DOCTORAL THESIS

Ergonomic Risk Assessment and Intervention through Smart Workwear Systems

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Ergonomic Risk Assessment and Intervention through Smart Workwear Systems

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Doctoral Thesis

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Ergonomic Risk Assessment and Intervention through Smart Workwear Systems

THESIS FOR DOCTORAL DEGREE (Ph.D.)

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Abstract

The rapid development of wearable technology has provided opportunities to ergonomics research and practice with new ways for workload measurements, data analytics, risk assessment and intervention. This thesis aims at developing and evaluating methods using wearable technologies to assess physical risk factors at work, and further to give feedback to employees to improve their work techniques.

One smartphone application (ErgoArmMeter) was developed for the assessment of upper arm postures and movements at work. The application uses integrated signals of the embedded accelerometer and gyroscope, and processes and presents the assessment results directly after a measurement. Laboratory validation with 10 participants was performed using an optical tracking system as standard measurement. The results showed that the application had similar accuracy compared to standard inclinometry for static postures and improved accuracy in dynamic conditions. With its convenience and low cost, the application may be used by researchers and practitioners in various scenarios for risk assessment.

Three models for assessment of work metabolism (WM) using heart rate (HR) and accelerometers (ACCs) were evaluated during simulated work tasks with 12 participants against indirect calorimetry as standard measurement. The HR + arm-leg ACC model showed best accuracy in most work tasks. The HR-Flex model showed a small bias for the average of all tasks. For estimating WM in the field using wearable technologies, the HR-Flex model or the HR + arm-leg ACC model may be chosen depending on the need for accuracy level and resource availabilities. Further improvement of the classification algorithm in the HR + arm-leg ACC model is needed in order to suit various types of work.

Two smart workwear systems were developed and evaluated. Smart workwear system 1.0 consisted of a sensorized vest, an inertial measurement unit (IMU) and an Android tablet application. It assessed risks of high physiological workload and prolonged occupational sitting/standing. The results were visualized by color-coded risk levels. The system was evaluated with 8 participants from four occupations in a field study. It was perceived as useful, comfortable and not disturbing by most participants. Further development is required for the system for automated risk assessment of various ergonomic risk factors in real work situations.

Smart workwear system 2.0 consisted of an instrumented t-shirt with IMUs, vibration units and an Android smartphone application. It provided vibrotactile feedback to users' upper arm and trunk when predefined angular thresholds were exceeded. The system was evaluated for work postures intervention in industrial order picking among 15 participants. It showed to be effective in improving the trunk and dominant upper arm postures. The system was perceived as comfortable and useful. The vibrotactile feedback was evaluated as supportive for learning regarding workplace and task design among the participants.

In conclusion, the research in this thesis showed that wearable technologies can be used both in the laboratory and field for assessment of physical risk factors at work and intervention in work technique improvement. With further research and development, smart workwear systems may contribute to automated risk assessment, prevention of work-related ill health, and improvement of the design and overall quality of work.

Keywords

Physical Workload; Work Postures; Energy Consumption; Oxygen Uptake; Risk Assessment; Measurement Methods; Work-Related Musculoskeletal Disorders; Work-Related Ill Health; Wearable Sensors; Wearable Systems; Feedback; Ergonomic Intervention.

Sammanfattning

Den snabba utvecklingen av bärbar teknik har skapat möjligheter för ergonomisk forskning och tillämpning genom nya sätt att mäta arbetsbelastning, dataanalys, riskbedömning och intervention. Denna avhandling syftar till att utveckla och utvärdera metoder att använda bärbar teknik för att utvärdera fysiska riskfaktorer i arbetet samt ge feedback till anställda för att förbättra sin arbetsteknik.

En smart mobilapplikation (ErgoArmMeter) utvecklades för att bedöma överarmställningar och -rörelser på jobbet. Applikationen använder integrerade signaler från den inbäddade accelerometern och gyroskopet, samt bearbetar och presenterar bedömningsresultaten direkt efter en mätning. En laboratorievalidering med 10 deltagare utfördes där ett optiskt spårningssystem användes som standardmätning. Resultaten visade att applikationen hade jämförbar noggrannhet med standard inklinometri för statiska arbetsställningar men bättre noggrannhet under dynamiska förhållanden. Applikationens enkelhet, bekvämlighet och låga kostnad gör att applikationen kan användas av forskare och praktiker i olika scenarier för ergonomisk riskbedömning.

Tre modeller för bedömning av arbetsmetabolism med hjälp av hjärtfrekvens (HR) och accelerometrar (ACCs) utvärderades i simulerade arbetsuppgifter med 12 deltagare mot indirekt kalorimetri som standardmätning. “HR + arm-leg ACC modellen” visade bästa noggrannhet i de flesta arbetsuppgifter. “HR-Flex modellen” visade en liten avvikelse för genomsnittet av alla uppgifter. För att bedöma arbetsmetabolism i arbetslivet med användning av bärbar teknik kan “HR-Flex modellen” eller “HR + arm-leg ACC modellen” väljas beroende på behovet av noggrannhet och tillgängliga resurser. Ytterligare förbättring av klassificeringsalgoritmen i ”HR + arm-leg ACC modellen” behövs för att passa olika typer av arbete.

Två system för smarta arbetskläder utvecklades och utvärderades. Smarta arbetskläder 1.0 bestod av en sensoriserad väst, en IMU-sensor (Inertial Measurement Unit) och en applikation på en Android surfplatta. Systemet bedömde riskerna för hög fysisk arbetsbelastning och långvarigt sittande/stående på arbetet. Resultaten visualiserades med färgkodade risknivåer. Systemet utvärderades med 8 deltagare från fyra yrken i en fältstudie. Det upplevdes som användbart, bekvämt och inte störande av de flesta deltagare. Vidareutveckling av systemet krävs för automatiserad riskbedömning av olika ergonomiska riskfaktorer i arbetslivet.

