cf. Ingram et al. 2008). What amplitudes and directions are most commonly used? And are the movements straight? No knowledge about the statistics of such basic parameters is available.

To gain insight into natural movement behaviour, we chose to measure computer mouse use because it is a frequently occurring type of arm movement that can be recorded without interfering with natural behaviour. Using custom-built registration software, we registered mouse movements in a group of 20 computer users for a period of 50 work days during real-life computer work. These movement trajectories were subsequently used to identify and characterize movement amplitudes, directions, velocities and curvatures of more than 7 million naturally occurring arm movements. We will show that shape of the distributions of mouse amplitude and direction is similar across all participants, although highly participant-specific variations do exist (i.e., participants have a mouse signature).

To investigate how these movement statistics influence motor execution, we reasoned that the uncertainty regarding movement amplitude and direction decreases during movement execution. At the onset of the movement, there is significant uncertainty regarding the inverse kinematics and dynamics calculations needed to start a movement (Flash and Sejnowski 2001) due to proprioceptive and visual errors (Smeets and Brenner 2004, Sober and Sabes 2005). In a Bayesian approach this uncertainty is minimized by using prior experience (Kording and Wolpert 2006). Moreover, Bayesian theory explains how this uncertainty (in terms of the likelihood) and the prior experience (the Bayesian Prior) are to be combined to minimize errors in endpoint direction. This would mean that the initial muscle activation chosen to start a movement would be influenced by how likely it was to make a movement in a particular direction. Such a control scheme implies that the initial movement direction for a certain endpoint direction can be predicted on the basis of the frequency distribution of endpoint directions. The advantage is that during the initial stages of the movement, execution can be quickened by relying on the most common motor commands speeded-up. In this article, we will show that this is the case.

Methods

Participants and data acquisition

We installed custom-built registration software on the computers used by 20 participants, healthy employees (9 men, 11 women; mean ± SD age = 33.9 ± 8.7 years) of the Erasmus MC in Rotterdam, the Netherlands. Participants signed informed consent forms before entering the study. The participants performed a variety of computer-intensive work; 8 had an administrative job, 6 were researchers and 6 had managerial or other functions. Participants' monitors had an aspect ratio of 4 to 3. In all, 12 participants worked behind a monitor with a resolution of 1024 by 768 pixels, 7 worked with a higher resolution screen and 1 worked with a lower resolution screen. Of the participants, each of 14 worked behind a single computer, whereas each of 6 worked with 2 different computers.

Participants were instructed to turn off the acceleration setting of the mouse and not to change the mouse gain during the measurement period. To establish how much the hand moved relative to the movement of the cursor on the screen, we had all participants perform a small calibration experiment in which they traced a square with a side of 3 cm on a piece of paper using the mouse. Across all participants, we found a gain of 197 ± 58 pixels/cm hand displacement.

The software registered the position of the cursor (x-, y-coordinates in pixels) with a frequency of 10 Hz and logged these data in the background not to interfere with the regular work of the participants. The unobtrusive nature of the installed monitoring software ensured that they quickly forgot that they were monitored. It is unlikely that participants altered their working behaviour as a consequence of participating in the study. Data were transferred automatically to a central server and processed offline (Slijper et al. 2007). To ensure that the data files (for each participant for every day) contained sufficient data, data files containing fewer than 10,000 position changes of the cursor (>1 pixel) were not selected. For this study, we processed a random sample of 50 workdays for each of the participants.

Data processing

Identification of individual cursor movements

For each of the 1000 recorded days, we extracted the times at which the cursor changed position. These time series, containing the corresponding displacements of the cursor in horizontal direction (x) and vertical direction (y), were used for further analysis.

To identify the start point and endpoint of cursor movements (see Figure 6.1a) from the recorded time traces, we calculated the (vector) combined displacement in x and y directions (xy). We considered as the *start point* of a cursor movement the sample after which the Δxy exceeded a threshold. The *endpoint* was defined as the sample after which Δxy became subthreshold. We chose a threshold of 5 pixels/sample (about 0.25 mm hand movement) to ensure we could calculate movement direction accurately for small amplitude movements (because the screen forms a grid of pixels, only a small number of movement directions are defined for very small movements). By using a threshold of 5 pixels, we excluded only 10.7± 2.4 % of the movements.

For every cursor movement, we determined subsequently the movement time, the amplitude (straight distance from start point to endpoint), and the endpoint direction. To estimate the magnitude of hand displacements (in cm) for the recorded cursor displacements, we divided the found amplitudes by the individual's gain factor from the calibration experiment. For every working day and for every computer separately these values were used to determine individual usage patterns (see Figure 6.2).

Bayesian predictions

To investigate whether the statistics of movement directions influenced the initial movement direction of individual movements, we analysed movements for which this initial direction could be reliably determined. As our measurement method does not permit us to determine the direction of short movements, we restricted ourselves for this analysis to movements with amplitudes of at least 12 pixels and containing 5 data points or more (40% of the total number of movements).

According to Bayes's rule, the chance of a (initial) movement direction (φ_i) given the sensory estimate φ_e, is described as:

$$P(\varphi_e \mid \varphi_i) = \frac{P(\varphi_e \mid \varphi_i)P(\varphi_i)}{P(\varphi_e)}$$

Equation 6.1

where $P(\varphi_e|\varphi_i)$ is the sensory precision (given a direction φ_i, the chance that the sensory estimate equals (φ_e), and P(φ_i) is the a priori chance for φ_i to occur. The chance P(φ_e) is simply a normalization factor and does not change the relative probabilities between φ_e and φ_i. In the analysis, we modeled the sensory precision by a Gaussian distribution with SD = 17° and used the measured distribution of endpoint directions (histogram) as the prior.

To find the most likely value for the initial movement direction given a certain sensory estimate, $\varphi_i(\varphi_e)$, we calculated the weighted average, or each value φ_i multiplied by its chance to occur:

$$\hat{\varphi}_i(\varphi_e) = \sum_{\varphi_i} \varphi_i P(\varphi_i \mid \varphi_e) = \sum_{\varphi_i} \varphi_i P(\varphi_e \mid \varphi_i) P(\varphi_i)$$

Equation 6.2

To compare this prediction with the actual relation between φ_i and φ_e, we calculated $\varphi_i - \varphi_e$ by the angle between a straight line distance between *start* (S) and *end location* (E) and the line from S to the *sample point* (M), where the distance between the trajectory and the straight line distance between S and E was maximal (see Figure 6.3). If the initial movement direction deviated in clockwise direction compared with the endpoint direction, the angle was denoted as positive.