Smarta arbetskläder 2.0 bestod av en instrumenterad t-shirt med IMU-enheter, vibrationsenheter och en applikation på en Android smart mobil. Systemet gav vibrotaktil återkoppling till användarnas dominanta överarm och bål/rygg när fördefinierade vinkeltrösklar överskreds. Systemet utvärderades beträffande arbetsställningar i en intervention i industriell materialplockning med 15 deltagare. Det visade sig effektivt förbättra arbetsställningar av bålen/ryggen och överarmen. Systemet upplevdes som bekvämt och användbart. Den vibrotaktila återkopplingen befanns stödjande för inlärning av deltagarna när det gäller utformning av arbetsplats och arbetsuppgift.

Sammanfattningsvis visar forskningen i denna avhandling att bärbar teknik kan användas både i laboratoriet och arbetslivet för att bedöma fysiska riskfaktorer i arbetet samt för

interventioner syftande till förbättring av arbetsteknik. Med ytterligare forskning och utveckling kan system för smarta arbetskläder bidra till automatiserad riskbedömning, förebygga arbetsrelaterad ohälsa och förbättra utformningen av arbetet och arbetsplatsen.

Nyckelord

Fysisk arbetsbelastning; Arbetsställningar; Energiförbrukning; Syreupptag; Riskbedömning; Mätmetoder; Arbetsrelaterade muskuloskeletala besvär; Arbetsrelaterad ohälsa; Bärbara sensorer; Bärbara system; Återkoppling; Ergonomisk intervention.

List of appended papers

Paper A
Yang, L., Grooten, W.J.A., Forsman, M., 2017. An iPhone application for upper arm posture and movement measurements. *Applied Ergonomics*. 65, 492–500.

Paper B
Yang, L., Lu, K., Forsman, M., Lindecrantz, K., Seoane, F., Ekblom, Ö., Eklund, J., 2019. Evaluation of physiological workload assessment methods using heart rate and accelerometry for a smart wearable system. *Ergonomics* 62, 694–705.

Paper C
Yang, L., Lu, K., Diaz-Olivares, J.A., Seoane, F., Lindecrantz, K., Forsman, M., Abtahi, F., Eklund, J.A.E., 2018. Towards Smart Work Clothing for Automatic Risk Assessment of Physical Workload. *IEEE Access* 6, 40059–40072.

Paper D
Lind, C.M., Yang, L., Abtahi, F., Hanson, L., Lindecrantz, K., Lu, K., Forsman, M., Eklund,J. Reducing postural load in order picking through a smart workwear system using real-time vibrotactile feedback. Manuscript submitted.

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Author contributions

Paper A

The study design was done by Yang, Forsman and Grooten. The iPhone application was developed by Yang under supervision of Forsman. Yang performed the experiments, analyzed the results and wrote the manuscript. All authors critically reviewed the manuscript.

Paper B

The study design was done by Yang, Lu and Eklund. Yang and Lu performed the experiments and analyzed the results. Yang wrote the manuscript under supervision of Eklund. All authors critically reviewed the manuscript.

Paper C

The study design was done by Yang and Eklund. The wearable system was developed by Yang, Lu and Diaz-Olivares with the project team. Yang, Lu and Diaz-Olivares collected the data and analyzed the results. Yang wrote the major part of the manuscript with contributions from all authors. All authors critically reviewed the manuscript.

Paper D

The study design was done by Lind, Abtahi, Hanson and Eklund. The wearable system was developed by the project team. Lind, Abtahi and Eklund performed the experiments. Yang and Lind analyzed the results from technical measurements. Yang and Eklund analyzed the results from questionnaires. Eklund analyzed the results from interviews. Yang wrote part of the manuscript and revised it through the whole process. All authors critically reviewed the manuscript.

Other scientific contributions (not included in this thesis)

Journal articles

Lu, K., Yang, L., Seoane, F., Abtahi, F., Forsman, M., Lindecrantz, K., 2018. Fusion of Heart Rate, Respiration and Motion Measurements from a Wearable Sensor System to Enhance Energy Expenditure Estimation. *Sensors* 18, 3092.

Yu, D., Dural, C., Morrow, M.M.B., Yang, L., Collins, J.W., Hallbeck, S., Kjellman, M., Forsman, M., 2017. Intraoperative workload in robotic surgery assessed by wearable motion tracking sensors and questionnaires. *Surgical Endoscopy*. 31, 877–886.

Conference Proceedings

Lu, K., Yang, L., Abtahi, F., Lindecrantz, K., Rödby, K., Seoane, F., 2019. Wearable cardiorespiratory monitoring system for unobtrusive free-living energy expenditure tracking, in: Lhotska, L. et al. (eds), *World Congress on Medical Physics and Biomedical Engineering 2018*. IFMBE Proceedings, vol 68/1. Springer, Singapore, pp. 433–437

Lind, C.M., Sandsjö, L., Mahdavian, N., Högberg, D., Hanson, L., Olivares, J.A.D., Yang, L., Forsman, M., 2019. Prevention of Work-Related Musculoskeletal Disorders Using Smart Workwear – The Smart Workwear Consortium, in: Ahram, T., Karwowski, W., Taiar, R. (Eds.), *Human Systems Engineering and Design*. Springer International Publishing, Cham, pp. 477–483.

Yang, L., Borgström, D., Forsman, M., 2019. Validation and Comparison of Three Positioning Protocols of Inertial Measurement Units for Measuring Trunk Movement. In: Bagnara, S. et al. (eds) *Proceedings of the 20th Congress of the International Ergonomics Association 2018*. Advances in Intelligent Systems and Computing, vol 820. Springer, Cham, pp. 205–211.

Mahdavian, N., Lind, C.M., Diaz Olivares, J.A., Iriondo Pascual, A., Högberg, D., Brolin, E., Yang, L., Forsman, M., Hanson, L., 2018. Effect of giving feedback on postural working techniques, in Thorvald, P. and Case, K. (eds) *Advances in Manufacturing Technology XXXII: Proceedings of the 16th International Conference on Manufacturing Research*. pp. 247–252.