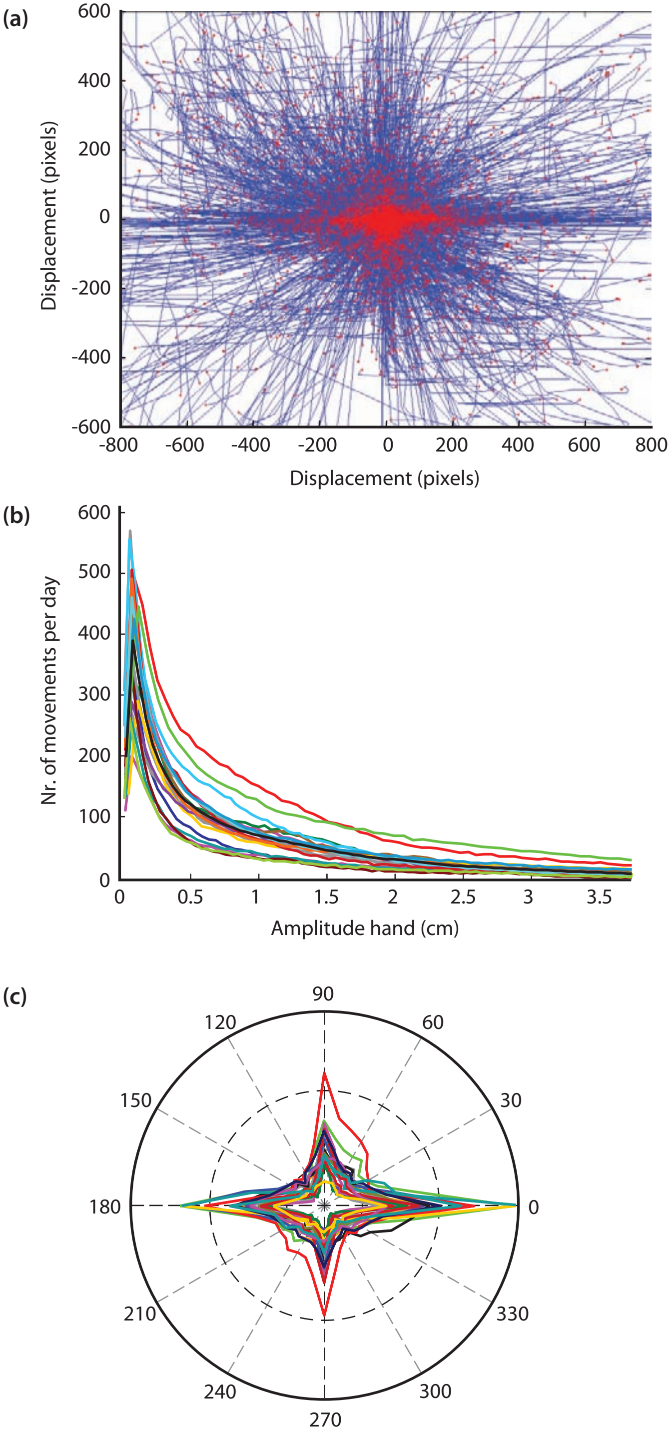
Results

General characteristics

On average participants worked 8 hr and 29 min per day (computer on-off time). During this period, they made on average 7192 (± 1967: *SD* between participants) cursor movements with a total duration of 1 hr and 12 min (± 23 min). During a day, the cursor followed a path of more than 1.5 million pixels (± 480,580), corresponding to approximately 74 m of hand movement. Figure 6.1a shows an example of the displacements during cursor movements made by 1 participant during 1 day of work. We translated the starting location of each movement to the origin (0,0). Note the non-uniform distribution of movements and the abundance of horizontal and vertical movements. This was not a specific characteristic of this participant but was true for all participants (Figure 6.1b and c, compare the different lines). The average median amplitude of the hand movements was 0.32 ± 0.08 cm (corresponding to 62 ± 15 pixels of cursor movement). Shown in Figure 6.1b is the amplitude distribution of the hand movements for all the participants. The average median duration of the movements was 0.29 ± 0.05 s. Additionally, we found that the movements had a low average velocity (path length divided by the duration). The distributions of the average velocities showed that the majority (>50%) of mouse movements were performed with a hand velocity smaller than 1 cm/s.

Distribution of movement directions

The preference for movements in cardinal directions on an average day for each of the 20 participants is shown in Figure 6.1c. Horizontal and vertical movements are most common in all participants. Almost half the movements (47.5%) were horizontal (within 22.5° from 0° [right] and 180° [left]), and 27% were vertical


(a)
Displacement (pixels)
Displacement (pixels)
600
400
200
0
-200
-400
-600
-800
-600
-400
-200
0
200
400
600
800
(b)
Nr. of movements per day
Amplitude hand (cm)
600
500
400
300
200
100
0
0
0.5
1
1.5
2
2.5
3
3.5
(c)
90
120
60
150
30
180
0
210
330
240
300
270

◂ *Figure 6.1: Overview of results. (a) Typical example of cursor movements made by Participant 3 during 1 day. Starting points of the movements have been translated to the origin (0,0); the endpoints of the movements are marked with a black dot. (b) Distribution of amplitudes of hand movements for all 20 participants (the different lines) across days. The distribution (thick line group average) is skewed: Movements between 0.2 and 0.4 cm occur most often (median, 0.32 cm). (c) Directional distribution of movements (averaged across days) for the 20 participants (the different lines). The dashed line shows the distribution for random movements. Note the preference for movements in cardinal directions. Directions are binned using 10° bins. Outer circle = 1000 movements.*

(within 22.5° from 90° and 270°). Figure 6.1c shows that the directional patterns for different participants (the different lines) are quite similar. Note that horizontal and vertical cursor movements correspond to hand movements to the left and to the right and away and toward the body, respectively.

Variability in amplitude between individual movements (reflected in the coefficient of variation across all directions and participants) was on average 13% larger for diagonal directions than for cardinal directions.

When we looked into the data of individual participants in more detail, we found that the directional pattern was surprisingly invariant across days and that there were idiosyncratic differences between the participants (see Figure 6.2). For instance, the difference in number of horizontal and vertical movements is much larger for Participant 1 than for Participant 3. Similar distinctive patterns were found in all other participants. Such differences are not due to differences in hardware, as the directional pattern was also invariant across computer used for participants that worked on more than one computer (see data of Participants 5 and 6 in Figure 6.2).

Predicting initial movement direction

Initial movement directions deviated systematically from the direction of the endpoint of movements. Averaged across all participant and days, these errors were up to 8°, depending on the movement direction (see Figure 6.3, solid line). It is interesting that the directional error changed sign at the peaks in relative

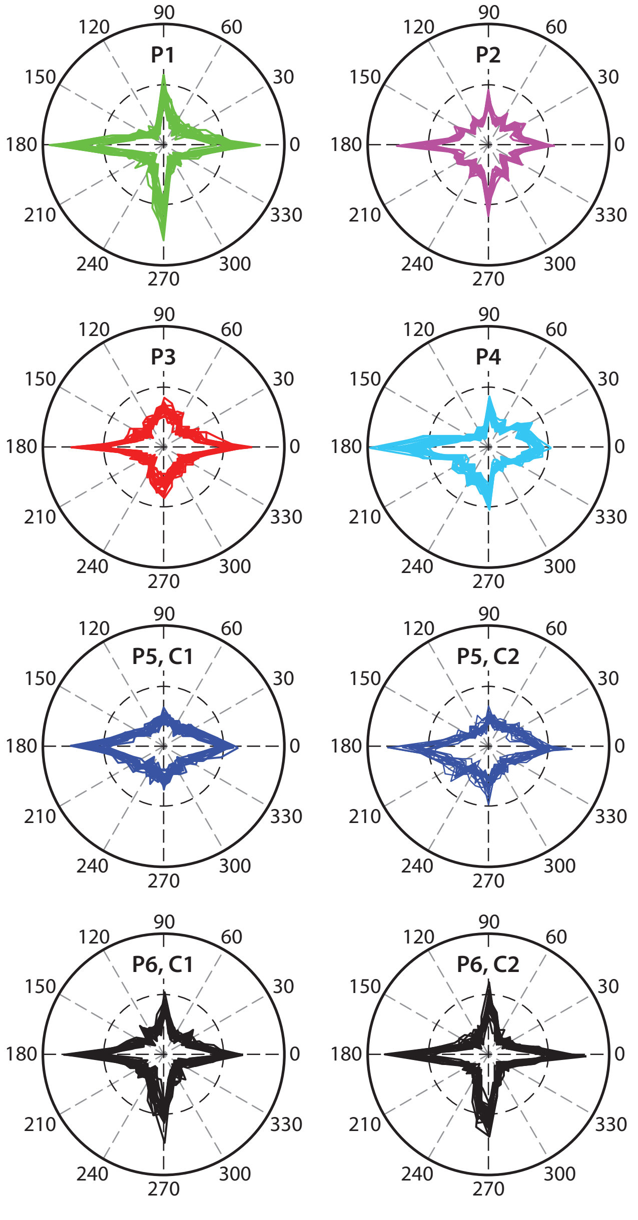


Figure 6.2: Examples of individual directional distributions. The top 4 panels show data across 25 days (the different lines) from Participants 1–4. Histogram data were normalized by dividing through the total number of movements for each day (scale: dimensionless units). Note the marked differences between the participants and the invariance of the pattern across days and computers. The lower four panels represent data generated by 2 participants working on two computers (left vs. right panels). Note the similarity in pattern between computers used by a single participant. P = participant; C = computer.

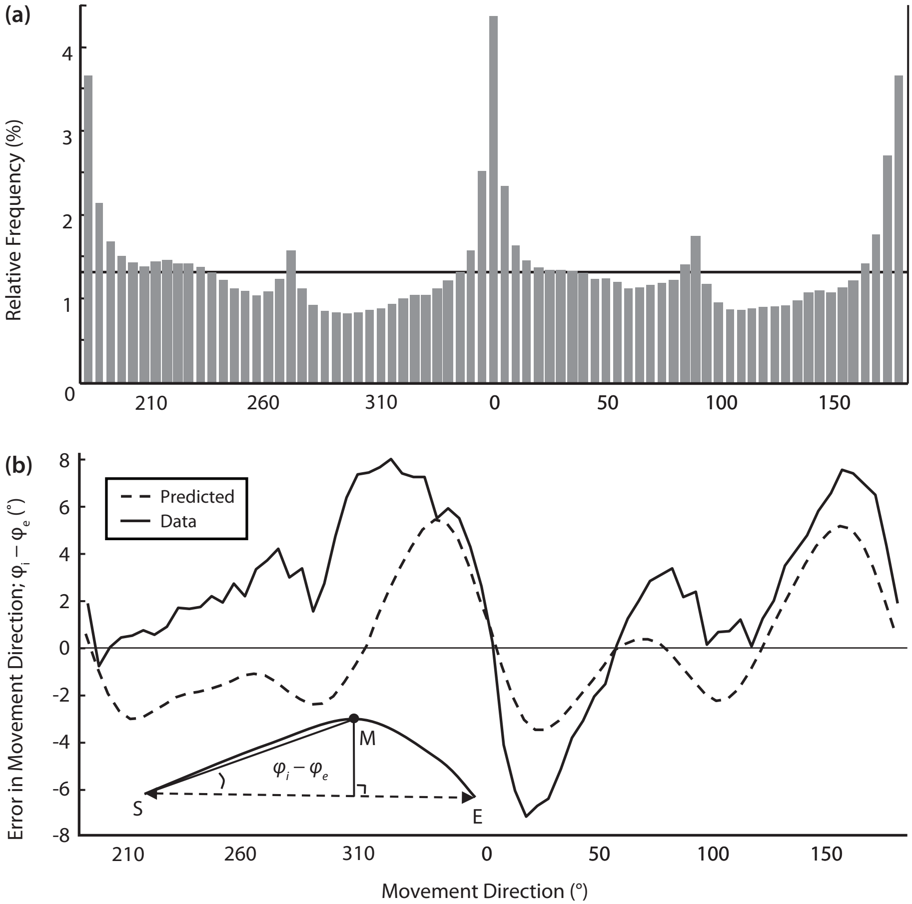


Figure 6.3: Relation between initial movement direction and direction of the endpoint. Shown are results for mouse movements across all participants. (a) Relative frequency of movements in particular directions (bins of 5°). A higher frequency of occurrence is related to smaller deviances in initial movement direction. The horizontal line denotes the average frequency across all movement directions. (b) Error in initial movement direction (φ_i - φ_e) was defined using the sample point M where the distance between the line S-E and movement trajectory was largest. φ_i - φ_e is shown as a solid line. The results of a Bayesian prediction of how initial movement direction depends on the distribution of mouse movement directions is shown by the dashed line. The found and predicted error in movement direction follow a similar shape across the movement directions.

frequency (0° and 180°; Figure 6.3) or was very close to zero (at 90° and 270°), and that the slope of the curve was positive. In other words, the movements that occurred most often were those that had the smallest error in initial movement direction, and movements that had endpoints close to these frequently occurring directions were biased to these directions.

Using Bayesian inference, we made a prediction of how initial movement direction would deviate from the direction of the endpoint, on the basis of how often movements occurred in specific movement directions, as previously mentioned in the introduction. Figure 6.3 (dashed line) shows the results of this prediction. After averaging the predicted values across all participants, we found a highly significant correlation of 0.703 ($p < 0.0001$) between the predicted errors and the found errors in initial movement direction. Note how the data follows the shape of the prediction across all movement directions. The quality of this correspondence varied per participant, but we found a positive correlation for all 20 participants (on average, 0.44 ± 0.20; $p < 0.01$).

Discussion

Directional pattern of the mouse movements

An important finding of the current study is that participants have strong directional preferences when making mouse movements. That is, movements in cardinal directions occur more often than diagonal movements (see star shapes in Figures 6.1c and 6.2).

At least two factors might explain such preferences: (a) the structure of the visual field (here the computer-user interface) and (b) factors involving the motor control system (i.e., biomechanics and the visuo-motor transformation). The structure of the visual field has a large influence on the direction and amplitude of target-directed eye movements (saccades; Hooge et al. 2005), which are likely to precede the majority of mouse movements. Moreover, during computer use, the visual field also directly evokes certain motor performance, because many of the objects on the screen are interactive. That is, they allow the participant to click, select, move, or drag visual objects by using the mouse.

Over et al. (2007) showed a preference for horizontal and vertical eye movements in tasks where the participant is to search for a target within a rectangular field. That is, participants' eye movements tend to follow luminance edges surrounding the workspace. A similar effect could occur for mouse movements. Because the user interface of most computers consists of rectangular elements organized in rows and columns (lists, menus, tabs, fields, buttons, etc.), it would provide a large number of horizontal and vertical lines that could induce a preference for mouse movements in cardinal directions.

Although the directional pattern across participants looked quite similar (Figure 6.1c) the pattern also seemed to contain some idiosyncratic characteristics that were specific for the individual user (see Figure 6.2). Thus, it seems that individuals have a *mouse signature*, or a typical way in which they move their mouse. It is likely that idiosyncrasies of the used software, such as the characteristics of the user interface of different programs, influence a participant's movement pattern in subtle ways, giving rise to reliable inter-individual differences as observed in the directional distributions of the movements. Further study is needed to determine whether this signature is more indicative of which software a participant uses or which participant uses particular software. Either way, it is important to notice that these small amplitude movements, occurring thousands of times each day, compromise our exposure and are therefore a prior for future movements.

A second factor that might underlay directional biases is a mechanical one. Because different joint motions are involved when moving in different directions, the inertia of the arm is not equal for all directions (inertial anisotropy; Flanagan and Lolley 2001, Gentili et al. 2004, Sabes et al. 1998). Maximum inertia is commonly seen for movements in the sagittal direction (movements that would be vertical on the computer screen) because of larger motion in the elbow and shoulder. This effect might explain the preference for horizontal cursor movements over vertical cursor movements, but not the preference for the cardinal axes over the diagonals. Control schemes based on the optimization of variables related to inertial properties of the arm seem therefore unlikely to be able to explain the observed directional preferences. Moreover, it is not very likely that this factor has a large influence because of the low velocities (and thus low acceleration) of the movements.

We have found that initial movement errors were largest for diagonal directions (see Figure 6.3), that the error in initial movement direction depends on the direction of the endpoint, and that amplitude variability was largest for diagonal movements. These findings are in line with several experimental studies using relatively large arm movements (30–40 cm). Movements in oblique directions have the largest error in start direction (de Graaf et al. 1991), have the largest endpoint errors without visual feedback (Baud-Bovy and Viviani 2004), and are more curved (Smyrnis et al. 2007).

Several studies have assumed that these directional biases originate in a distorted internal representation of target direction. The present data show that such a distortion may originate partly from the statistics of our actions. Using a Bayesian approach (Ghahramani 2000, Kording 2007), we showed that directional distribution of movements could be regarded as a prior for the initial movement direction. For instance, we found that movements slightly above or below the horizontal direction had an initial movement direction along the horizontal direction in line with the high occurrence of these movements. This could mean that participants move in a direction in which they are likely to make the least movement error. However, mouse movements are not totally unconstrained. Usually movements are made toward a target, which can have any location relative to the current cursor location. Most movements will thus require a movement in a specific movement direction, so that moving in the direction in which the individual makes the least error will therefore not be effective.