Abtahi, F., Forsman, M., Seoane, F., Teriö, H., Diaz-olivares, J.A., Yang, L., Lu, K., Eklund, J.A.E., Lindecrantz, K., Martinez, C.M., Tiemann, C., 2017. Big Data & Wearable Sensors Ensuring Safety and Health @ Work, in Khachfe, H. et al. (eds): *Global Health, the Sixth International Conference on Global Health Challenges*. pp. 45–48.

Conference Abstracts

Yang, L., Målqvist, I., Alderling, M., Lind, C.M., Rentzhog, A.B., & Forsman, M., 2019. Psychosocial health risk factors and perceived work ability in the home care sector, *in 2019 International Symposium on Human Factors and Ergonomics in Health Care, Chicago, US*.

Yang, L., Abtahi, F., Eklund, J., Hanson, L., Lindecrantz, K., Forsman, M., Lind, C.M., 2019. Smart workwear system with real-time vibrotactile feedback for improving postural behaviour in industry, in: *Book of abstracts, the 10th International Scientific Conference on the Prevention of Work-Related Musculoskeletal Disorders (PREMUS), Bologna, Italy*, p. 160.

Yang, L., Lu, K., Abtahi, F., Lindecrantz, K., Seoane, F., Forsman, M., Eklund, J., 2017. A pilot study of using smart clothes for physical workload assessment, in Osvalder, A.-L., Blomé, M., and Bodnar, H. (eds) *Conference Proceedings of Nordic Ergonomics Society 49th Annual Conference, Lund, Sweden*, pp. 169–170.

Preface

Sitting by my desk and typing on my laptop, I started to feel the dull pain in my neck, shoulders and low back. It was hard for me to continue working with my best performance, even though I'd love to. The thought and worry arose, "will I live with this pain as long as I have the same type of work?"

When I first learned about ergonomics during my master education at KTH, I became so excited. "To design work better in order to prevent musculoskeletal disorders and to achieve optimal human well-being and system performance, isn't that exactly what I need?" I could possibly find the cure for myself, and even contribute to others who have the same trouble.

After a while, with having my workplace in a new office building, I got my first sit-stand table and loved it. It was so nice to be able to stand and continue working. My low back pain diminished a lot! However, I was not aware of the risk of prolonged standing and hadn't heard about taking microbreaks at work. Adjustment of the screen or keyboard when shifting postures from sitting to standing? – Not a clue. At the same time, I worked with high engagement, and perhaps sometimes a bit of stress before deadlines on my first study. One day, I suddenly felt tingling pain in my wrists, but they were pain-free before I started doing research! It was probably triggered by my repetitive hand movements while using the computer at work and the smartphone during leisure time. The pain lasted for some months. I got a valuable advice from my colleague to visit an experienced physical therapist. Then I learned about the importance of targeted muscle trainings, accepted individual differences and started to take care of my body in day-to-day work and life. Group trainings at work, short breaks with stretching, and ergonomics awareness of risks…With all these factors, gradually, the musculoskeletal pain which I had subsided to a large extent. Still, stories of other friends and family members who started to have the same trouble were mentioned from time to time.

It's never that easy to find the cure.

It is lucky for me to have been in an occupation with quite a bit of freedom to arrange my activities and breaks during a working day. But there are still many occupations that have constrained tasks and schedules. And there are various risk factors such as repetitive movements on an assembly line, heavy workload in the construction industry, or awkward and static postures in an operating room. To evaluate work tasks, improve work design and reduce ergonomic risks are therefore of great significance. Nevertheless, organizational factors, ergonomics awareness and individual work techniques also play an important role. This doctoral thesis includes work on developing and applying wearable technologies to facilitate ergonomic risk assessment and intervention. This work may hopefully contribute to the improvement of work environments and the prevention of work-related ill health, including, but not limited to, musculoskeletal disorders.

Liyun Yang
Stockholm, October 2019

Abbreviations and Concepts

ACC: accelerometer

ECG: electrocardiogram

HR: heart rate

IMU: inertial measurement unit

LoA: limits of agreement

MSD: musculoskeletal disorder

OHS: occupational health and safety

OTS: optical tracking system

RAS: relative aerobic strain

REE: resting energy expenditure

RHR: resting heart rate

RMSE: root mean square error

RPE: rating of perceived exertion

SD: standard deviation

VO_2: oxygen consumption

VO_{2max}: maximal oxygen consumption, also known as maximal aerobic capacity

WM: work metabolism

Smart workwear system: the concept of a wearable system designed to be suitable to wear at work, which collects data through wireless sensors, analyzes and evaluates the risks autonomously, and provides feedback and results to the targeted users.

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1 Introduction

Despite worldwide concern and effort for preventing work-related musculoskeletal disorders (MSDs), this progress is still slow and MSDs remain a substantial burden. Questions have been raised regarding the assessment of ergonomic exposure and the validity and reliability of different methods being used (Wells, 2009). Assessment methods with low validity, different definitions and classifications of ergonomic exposure may explain the lack of quantitative exposure-response relationship for MSDs (Winkel and Mathiassen, 1994; Punnett and Wegman, 2004), which further impedes the effectiveness of interventions. Moreover, it is important to consider the amplitude, frequency and duration of ergonomic exposure when assessing the risks (Mathiassen, 2006), which requires assessment methods that can provide detailed information.

Demographic changes worldwide also lead to an aging workforce and a higher burden on welfare systems. People are expected to work longer in their life span, which calls for better design of work so that people at higher ages can continue working. The changes have brought new challenges to society that call for sustainable working conditions (Eurofound, 2012). In addition, with a shift into the information age, working life is becoming more physically inactive (Straker and Mathiassen, 2009). Today, the risk factors of work-related ill health include not only high physical load, but also static load and the lack of physical activity.