Alternatively, the results we obtained could be explained by using an optimization approach (Ghez et al. 1991), for instance, by minimizing jerkiness of the movement trajectory or energy expenditure. However, it will be difficult to find a cost function that can explain the large (on average up to 8°; see Figure 6.3) deviations in start direction, because highly curved trajectories are likely to cost more than straight trajectories.

Moreover, because the prior that is used in the Bayesian statistics method is known and the cost function that is used in a cost function analysis is an unknown, the most obvious method to model our mouse movement data is to use Bayesian statistics. Therefore, a more likely explanation would be that individuals used prior experience and used this information to optimize the probability of moving in the right movement direction. Therefore, the statistics of individuals' actions influence movement execution: The more often movements are made in a particular direction the more likely the initial movement will point in that direction.

7

Chapter 7

Discussion

In this chapter, the main results of the Chapters are summarized and interpreted, based on the five research questions that were posed in the General Introduction. Secondly, the possible associations between computer use patterns and the occurrence of CANS are explored. Thirdly, the practical implications for research and practice and suggestions for future studies are described. To conclude, the question is answered whether we can use registration software to assess measures of physical exposure during office work.

Answers to the research questions and interpretation

1. What is the relationship between the non-computer threshold (NCT) used and the duration of computer use? Is this relationship different for different groups of computer users? (Chapter 2)

For a large range of NCTs (1–120 s), we found a log-linear relationship between computer work duration and NCT, and a second-order relationship between both keyboard and mouse work duration and NCT. Furthermore, a two-fold increase in NCT resulted in a mere 3.5% increase in computer use duration, while for keyboard and mouse use, a two-fold increase in the NCT resulted in a variable increase in work duration of maximal 6%. Since both relationships were reliable and robust, these equations can be used as benchmarks for comparing work duration estimates in existing studies. Additionally, the differences in subject characteristics (gender, age and main job functions) in the relation between NCT and computer work duration were assessed. The subgroup differences that were found were mostly reflected in differences in intercept, which is an indication that subgroups differ in the daily amount of computer use. Also, some interaction effects were found in the relationship between NCT and computer use duration.

With the equations presented in Chapter 2, any NCT value between 1 and 120 seconds can be used in calculations of computer use duration. However, previous research comparing computer use duration as measured both by registration software and by (video) observation shows that an NCT in the range of 28–60 seconds (Chang et al. 2008) or, more specifically, 30 seconds (Blangsted et al. 2004a) results in a satisfactory correspondence between the two methods. Therefore, using 30 seconds as NCT is recommended. Nevertheless, researchers should bear in mind that this is only an average value, so in real-time, the observer and the software may not necessarily agree on the occurrence of a single episode of computer work, even though the overall duration of 'computer work' might be the same.

Furthermore, interaction effects were found between the relationship between NCT and the amount of computer work and subject characteristics (gender, age and job functions). Although these effects were rather small, this could theoretically lead to misclassification of the exposure level if different studies use different NCTs. However, this problem will be solved if future studies use a NCT of 30 seconds. In current studies, this should be taken into account, but the interactions we found were too small to recommend ergonomists to analyse subgroups of office workers separately when assessing computer use duration.

Additionally, adding keyboard and mouse use duration does not necessarily result in total computer use duration (but often in a higher value). This can be explained by the fact that mouse and keyboard use are often interlaced. For high NCTs, large time intervals between keyboard events (with possibly also mouse use) are classified as keyboard use. When mouse use was used in between keyboard use, that whole period will also be classified as mouse use, leading to a total of - theoretically - twice the duration of total computer use. Knowing this, researchers and ergonomists should not use keyboard and/or mouse use duration as a proxy of total computer use.

2. What personal or psychosocial factors influence the level of bias associated with self-reported computer use duration? (Chapter 3)

When measuring computer use duration with self-reports, participants usually overestimate duration when compared to registered computer use duration. We found that gender and psychological job demands were significantly associated with the level of absolute relative bias (aRB), which is the absolute percentage of the difference between *self-reported and registered duration. Males had lower aRB than females, and aRB increased with increasing psychosocial job demands. Gender and job demands accounted for nearly 50% of the systematic bias in aRB, but these two factors only slightly reduced the within-subject variability (7%), and left the between-subject variability virtually unchanged (1.9% reduction). Due to a large amount of variation in aRB within the subgroups we analysed, the predictive values of these factors were low for individual computer users. These results indicate that both estimates of computer use duration measure a different construct of duration, and therefore both measures are important for assessing the impact of prolonged computer use.*

Compared to computer use duration measured with registration software, computer use duration measured by self-report has been found to hold a certain level of bias. Comparing these two is difficult, since in previous research using self-reports, a large variety of definitions is used to describe computer work. Some studies gave no specifications other than to estimate 'computer use at work' in self-reports (Douwes et al. 2007, Mikkelsen et al. 2007, Unge et al. 2005), while other researchers asked participants to distinguish between keyboard and mouse use duration (Heinrich et al. 2004, Homan and Armstrong 2003, IJmker 2008, Lassen et al. 2005) or about computer use in specific tasks (e.g. copy entry, copy editing, information retrieval (Faucett and Rempel 1996)). Other researchers included specifications in questionnaires on what should be counted as computer use, e.g. 'active mouse and keyboard time' (Lassen et al. 2005) or 'computer use including reading from the screen' (IJmker 2008). This may lead to large differences in estimated computer use duration and makes interpretation of differences difficult.

Apart from this discrepancy in definition, it is largely unknown what factors influence the bias in self-reported computer use duration. The low predictive value of gender might explain the fact that often no influence of gender on duration estimation was found in literature (Balogh et al. 2004, Douwes et al. 2007, Faucett and Rempel 1996); the studies probably did not have enough discriminatory power to prove the small influence of gender.

3. What are the pause patterns that computer users display and how does pause software influence the work-pause pattern? (Chapter 4)

The work-pause pattern of computer users can be described as highly intermittent behaviour with short duration work periods being followed by slightly longer, and very variable pauses. Furthermore, the distribution of pause duration follows a power law with a slope of approximately -2, meaning that pauses with twice the duration are twice less likely to occur.

When pause software is used on the computer, it adds on average 25% micro pauses (5–10 s) to the number of micro pauses participants take spontaneously, and 57% macro pauses (5–8 min). However, these inserted pauses on average only add 7.2% extra 'pause time' to a working day. The majority (89%) of all inserted pauses are micro pauses, and we found that those pauses are inserted only shortly (45 s) before participants would take a spontaneous pause. On the other hand, macro pauses were inserted much earlier (53 min) than the natural pauses participants would take.

These findings led to the conclusion that it is unlikely that pause software contributes to reducing cumulative load, since it doesn't add substantial 'pause time' to the working day. Secondly, the benefit of adding micro pauses is doubted, since it does not considerably change the structure of the variability of the work-pause pattern of the working day. This might be the reason that two reviews on interventions against CANS have found limited or even mixed evidence for the effectiveness of introducing additional pauses (Brewer et al. 2006, Verhagen et al. 2007).

The reason that pause software inserts micro pauses only shortly before users take spontaneous pauses (45 s) is that the NCT that is used (30 seconds) is larger than the duration of micro pauses (5–10 seconds in most pause regimes of

Workpace). Spontaneous, short-duration pauses taken by the computer user are therefore still classified as computer work, and the micro pauses that the pause software offers are therefore abundant. The timing of micro pauses may even decrease the willingness of computer users to use pause software. We therefore suggest that computer users switch off this functionality in their pause software, at least the group of computer users with no CANS. Since we did not study pause behaviour in computer users with CANS, we don't know if their work-pause pattern is similar to the patterns we found in our (healthy) participant group.

A limitation of the current simulation study is that the work-pause behaviour that occurs if participants would actually receive micro and macro pauses from software could not be measured. Some mechanisms that could occur are speeding up computer work, working through regular pauses, or non-compliance to the pause regime (Mathiassen 2006, van den Heuvel et al. 2003). However, in a review, Lötters and Burdorf concluded that a 14% reduction in physical load is needed to induce a corresponding decline in CANS (2002). It is unlikely that the above described compensatory mechanisms could result in a two-fold increase of the pause time we found in our study (7.2%).

4. What are the differences in exposure between computer and non-computer work and how do these differences contribute to overall exposure levels and variability? (Chapter 5)

Mean EMG (electromyography) in three muscles in the lower arm and shoulder was higher during non-computer work (NCW) than during computer work (CW). Also, EMG variability was higher in NCW than in CW. At small NCT values (2–5 s), computer work was characterized by low muscle activity with little variability. The maximal contrast between CW and NCW was reached at NCTs between 7 and 20 s. However, this contrast was rather low (range 0.13–0.21), mainly caused by substantial within-subject variability in CW and especially in NCW. With standard *discrimination thresholds instead of individual optima, discriminative power decreased even further.*

Based on the rather low contrast that was found between computer work and non-computer work, which further decreased when using a standard NCT, we conclude that computer activity logs should be used cautiously as proxies of biomechanical exposure. According to the results of the EMG measurement performed in a subgroup of our total research population, conventional non-computer tasks may have a limited potential to increase exposure variation in terms of muscle activity to the work day in computer-intensive office work. The design of the study did not allow for further analysis of whether *specific* non-computer tasks or activities may have had higher exposure contrast compared to computer work. Some specific non-computer tasks may have a greater potential to increase variation to the work day than the overall 'non-computer work' of our participants. However, some additional information on NCW tasks was present in the current study. We know that our participants did not perform high-intensity non-computer tasks such as sports, and did not leave the building during the measurement. We therefore hypothesize that more radical non-computer tasks, such as organized physical exercise at work, may be necessary to increase exposure variation, which in turn might help to reduce the risk of developing musculoskeletal complaints (CANS).

We used EMG as a measure of biomechanical exposure because it is widely used in studies of computer work to assess the duration, level and variability of muscle activity in the upper extremity (e.g. Huysmans et al. 2008, Larsman et al. 2009, Mork and Westgaard 2007). However, we realize that EMG is not the only measure of exposure. Other measures, like registration of upper arm postures or movement velocities and accelerations of the arm and hand, used to measure forces on the skeleton and muscles, are needed to gain full understanding of the physical exposure office workers are experiencing. However, so far, our study using EMG is one of the few studies available on physical exposure of office workers. It shows that it is difficult to discriminate computer work from non-computer work on the basis of the level and variability of muscle activity. This indicates that physical risk factors for CANS cannot be solely attributable to computer use per se. Also non-computer work episodes during office work might present similar risk factors for CANS, which suggests that studying merely computer work is not sufficient in understanding the complex of risk factors associated with CANS. This could even implicate that computer use might not be the main risk factor for CANS, but that the research focus should be on going to the office.

5. What are the characteristics of mouse movements during daily computer use and how can these patterns be explained? (Chapter 6)

On average, mouse movements during daily computer use were quite small (0.32 ± 0.08 cm from start point to end point), had a short duration (0.29 ± 0.05 s) and a low average velocity (>50% had a hand velocity smaller than 1 cm/s). Additionally, the participants had strong directional preferences when making mouse movements; movements in cardinal directions (horizontal and vertical) occurred much more often (in 75% of all movements) than movements in diagonal directions. One of the factors that might explain this preference is the lay-out of the computer-user interface, for instance the fact that buttons and program menu structures are grouped horizontally and vertically. What's more, the mouse patterns we found seemed to contain some idiosyncratic (i.e. subject-specific) characteristics in the directional pattern. It thus seems that individuals have their own 'mouse signature'. Finally, the mouse movements that occurred most often had the smallest error in initial movement direction compared to the direction of the endpoint (the movements were straighter). This suggests that computer users use prior experience to move in the right movement direction.

The current study reveals that some characteristics of mouse movements were very subject-specific. Large between-subject variability in mouse use behaviour and markedly smaller within-subject variability over days was found. In our study, the acceleration setting of the mouse was turned off, and we compensated for the differences in mouse cursor velocity. When we measured mouse movements in single participants who worked at different computers, these subject-specific directional preferences remained. Because of privacy regulations in the hospital, it was not possible to measure the different programs participants worked with. Therefore, the question remains whether the found mouse signature is more indicative of which software a participant uses (software characteristic) or which participant uses particular software (personal characteristic).

Furthermore, we found that the initial mouse movement direction did not always point towards the endpoint direction, creating a certain level of curvature in the movement trajectory. This curvature was largest in movements that occurred in diagonal direction. We found that the discrepancy between initial and endpoint direction could be partly explained by how often a particular participant moved in a particular endpoint direction (using Bayes Rule). The more often a movement was made in a particular endpoint direction, the smaller the discrepancy between initial and endpoint direction and therefore, the straighter the movement.

CANS and patterns of computer use

The aim of the current dissertation was to describe (natural) patterns of computer use and provide suggestions on how these patterns might be related to complaints of arm, neck and/or shoulder (CANS). As described in the General Introduction and according to the Brussels Model, long-duration repetitive and static loading of the upper limb with little exposure variability is thought to be related to CANS (Flodgren et al. 2007, Jensen 2003, Johansson 2003, Tittiranonda et al. 1999, van Rijn et al. 2009). Below, we describe in what way the results in the dissertation relate to these measures of physical exposure.

Computer use duration

In the current dissertation and previous research, the level of computer use duration was found to depend on the method of assessment (Douwes et al. 2007, Faucett and Rempel 1996, Heinrich et al. 2004, Homan and Armstrong 2003, Lassen et al. 2005, Mikkelsen et al. 2007, Unge et al. 2005). This is consistent with the finding that the relationship between computer use duration and the onset of CANS is much stronger for self-reports than for registration software (IJmker 2008). This indicates that these two measures measure a different construct.

In this dissertation, the relation between NCT (non-computer threshold) and the duration of computer use was compared for different participant characteristics (gender, age, job function). Mostly interactions were found between subject characteristics in the relationship between NCT and computer work duration. This means that with different NCTs, different subgroups might be classified as having the longest duration, and therefore, misclassification in exposure might occur.

Static loading and exposure variability

The number of days that was needed to reliably estimate a six-month exposure period of computer use duration was calculated in this dissertation. We found that measuring computer use duration for at least 44 days within a period of six months was needed for our chosen level of reliability (CV<10% for 90% of participants). Thus, for a reliable measure of natural computer use duration over an extended period of time, it is necessary to take the large between-day variability into account and measure computer use duration longer than one day or one week.

Furthermore, we found that pause software does not introduce enough pause time (7.2% extra) to substantially change the natural work-pause pattern of a group of office workers. This is an indication that pause software does not substantially decrease cumulative loading during computer work. Secondly, the office workers we measured took relatively many spontaneous pauses before the pause administered by the software. These additional pauses did not substantially increase exposure variation. We therefore conclude that pause software only marginally changes computer pause patterns, and thereby does not reduce the occurrence of CANS. However, pause software might work through different mechanisms that we did not look at (e.g. an awareness effect by the introduction of extra pauses), which could possibly have a positive effect on the prevention of CANS.

On the other hand, we found that episodes of computer work are poorly discriminated from episodes of non-computer work, because of the large within-subject variability in EMG level in both types of episodes. This would mean that physical exposure during non-computer work (including breaks) is not substantially different from exposure during computer work. It suggests that adding additional pauses will not help to increase exposure variability.