In order to facilitate the ergonomic risk assessment and prevention of work-related ill health, there is a need for valid and reliable measurement methods, which are easy and efficient to use (Forsman, 2017). The recent development of wearable technology has made it possible to develop easy-to-use wearable measurement systems, which can be used without constraints of place or time (Iosa *et al.*, 2016; Alberto *et al.*, 2018). These wearable systems can also be used to train employees for better work technique with real-time feedback (Agruss, Williams and Fathallah, 2004; Vignais *et al.*, 2013; Bazazan *et al.*, 2018; Doss *et al.*, 2018), and provide a basis for organizational risk management including risk assessment, design and redesign of work, as well as establishing new ergonomic guidelines. The strive to improve the work environment and reduce the risks for work-related ill health need to be facilitated for workers, occupational health and safety (OHS) services, safety engineers and researchers. Therefore, more research on developing and applying wearable technology as tools and methods for risk assessment and prevention is required.

2 Theoretical framework and background

2.1 Ergonomics

Ergonomics, comes from the Greek roots *ergon*, meaning “work”, and *nomos*, meaning “natural law”, with its meaning literally translated as ‘the science of work’. The term Ergonomics and Human Factors are now used as synonymous. According to the International Ergonomics Association (2019), the definition of ergonomics is as a scientific discipline which is concerned with

“…the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance.”

Therefore, ergonomics as an interdisciplinary knowledge field promotes a holistic view. It can be described as consisting of several domains, and the most common is the three main domains: the physical, cognitive and organizational ergonomics. This thesis has its focus in the physical ergonomics domain.

Two approaches exist when ergonomics is of concern, as illustrated in Figure 1. One often preferred approach is ‘fitting the task to the person’, which focuses on improving work design to reduce ergonomic risks. It can refer to designing of workplaces and equipment to reduce physical load (Kroemer and Grandjean, 1997), and also to designing and reorganizing tasks and jobs, so that work activities and loads can be at a suitable level for sustained or improved health (Holtermann, Mathiassen and Straker, 2018). The other approach is ‘fitting the person to the task’. One way is to select workers, which was once used by employers for choosing workers with good physical capacities. For normal occupations, it is sometimes considered unethical. But for certain occupations, such as firefighters or fighter pilots, high physical and cognitive capacities can be a necessary requirement. Another way is to train the person to fulfill the job demands. One example is training that aims at improving work technique and workstyle (Kilbom and Persson, 1987; Feuerstein, 2007; McGill, 2009). Another example is tailored physical exercise training that aims at improving individual fitness and capacity (Sjøgaard *et al.*, 2014). In practice, these two approaches are both of importance and should be considered as a two-way process to achieve optimized human well-being and task performance.

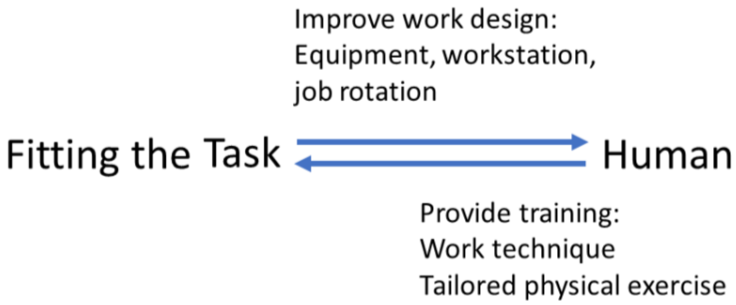

Figure 1. Illustration of two approaches in ergonomics. Based on Kroemer and Grandjean (1997), McGill (2009), Kilbom and Persson (1987) and Sjøgaard and colleagues (2014).

2.2 Work-related ill health

Musculoskeletal disorders (MSDs) are the most prevalent occupational diseases in the European Union, and a rising trend of MSDs can still be observed in many European countries (Schneider and Irastorza, 2010). They can lead to poor health, reduced work performance, sick leave and inability to carry out household and leisure-time activities, causing individual suffering and economic burdens to organizations as well as the society (Luime *et al.*, 2004; van Rijn *et al.*, 2010). They are the leading cause of years lived with disability in the United States (US Burden of Disease Collaborators, 2013). The cost of MSDs, however, can be hard to assess, since it consists of both direct costs, i.e. visible costs due to medical costs, insurance and compensation, and indirect costs, i.e. hidden costs due to e.g. staff turnover, reduced productivity and quality (Rose, Orrenius and Neumann, 2013). One study estimated that work-related MSDs accounted for 13 billion US dollars in the United States in 1996 (Bernard, 1997). The fraction of MSDs attributable to work was estimated between 15% to 49% worldwide (Punnett *et al.*, 2005; Niu, 2010).

The relationship between physical work and its effect on health is modified by many factors (one model is shown in Figure 2). It is important to point out that there are also many other risk factors and their interactions that are not included in this model, such as the organizational and psychosocial factors. Work is defined by the tasks, workplace, equipment and schedules, which is referred to as the prescribed work (Guérin *et al.*, 2007). All individuals are different and have different influences on how real work activities are performed. Personal characteristics, such as height, work technique and experience, as well as current personal state play an important role for the real work activity. An internal physiological response will take place, such as muscular activations and metabolic changes, depending on the activity performed and individual capacity. The response can further lead to fatigue and deteriorated health, or sustained and improved health, depending on the duration, frequency, and relative intensity level of the real work activity (Sjøgaard and Søgaard, 2015). Therefore, by measuring the real work activity, through e.g. assessing posture, force and energy demand, researchers and practitioners are able to evaluate the ergonomic risks and improve the work design.

Interventions aiming at reducing ergonomic risks can target the factors of prescribed work, the personal workstyle or physical capacity, which are described later in section 2.4.

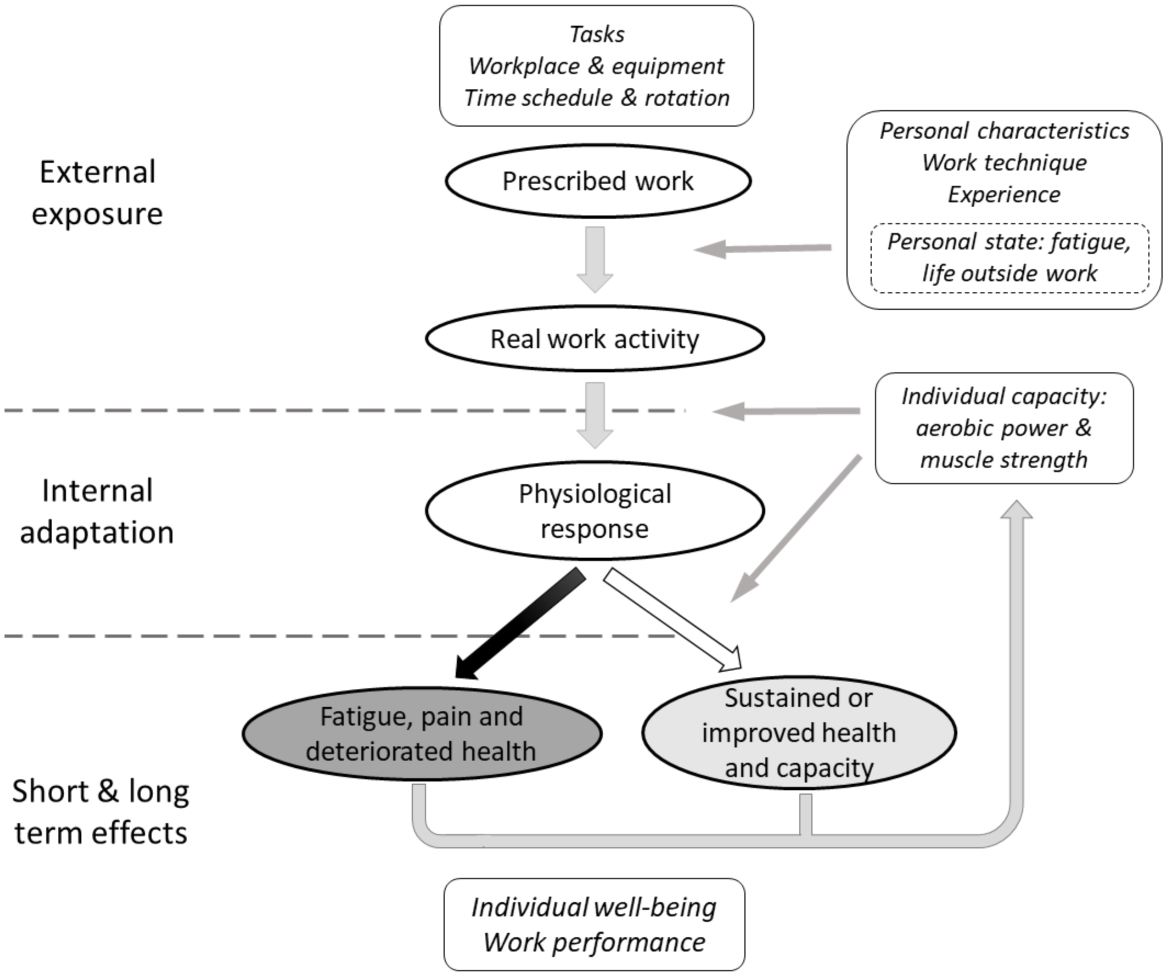

Figure 2. Model illustrating the relationships between physical work and its effects on health, with modifying factors. Model developed based on Guérin and colleagues (2007) and Sjøgaard and Søgaard (2015).

Despite worldwide concern and effort for preventing work-related MSDs and ill health, they remain a substantial burden for individuals and society (Wells, 2009; James *et al.*, 2018). Various assessment methods with insufficient validity and reliability, as well as different classifications of ergonomic exposure that have been used may point to the lack of quantitative exposure-response relationship (Winkel and Mathiassen, 1994; Punnett and Wegman, 2004). A lack of clearly identified risk factors and underlying mechanisms may further impede the design of effective ergonomic guidelines and interventions (van der Beek *et al.*, 2017). Moreover, when assessing ergonomic exposure, it is important to consider the intensity, duration, and repetition (Winkel and Mathiassen, 1994; Mathiassen, 2006). This calls for better assessment methods which can provide accurate information with enough details to facilitate the prevention of work-related ill health.

2.3 Risk assessment

2.3.1 Risk factors

Work-related MSDs have multifactorial causes, including physical, psychosocial, organizational and individual factors. The major physical risk factors for developing work-related MSDs include repetitive movements, forceful exertions, lifting or moving heavy loads, frequent non-neutral postures and vibration (Bernard, 1997; Punnett and Wegman, 2004; Da Costa and Vieira, 2010; Schneider and Irastorza, 2010). Specifically, work with elevated arms is shown to be a critical risk factor for shoulder and neck disorders (Viikari-Juntura *et al.*, 2001; Svendsen *et al.*, 2004; van Rijn *et al.*, 2010; Petit *et al.*, 2014). Work with a bent or twisted trunk is shown to be a critical risk factor for low back pain (Punnett *et al.*, 1991; Hoogendoorn *et al.*, 2000; Jansen, Morgenstern and Burdorf, 2004; Van Nieuwenhuyse *et al.*, 2006; Coenen *et al.*, 2016).