We found that office workers mostly make mouse movements with a small amplitude, short duration and low average velocity. Furthermore, horizontal and vertical movements are most common, and the directional mouse movement pattern is very subject-specific, non-uniform and invariant over days. There are indications that mouse movement is related to CANS through three pathways: The hand amplitude in mouse use is small (average median amplitude in our study was 0.32 cm), which shows that mouse movement is quite a static movement. Secondly, with only small movements, the whole computer screen can be reached, meaning that a high precision is demanded during mouse use. It has been suggested that these precision demands play an important role in the etiology of CANS (Huysmans 2008). Thirdly, the non-uniformity of mouse movements (depicted by the 'star shape') would impose hand and/or arm kinematics with less exposure variability.

Recommendations for research and practice

Ever since the introduction of registration software, ergonomists have been eager to use software to estimate workers' computer behaviour. However, as this dissertation has pointed out, while the process of installing registration software and monitoring input device use for an extended period of time is relatively simple, the analysis and the interpretation of the recorded time traces are by no means straightforward. Below, some suggestions are given on how to make optimal use of registration software as a measure of physical exposure.

Practical implications

- Although the equations in Chapter 2 have made it easy to recalculate computer use duration in case studies use different NCTs, using a NCT of 30 s is recommended when measuring computer use with registration software. However, for the ergonomist in the field, it might not always be possible to install registration software. In this case the ergonomist could assess work duration manually (observation) with a relatively large NCT like 120 s (which is less labour-intensive than a smaller NCT), and the use the formula in Chapter 2 to calculate the duration at a NCT of 30 s. Theoretically, one could set a timer every two minutes and decide after the time has passed whether or not the behaviour in question was performed (e.g. mouse or keyboard use).
- If one is interested in exposure across a long time span (for example six months), a substantial amount of days should be measured in order for the daily exposure to be a reliable estimate of the average exposure across the measurement period (44 days in a measurement period of six months). This amount is a conservative measure in order to represent 90% of all

participants and keep the relative error to a minimum (CV <10%). In ergonomic research, it will not always be possible or even necessary to monitored office workers for such a long time. However, this is an indication that in order to reliably estimate regular computer use duration in office workers, measuring computer use for only one work day or even a part of a work day does not represent the natural between-day variability in duration.

- In previous epidemiological studies measuring computer use with registration software, the computer-related factors that were assessed were averaged over days by the mean or median of individual days (IJmker 2008, Andersen et al. 2008, Chang et al. 2007). With this method, all information on the within-day variability disappears. In this dissertation, it was revealed that several computer-related variables (such as pause durations, mouse movement distribution, mouse amplitude) do not follow a normal (Gaussian) distribution when measured throughout a working day. This means that averaging these variables without taking the dispersion into account is arbitrary and thus not representative for the within-day variability in computer use. In order to measure this within-day variability, registration software should be used that not only stores daily statistics about computer events, but also takes the daily dispersion of computer events into account.
- Since individual contrast values were low, this is an indication that registration software may provide limited information on muscle activity patterns during daily computer use and that the results should be used with caution as proxies of biomechanical exposure. The low contrast between conventional office tasks may seriously limit the potential for creating an office job with adequate variation (Mathiassen 2006), which, in turn, may call for more radical initiatives, such as introducing physical exercise at work.

Future research

- In the current research, the occurrence of CANS was only assessed once every six months. Combining this with the fact that CANS in the upper extremity have a strong episodic nature, this indicates that when researchers study the relation between computer work and CANS, CANS should be assessed more often in order to identify the onset of an episode. One of the solutions might be a daily or weekly pop-up screen in the registration software, in which questions on CANS (or effects of CANS, like productivity) are asked.
- In Chapter 4, we described the effects of pause software in participants without CANS, and did not find a large effect of additional pauses on the natural work-pause pattern of participants. However, it would be interesting to perform these analyses for participants with (recovered) CANS. It might be that these participants have a different work-pause pattern, thus altering the effect of pause software.
- Since much variability in EMG existed between episodes within computer tasks and non-computer tasks, the contrast between the two tasks was low. A more strict definition of 'computer tasks' and 'non-computer tasks' might be necessary to arrive at better prospects for comparing and combining studies of computer-related activities, and thus to come to a better understanding of the associated biomechanical exposure and their relation to CANS. This could be achieved by software that logs the computer programs and applications that office workers use, or by an additional diary or observation method. Hereby, more specific information can be obtained on potential harmful or peculiar computer use behaviour, which in turn also will help the producers of these programs or applications improve their software.

Can we use registration software to assess physical exposure during office work?

Yes, registration software can be used for unobtrusively and objectively assessing parameters of natural computer use input, since software is an unobtrusive, easy to collect and cheap method to measure computer use input over an extensive period of time. A large within- and between day variability in certain computer use parameters exists, so in order to reliably capture day-to-day physical exposure, a method that enables longer duration measurements is important. Second, by measuring only the cumulative duration of computer use as a measure of physical exposure during computer use (and often averaging this duration over days or even weeks), important sources of variability in exposure within and between days are lost. Third, CANS have an episodic nature, meaning that episodes of CANS might be short, but recurrence rates are high. The exact time of onset of an episode of CANS is hard to define, and CANS may require a certain induction time of exposure and a latency time before the onset of symptoms. Therefore, detailed information on exposure is required over an extensive period of time, and registration software is to date the only exposure method that ensures this.

No, because with the present knowledge, self-reported computer use duration predicts the onset of CANS better than duration measured with registration software. Apparently, the perception of computer duration is not comparable to duration measured with software, and software thus cannot replace self-reports. However, as a reference method, software can provide insight in the factors that influence the level of self-reported duration.

Maybe, because little contrast in muscle activity was found between periods of computer work and periods of non-computer work. In this regard, registration software may not be optimal as a proxy of biomechanical exposure. However, a full understanding of exposure during office work has not yet been reached, and therefore, future research should explore different measures for exposure in different groups of office workers in order to come to a better understanding of the biomechanical exposure during office work.

Appendix

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List of Abbreviations

Δ	Difference
$\circ$	Degrees
σ^2_b	Between-worker variance
σ^2_w	Within-worker variance
φ	Direction
AIC	Akaike Information Criterion
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
aRB	Absolute value of Relative Bias
CANS	Complaints of the Arm, Neck and/or Shoulder
C	Contrast
CV	Coefficient of Variation
CW	Computer Work
D	Dominant body side
DASH	Disabilities of the Arm, Shoulder and Hand
ECR	Extensor Carpi Radialis
EMG	Electromyography
E_{tot}	Total number of computer events
FCR	Flexor Carpi Radialis
Hz	Hertz
IQR	Interquartile Range
LMM	Linear Mixed Model
Ln	Natural logarithm
Log	Logarithm
MSC	Musculoskeletal Complaints
MSE	Mean Squared Error
NCT	Non-Computer Threshold
NCT_{opt}	Non-Computer Threshold for maximum Contrast

NCW	Non-Computer Work
ND	Non-Dominant body side
OR	Odds Ratio
P	Precision
PWT	Percentage computer work of the Work Time
PWT_k	Percentage keyboard work of the Work Time
PWT_m	Percentage mouse work of the Work Time
RB	Relative Bias
RSI	Repetitive Strain Injury
RVE	Reference Voluntary Exertions
s	seconds
s^2	Variance
Trap	Trapezius pars descendens
SD	Standard Deviation
WT	Work Time

Summary

The introductory **Chapter 1** describes the background of the studies included in this thesis. Consistent evidence has been found for a relationship between computer use and complaints of the arm, neck and/or shoulder (CANS, or upper extremity complaints). However, a gap exists in the knowledge on which factors best describe physical exposure during computer use, and, consequently, which exact exposure factors pose a risk for CANS. The aim of the current dissertation is to describe patterns of computer use and provide suggestions how these patterns might be related to CANS. For this purpose, a longitudinal study was performed on 571 office workers with diverging professions but all with regular computer work. Patterns of computer use were studied by monitoring each participant by means of registration software, and participants also filled in questionnaires throughout the study. This registration software registered mouse and keyboard use with high precision (10 Hz) for a total period of two years. This dissertation has pointed out that while the process of gathering input device use through software is relatively simple, the analysis and interpretation of the recorded time traces are by no means straightforward. Software stores single computer events (as an example: one mouse click occurs at 10 a.m. and another one 20 seconds later), and in order to measure a *period* of computer use, a certain threshold (non-computer threshold or NCT) has to be chosen to connect these single events. Exceeding this threshold classifies the time between the mouse clicks (or other computer events) as *non-computer work*. Dependent on which NCT one chooses, the total duration of computer throughout a work day either increases or decreases.