A U-shape relationship is suggested between the physical workload and the risks of adverse health (Heneweer, Vanhees and Picavet, 2009; Sjøgaard and Søgaard, 2015). Both too high and too low exposures of physical workload are associated with adverse effects on health and performance. On the one hand, jobs with high metabolic demands can lead to physical and mental fatigue, increase in work injuries and decrease in work performance, higher risk for cardiovascular diseases, and early retirement (Karpansalo *et al.*, 2002; Krause *et al.*, 2007, 2014; Wigaeus Tornqvist, 2011; Wultsch *et al.*, 2012). On the other hand, prolonged sitting is related with cardiovascular diseases, musculoskeletal disorders, diabetes and cancer (Lis *et al.*, 2007; Owen *et al.*, 2010; van Uffelen *et al.*, 2010; Carson *et al.*, 2014). In addition to adverse health effects, sedentary behavior is also shown to be associated with lower cognitive performance (Falck, Davis and Liu-Ambrose, 2017). Moreover, prolonged standing can lead to pain in the back and lower limbs, cardiovascular problems, fatigue, and pregnancy issues (Leroux *et al.*, 2005; Andersen, Haahr and Frost, 2007; Gallagher, Campbell and Callaghan, 2014; Waters and Dick, 2015). These risk factors are, however, prevalent in today's work force. About 44% of the European workers have reported working in tiring positions for more than one-quarter of the time (Eurofound, 2017). About 25% of men and 31% of women in the EU workforce have reported to be sitting for more than three-quarters of the time at work (Eurofound, 2017).

2.3.2 Risk assessment methods

There are mainly three types of risk assessment methods for ergonomic research and practice, namely self-reports, observational methods and direct measurement methods. Self-reports are inexpensive and easy to use, but the validity and reliability is usually low (Hansson *et al.*, 2001; Prince *et al.*, 2008). Observational methods include on-site or videotaped direct observation, and computer assisted observation. They can cover multiple factors and provide risk evaluation in a systematic approach (Lind, 2017). However, some drawbacks of observational methods are the low inter- and intra-observer reliability, especially regarding

small body segments and quick movements (Takala *et al.*, 2010). Different observational methods may give differing assessment results (Chiasson *et al.*, 2012). Additionally, observations are usually performed for relatively short periods and limited population sizes due to that they are generally time consuming and expensive per unit of working time assessed (Rezagholi, Mathiassen and Liv, 2012; Trask *et al.*, 2013). Direct measurements can provide results with relatively high validity and reliability. They are also able to assess the workload exposure regarding intensity, duration and frequency, which further can provide important information for risk assessment and prevention. However, traditional direct measurement systems have been considered as expensive to purchase, uncomfortable to wear and resource demanding for the data analyses and interpretation (David, 2005). On the contrary, Trask and colleagues (2014) showed that direct measurement methods, e.g. using accelerometers, were more cost-efficient comparing to observational methods for trunk and upper arm posture assessment when statistical performance was measured in terms of precision.

Measurement with higher reliability and validity is crucial for obtaining the underlying exposure-response relationships on physical risk factors (Winkel and Mathiassen, 1994; Punnett and Wegman, 2004). Therefore, to facilitate the risk assessment at work and prevent work-related ill health, there is a need for measurement methods that are valid and reliable, as well as easy, feasible and efficient to use (Forsman, 2017; Holtermann *et al.*, 2017).

2.3.3 Risk assessment criteria

Various criteria for defining acceptable workload and ergonomic exposures have been proposed. Some recent studies proposed threshold limit values based on direct measurement data and quantitative exposure-response relationships (Coenen *et al.*, 2016; Balogh *et al.*, 2019). However, there is still a lack of consensus in exposure metrics and limits.

Relative aerobic strain (RAS) is commonly used for defining acceptable workload. It is calculated as the ratio of oxygen consumption relative to individual's maximal capacity. The International Labor Organization has used a limit of acceptable workload at 33% RAS in dynamic work tasks during an 8 hour working day (Smolander and Louhevaara, 2011), which is in agreement or close agreement with several studies (Jorgensen, 1985; Waters *et al.*, 1993; Wu and Wang, 2002). However, regarding work involving muscle groups with smaller mass or static components, there is no consensus of RAS limit in the research communities. For example, as shown by Asfour and colleagues in a review (1988), the limits of an acceptable workload varied, e.g. at 18.5%, tested on lifting from table to shoulder height by students; at 25%, tested on lifting from floor to shoulder height by students; or at 29%, tested on lifting tasks by female workers.

Risks of prolonged sitting has been recognised as an emergent issue worldwide (Coenen *et al.*, 2017). However, the assessments were previously mainly based on self-reported data with low validity and reliability, which also lacked information regarding the temporal pattern of the behaviour (Owen, Bauman and Brown, 2008; van Uffelen *et al.*, 2010). Thanks to the rapid development of technical measurement methods in recent years, researchers could start to

quantify the temporal patterns of those behaviors with higher accuracy levels (Atkin *et al.*, 2012; Callaghan *et al.*, 2015; Holtermann *et al.*, 2017).

2.4 Intervention

Interventions are intentional change strategies, which may operate at the individual, organizational, regional or other levels (Fraser *et al.*, 2009). Interventions may consist of a single action or a group of actions. Ergonomic intervention was defined as a change process with the aim of promoting musculoskeletal health by Westgaard and Winkel (1997). It can be targeted at occupational mechanical exposures with a focus on the external exposure factors, e.g. through redesign of tasks, work stations and equipment, or on the individual workers, e.g. through training to improve workstyle or individual physical capacity (Westgaard and Winkel, 1997; Feuerstein, 2007; McGill, 2009; Søgaard and Sjøgaard, 2017). It can also be targeted at organizational culture, psychosocial exposure or other factors. Multicomponent interventions usually have greater effect on risk reduction of MSDs compared to single action (Silverstein and Clark, 2004), while it may also be more difficult to evaluate the effectiveness of each single component. Training on work technique can be one of the strategies to prevent MSDs, especially for new employees (Kilbom and Persson, 1987).

2.4.1 Intervention using feedback

Feedback training systems have been used for various applications such as rehabilitation and sport. The feedback may be provided based on electromyogram, kinematic or kinetic information and in a form of auditory, visual or vibrotactile signals (van Dijk, Jannink and Hermens, 2005). Several studies have evaluated the effects of feedback based on electromyogram in the form of auditory and/or visual signals during computer work and showed reduced muscle activities (Madeleine *et al.*, 2006; Vedsted *et al.*, 2011). Based on kinematic signals, several studies have tested auditory or visual feedback training for improving work postures in lifting, manual handling or caregiving activities and showed reduced adverse postures in certain tasks (Agruss, Williams and Fathallah, 2004; Breen, Nisar and Ólaighin, 2009; Vignais *et al.*, 2013; Doss *et al.*, 2018). Another study showed that the intervention effects of training work postures with real-time feedback lasted after two weeks but the effects did not transfer to new tasks (Kamachi, Owlia and Dutta, 2020).

Vibrotactile feedback applies vibrational stimuli to the skin and is often guided by the position of a body segment (Alahakone and Senanayake, 2009). It can be delivered with varying frequency, amplitude and duration. Instant or real-time vibrotactile feedback enables spatial proprioceptive information to be provided directly during the process instead of after task completion (Van Breda *et al.*, 2017). One study applied vibrotactile feedback based on trunk angle among adults with neck pain during laboratory typing tasks (Kuo *et al.*, 2019). It showed that adverse neck and low back angles were reduced with feedback, while self-reported pain was not. Another study applied audio and vibrotactile feedback based on trunk posture among control room operators in a plant for 12 weeks (Bazazan *et al.*, 2018). It showed that

observation assessed neck and trunk postures were improved and self-reported MSDs and fatigue were reduced, with lasting effects observed at six- and twelve-month follow-up.

2.5 Wearable technologies

Wearable technologies have advanced rapidly in recent years. They have become smaller in size, cheaper in price and more capable in data storage and process. Wide applications of wearable technologies have been seen in sports, healthcare, and daily life (Papi, Koh and McGregor, 2017; Loncar-Turukalo *et al.*, 2019; Simpson, Maharaj and Mobbs, 2019). A rise of ergonomics applications can also be observed from laboratory validation studies to field uses (Nath, Akhavian and Behzadan, 2017; Alberto *et al.*, 2018; Khakurel, Melkas and Porras, 2018; Lin, Kirlik and Xu, 2018). Some barriers to application of wearable sensors for workplace risk assessment include data confidentiality, sensor durability, cost-benefit ratios, distraction from work and sensor validity (Schall, Sesek and Cavuoto, 2018). To implement wearable technologies in the workplace, one study suggested that organizations should involve employees in the implementation process, focus on workplace safety, provide information on data use and support employees' beliefs in the effectiveness of wearable systems (Jacobs *et al.*, 2019). Another study showed that workers with physically demanding work were positive towards using wearable sensors that focus on work exposure measurement (Spook *et al.*, 2019). They also stated their preference for real-time feedback which is delivered in a positive way and helps them to be aware of negative work exposure. The quality, comfort and ease of use of the wearable sensors as well as data access and data privacy were identified as important aspects. The commitment of organizations and worksite regulations should also be considered before the implementation, e.g. in a tailored approach (Spook *et al.*, 2019).

2.5.1 Smart workwear system

A *smart device* refers to a device that can perceive information through sensors, operate autonomously and some even interactively, and connect to other devices wire or wirelessly for data exchange (Silverio-Fernández, Renukappa and Suresh, 2018). The term *smart workwear system* was coined by the research group behind the publication by Lind and colleagues (2019). In this thesis, the concept of *smart workwear system* is defined as a wearable system, designed to be suitable to wear at work, which collects data through wireless sensors, analyzes and evaluates the risks autonomously, and provides feedback and results to the targeted users.

2.5.2 System usability

Usability can be defined as a measure of "the effectiveness, efficiency and satisfaction with which specified users achieve specified goals in a specified context of use" (ISO, 2018). Questionnaires and interviews can be used for assessing the system usability. For practical use, simple and quick scales are used to assess the overall level of system usability (Brooke, 1996).

3 Aims

The overall aim of this thesis was to develop and evaluate methods using wearable technologies to assess physical risk factors at work, and further to give feedback to employees to improve their work techniques.

The sub-aims were:

- To develop and validate a smartphone-based tool for assessment of upper arm postures and movements at work (study I)
- To evaluate models using wearable sensors, i.e. heart rate monitor and accelerometers, for assessment of work metabolism (study II)
- To develop and evaluate a smart workwear system (1.0) for ergonomic risk assessment of light and heavy physical work (study III)
- To develop and evaluate a smart workwear system (2.0) for work postures intervention using real-time vibrotactile feedback in industrial order picking (study IV)

4 Methods

This chapter describes the methods used in this thesis. A general overview of the four included studies in this thesis can be seen in Table 1.

4.1 Participants

Ethical approvals were obtained from the Regional Ethics Committee in Stockholm with Dnr 2016/724-31/5 (study I, II and III) and with Dnr 2017/1586-31/4 (study IV). All participants considered themselves healthy and gave their written informed consents prior to joining the studies. An overview of the participants is shown in Table 2.

In study I and II, ten and twelve participants were recruited through advertisements seeking volunteers from university students and staff. In study III, eight participants were recruited through personal networks as volunteers from four occupations, i.e. postal workers, construction workers, office workers and drivers. This choice was made in order to include a variety of work tasks with light to heavy physical workload. In study IV, fifteen participants were recruited through the help of a research collaborator who was employed by the vehicle factory, in which the study took place. Three of them were employees working with logistics applications in the factory and thirteen were employees working with industrial material handling or assembly where materials handling was included. For the measurement data, two participants (one working with logistics and one working with material handling) were excluded in the analyses due to system failure or incomplete data. For the questionnaire and interview analysis, all fifteen participants were included.

Table 1. Key features of the four studies included in this thesis.