In **Chapter 2** of this dissertation, we describe how computer use duration depends on which NCT is used. A log-linear relationship between NCTs and computer use duration was found to fit the data best, in which a two-fold increase in NCT led to an increase in computer use duration with only 3.5%. The relationship between NCT and mouse use duration and keyboard use duration was assessed

as well, and showed a similar slow increase. Only small differences in the relation between NCT and duration were found within subgroups (categorised based on gender, job function or age category), what implicates that groups of participants shared rather similar work-pause patterns. This is an indication that the relationships in this Chapter can be generalised to professions with different main job functions which consist of frequent computer use. With the equations presented in this chapter, studies measuring computer use duration can be compared, even though they use different NCTs.

In **Chapter 3**, different methods for assessing computer use duration are compared. Apparently, when participants were asked about the duration of their computer use, their estimate was higher than when this duration was measured with registration software. Furthermore, the results from this study showed that duration estimations by women deviated more from registered duration than estimations by men, and that the estimation deviated more with increasing psychosocial job demands. One of the reasons for the difference between the two methods is probably that the two methods measure different aspects of computer use, and therefore both measures are important to assess the impact of prolonged computer use.

In **Chapter 4**, the natural pause patterns of healthy office workers were studied, as well as the influence of pause software on this pattern. The work-pause pattern of computer users can be described as intermittent behaviour, in which short periods of computer use are being followed by longer, very variable pauses. When pause software (in this study Workpace was used) offered additional pauses during computer work, it added only on average 7.2% pause time to the work day. This was not sufficient to change the natural work-pause pattern of computers users, although this change is seen as possible solution against CANS. Furthermore, the timing of the added pauses was not optimal; most of the added pauses (short 'micro breaks') were offered on average only 45 s before users would take a similar, spontaneous pause. These results might be the reason that recent reviews concluded that the interventions against CANS that offer pauses are not effective.

In **Chapter 5**, the difference in muscle activity in shoulder and lower arm muscles between computer and non-computer activities was assessed, in order to find out if non-computer tasks can indeed increase exposure variation and thus reduce CANS. The results showed that the mean muscle activity and the mean level of variability of muscle activity are higher during non-computer work than during computer work. Nevertheless, registration software gave some, but not much information that was useful for discriminating muscle activity patterns during computer work and non-computer work (low contrast). This was mostly due to a high level of variation in the outcome measures between periods of non-computer work (or, simply said: periods of non-computer work are not alike). This lack of contrast indicates that physical risk factors for CANS are not solely attributable to computer work per se, but that physical risk factors might be present in non-computer work as well. It also suggests that the lack of variation in muscle activity during computer use is not compensated by regular non-computer tasks, so perhaps more radical initiatives to introduce more variation in the work day may be necessary, such as organized physical exercise at work.

In **Chapter 6**, patterns of computer mouse use during daily office work were analysed. On average, mouse movements were very small (hand movement of 0.32 cm), had a short duration (on average 0.29 s) and had a low average speed (>50% of hand movements were lower than 1 cm/s). Also, the participants were found to have strong directional preferences in movement direction: horizontal and vertical movements occurred much more often (in 75% of all movements) than movements in diagonal directions. Finally, the mouse movements that occurred most often had the smallest error in initial movement direction compared to the direction of the endpoint (the movements were straighter). This suggests that computer users can use prior experience to move in the right movement direction.

In **Chapter 7**, the studies in this dissertation are being discussed, based on the research questions posed in the General Introduction. Also, we discussed to what extent the main physical risk factors for CANS in computer use (prolonged computer duration, static loading and lack of exposure variability) were present in the computer use variables which are described in this dissertation. Subsequently, the practical implications for ergonomists and researchers are discussed, and suggestions are being made for future studies. Summarizing, the information from this dissertation can help with the analysis and interpretation of registered computer use, but the main take-home message is to think critically about when and how to use registration software in office work.

Samenvatting

Het inleidende **Hoofdstuk 1** beschrijft de achtergrond van de studies die in dit proefschrift beschreven staan. Er is een duidelijke relatie tussen computergebruik en klachten aan arm, nek en/of schouder (KANS, ook wel RSI genoemd). Toch is nog onvoldoende duidelijk welke factoren de fysieke blootstelling tijdens computergebruik het beste omschrijven, en ook is nog niet bekend welke van deze factoren precies een risico vormen voor KANS. Het doel van dit proefschrift is het beschrijven van patronen van computergebruik, en het geven van suggesties hoe deze patronen gerelateerd kunnen zijn aan KANS. Om dit te achterhalen is een longitudinale studie uitgevoerd met 571 kantoormedewerkers die uiteenlopende beroepen hadden, maar allemaal regelmatig computerwerk verrichtten. Patronen van computergebruik werden bij iedere deelnemer gemeten met behulp van registratiesoftware, en deelnemers vulden ook vragenlijsten in gedurende het onderzoek. De registratiesoftware registreerde muis- en toetsenbordgebruik met een hoge precisie (10 Hz) voor een totale periode van twee jaar. Uit dit proefschrift blijkt dat het verzamelen van computer-invoer weliswaar relatief gemakkelijk is met registratiesoftware, maar dat de analyse en interpretatie van de opgeslagen variabelen allerminst eenvoudig is. Zo slaat software losstaande computer-invoer op in de tijd (als voorbeeld: één muisklik wordt opgeslagen om 10 uur, en een tweede 20 seconden later), maar om een *periode* van computergebruik te kunnen meten moet er een bepaalde drempelwaarde (non-computer threshold of NCT genoemd) gekozen worden om die losse muisklikken met elkaar te kunnen verbinden. Als de tijd tussen twee opeenvolgende muisklikken (of andere computer-invoer) langer is dan de NCT, wordt de periode tussen de twee klikken *niet-computerwerk* genoemd. Afhankelijk van welke NCT je kiest, wordt de totale duur van computergebruik over een werkdag langer of korter.

In **Hoofdstuk 2** van dit proefschrift beschrijven we hoe de duur van computergebruik afhangt van welke NCT gebruikt wordt. Een log-lineaire relatie tussen

NCTs en duur van computergebruik beschreef de data het beste, waarbij een verdubbeling van NCT voor een stijging in computerduur van slechts 3.5% zorgde. Daarnaast is ook naar de relaties tussen NCT en de duur van muisgebruik en van toetsenbordgebruik gekeken, en deze lieten dezelfde trage stijging zien. Er zijn slechts kleine verschillen in de relaties tussen NCT en computerduur gevonden binnen subgroepen (gecategoriseerd naar geslacht, werktaak of leeftijdscategorie), wat impliceert dat de gevonden relaties bruikbaar zijn voor andere beroepen, zolang ze maar regelmatig met computers werken. Met de formules uit Hoofdstuk 2 kunnen studies worden vergeleken die computergebruik meten, ook al gebruiken ze hiervoor verschillende NCTs.

In **Hoofdstuk 3** worden verschillende methoden vergeleken om computergebruik te meten. Wanneer mensen gevraagd werd de duur van hun computergebruik in te schatten, gaven ze een hogere schatting dan wanneer deze duur met software gemeten wordt. Daarnaast bleek dat vrouwen een meer afwijkende inschatting van computerduur te maken dan mannen, en week de inschatting meer af naarmate mensen hun werk veeleisender vinden. Een reden voor het verschil tussen de twee methoden is waarschijnlijk dat de beide maten van computerduur een ander aspect van computergebruik meten, en dus beide maten belangrijk zijn om de impact van langdurig computergebruik te bepalen.

In **Hoofdstuk 4** is gekeken naar de natuurlijke pauzepatronen van kantoormedewerkers, en is onderzocht hoe pauzesoftware dat patroon kan beïnvloeden. Het werk-pauzepatroon van computergebruikers kan het beste omschreven worden als intermitterend, waarbij korte perioden van computergebruik worden opgevolgd door langere, erg variabele pauzes. Wanneer pauzesoftware (in deze studie is Workpace gebruikt) extra pauzes aanbood tijdens computerwerk, voegde dat gemiddeld maar 7.2% extra pauzetijd toe aan de werkdag. Dit was niet voldoende om het natuurlijke werk-pauzepatroon te veranderen, terwijl die verandering wel gezien wordt als mogelijke oplossing tegen KANS. Ook was de timing van de extra pauzes niet optimaal: het merendeel van de pauzes (korte 'micropauzes') werd gemiddeld maar 45 seconden voordat mensen een soortgelijke spontane pauze zouden nemen, aangeboden. Deze resultaten kunnen de reden zijn dat recente reviews concludeerden dat de interventies tegen KANS die pauzes aanbieden niet effectief zijn.

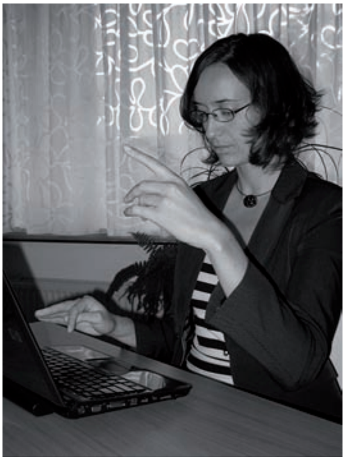
In **Hoofdstuk 5** is onderzocht of spieractiviteit in schouder- en onderarmspieren verschilt tussen computerwerk en alles dat niet geclassificeerd wordt als computerwerk, om zo te onderzoeken of 'niet-computerwerk' de variatie in blootstelling daadwerkelijk kunnen verhogen om zo KANS tegen te gaan. Uit de resultaten bleek dat zowel de gemiddelde spieractiviteit als de variabiliteit in spieractiviteit tijdens niet-computerwerk in alle onderzochte spieren hoger waren dan tijdens computerwerk. Toch bleek registratiesoftware maar weinig informatief voor het onderscheiden van spieractiviteit tussen computerwerk en niet-computerwerk (laag contrast). Dit kwam vooral door de grote variatie in spieractiviteit tussen periodes van niet-computergebruik (simpel gezegd: de ene periode van niet-computergebruik is de andere niet). Dit gebrek aan contrast impliceert dat fysieke risicofactoren voor KANS niet volledig toe te schrijven zijn aan computergebruik, maar dat voor het vinden van risicofactoren voor KANS wellicht ook in niet-computergebruik gezocht moet worden. Ook suggereert het dat het gebrek aan variatie in spieractiviteit tijdens computergebruik te weinig wordt gecompenseerd door normale niet-computertaken, en dat dus wellicht extremere maatregelen genomen moeten worden om meer variatie te introduceren in de werkdag, zoals sporten op het werk.

In **Hoofdstuk 6** is zijn patronen van muisgebruik tijdens dagelijks computerwerk gemeten. Muisbewegingen bleken gemiddeld erg klein te zijn (0.32 cm handbeweging), een korte duur te hebben (gemiddeld 0.29 seconden) met een lage gemiddelde snelheid (>50% van de handsnelheden was kleiner dan 1 cm/s). Ook hadden de proefpersonen sterke voorkeuren in bewegingsrichting: horizontale en verticale bewegingen kwamen veel vaker (in 75% van alle bewegingen) voor dan bewegingen in diagonale richtingen. Tenslotte hadden de muisbewegingen die het vaakst voorkwamen ook de kleinste afwijking in beginrichting ten opzichte van de richting van het eindpunt (de bewegingen waren dus rechter). Dit suggereert dat computergebruikers hun ervaringen kunnen gebruiken om de muis in de juiste richting te bewegen.

In **Hoofdstuk 7** zijn de onderzoeken in dit proefschrift besproken op basis van de vijf onderzoeksvragen die in de Introductie gesteld zijn. Ook is bekeken in hoeverre de belangrijkste fysieke risicofactoren voor KANS (lange computerduur, statische belasting en gebrek aan variabiliteit in blootstelling) aanwezig waren in de variabelen van computergebruik die beschreven zijn in dit proefschrift. Verder is de toepasbaarheid van dit onderzoek voor ergonomen en voor onderzoekers toegelicht, en worden suggesties gedaan voor toekomstige studies. Samengevat kan de informatie uit dit proefschrift helpen bij het analyseren en interpreteren van geregistreerd computergebruik, maar het belangrijkste aandachtspunt is toch om kritisch na te denken in welke situatie en op welke manier registratiesoftware het beste te gebruiken is.

About the Author

Janneke Margriet Richter was born on May 8th, 1979 in Eindhoven. She completed her secondary education at the Scholengemeenschap Augustinianum in 1997. In that same year she commenced her training in Health Sciences at Maastricht University. In September 2001, she obtained her master's degree, specialized in human movement science. As part of her master course, she conducted a research internship at the 'Movement and perception' research center of the University of the Mediterranean and CNRS in Marseille, France under the supervision of Prof. dr. Reinout Bootsma.



After her studies, she started working as an assistant-researcher at the NIVEL in 2003 (Netherlands institute for health services research) in Utrecht. There, she worked on two policy-supporting projects on home care technology and a patient panel of the chronically ill. During that year, she also started volunteering as an editor at the RSI patient organization. In 2004, she started a PhD-project in the department of neuroscience at the Erasmus MC in Rotterdam, resulting in the current dissertation. As of August 2009, she works as a researcher/advisor at TNO Quality of Life, working on occupational health.

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Harm, volgens mij beseften we allebei niet 100% waar we onszelf instortten na het runnen van de beruchte Matlabcode 'spam.m' in maart 2004. Vooral in het eerste halfjaar van het onderzoek leken we soms meer op helpdeskmedewerkers, data-entrymedewerkers of programmeurs dan op onderzoekers. Doordat we bij elkaar op de kamer zaten, kennen we elkaar waarschijnlijk beter dan menig andere copromotor en AiO elkaar kennen. Ik heb erg genoten van de afgelopen jaren, vooral onze eindeloze discussies met een bakje Senseo erbij. Dank je wel dat je mijn kamergenoot, mentor en inspiratiebron wilde zijn, en ik hoop dat we in de toekomst nog eens samen kunnen werken.

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lunches zorgden voor de broodnodige afleiding en motivatie, die ik op dat moment wel kon gebruiken.

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The aim of the current dissertation is to describe patterns of computer use and provide suggestions how these patterns might be related to CANS (complaints of the arm, neck and/or shoulder). Registration software was used to unobtrusively monitor computer use patterns over two years in a large group of office workers.

Four key findings of the studies described in this dissertation are presented. First, computer work did not differ to a large extent from non-computer work in terms of (variability in) muscle activity. This indicates that physical risk factors for CANS cannot be solely attributable to computer work per se, and that non-computer work might present similar risk factors for CANS. Second, large between-day variability in computer use duration was found, which should be taken into account when choosing the measurement period for registration software. Third, computer use duration as measured with registration software provides a conceptually different measure of duration than self-reported duration. Fourth, several computer use measures were found to have a non-normal distribution within a work day. Therefore, averaging these measures throughout a day or a week without taking the dispersion into account is not representative for office worker's computer use patterns.

In conclusion, this dissertation provides insight into the analysis and interpretation of natural computer use patterns by registration software, and challenges ergonomists and researchers to think critically about when and how to use registration software in office work.