Study Feature	Study I	Study II	Study III	Study IV
Research focus	Development and validation of a smartphone-based tool for assessment of upper arm postures and movements	Evaluation of models using heart rate and accelerometry for assessment of work metabolism	Evaluation of a smart wearable system (1.0) for ergonomic risk assessment of light and heavy physical work	Evaluation of a smart workwear system (2.0) for work postures intervention using real-time vibrotactile feedback in industrial order picking
Type of study	Laboratory study	Laboratory study	Field study	Factory laboratory study
Number of participants	10	12	8	15
Assessment methods	Optical motion tracking analysis & iPhone embedded inertial measurement units	Indirect calorimetry, heart rate monitoring & accelerometry	Heart rate monitoring, accelerometry & questionnaires	Inertial measurement units, video observation, questionnaires & semi-structured interviews
Wearable sensors/ system	A smartphone application (Ergoarmmeter) installed on iPhone 5s & 6	A heart rate monitor and accelerometers	The smart workwear system (1.0) including a vest with textile electrodes, an IMU and an Android tablet application	The smart workwear system (2.0) including three inertial measurement units, two vibration units and an Android smartphone application
Key analysis	Upper arm posture and movement	Work metabolism, assessed by oxygen consumption	Work metabolism & sitting/standing	Work posture measured as trunk inclination and upper arm elevation

Table 2. Background information of the participants in the included studies. Values are provided in median (range).

Participants	Study I	Study II	Study III	Study IV
Occupation	University students and staff	University students and staff	Postal workers, construction workers, office workers and drivers	Employees from a vehicle manufacturing factory
Age (years)	24.5 (23–52)	27 (21–65)	32 (27– 66)	43 (24–53)
Weight (kg)	67.5 (56–76)	75.0 (51–89)	79.5 (52–112)	85 (58–140)
Height (cm)	175 (158–190)	176.7 (164–199)	184 (158–191)	180 (160–197)
Gender	3 women and 7 men	3 women and 9 men	2 women and 6 men	3 women and 13 men

4.2 Study design

In study I, participants were instructed to perform three tests involving the dominant upper arm to validate the iPhone system under different conditions. The first test was static arm tests, when the participants held their arm straight at predefined elevation angles in the sagittal and frontal plane, starting from hanging by the body side, raising up to 45, 90 and 135 degrees. The second test was dynamic arm tests, when the participants kept their dominant arm straight and swung in the sagittal plane at three rates, i.e. 0.1 Hz, 0.4 Hz and 0.8 Hz, following the guidance from a metronome. The third test included two simulated work tasks, i.e. mail sorting and blow-drying hair, and the participants were instructed to use their dominant hand and perform the tasks similar to postal worker and hairdresser at their own pace. The iPhone system and optical tracking system (OTS) measured the upper arm angle simultaneously, and the OTS was used as the standard measurement.

In study II, participants performed three test sessions in order to evaluate the modelling techniques for estimating WM during different occupational activities. The first session included resting in lying, sitting and standing positions, when the resting heart rate (RHR) and resting energy expenditure (REE) were measured. The second session included five simulated work tasks, including office work, painting, postal delivery, meat cutting and construction work, and each lasted 8 to 10 minutes (as shown in Figure 3 and Table 3). These tasks represented a variety of work, which involved arm or leg muscles and ranged from light to heavy work as well as static to dynamic work. For the weight lifted in simulated construction work, the Alba Biomekanik software with Snook lifting recommendation was used to calculate the safe weight limits (Eklund, Liew and Odenrick, 1994). The last session included three submaximal tests, i.e. a Chester step test (Sykes and Roberts, 2004), an arm ergometer test and a treadmill test (Strath *et al.*, 2001).

Figure 3. The five simulated work tasks in study II, from left to right: office work, painting, postal delivery, meat cutting and construction work.

Table 3. Description of the simulated work tasks performed in study II.

Work activities	Duration	Type of work	Description
Office work	10 min	Static, arm work	The participants sit and type on a laptop.
Painting work	10 min	Dynamic, arm work	The participants stand and mimic painting using a painting pole with 0.5-kg weight on the top.
Postal delivery work	10 min	Dynamic, leg work	The participants pedal on a cycle ergometer at a frequency of 60 rev/min with a resistance of 0.75 kg.
Meat cutting work	4 + 4 min	Dynamic, arm work	The participants pull a resistance band every 2 seconds following a metronome, 4 minutes with the right arm and then 4 minutes with the left arm.
Construction work	4 + 1 + 4 min	Dynamic, mixed arm and leg work	The participants lift and lower a box (6 kg or 4.5 kg) from floor to table every 6 s for 4 min, named as 'construction work – mix'. After 1-min break, they lift a box (9 kg or 6.5 kg) from side to side on a table every 5 s for 4 min, named as 'construction work – arm'.

In study III, participants performed their normal work tasks to test the functionality and usability of the smart workwear system 1.0. Before the measurement started, participants filled in a pre-study questionnaire, as described in section 4.3.4. Then they were instructed to perform a Chester step test to calibrate the system and estimate individual's maximal aerobic capacity (VO_{2max}). The system was started to record for two to three hours when they

performed their work of the day. After the measurement, participants filled in a post-study questionnaire, as described in section 4.3.4 and 4.3.5.

In study IV, participants performed order picking tasks to evaluate the effect of the vibrotactile feedback using the smart workwear system 2.0 for improving work postures. The lab, located within a vehicle manufacturing company, resembles the existing order picking area of the company. Standard order picking tasks were designed for the study (see Figure 4), which included 10 items from 7 positions. One item was placed on 15 cm above floor level, and the others were placed in boxes at about waist or shoulder level. For each work cycle, participants were instructed to first pick and place all the items on a trolley and then return the items to their original places following the same sequence. They were also instructed to perform the tasks at their own pace with the dominant hand, except the one large item on floor level with both hands.

Figure 4. Examples of one participant performing the order picking tasks while equipped with the system.

The procedure of the test is shown in Figure 5, with the timeline going from the left to the right. The practice session consisted of at least three work cycles and the other sessions each consisted of three work cycles. To start with, participants were equipped with the system and asked to rate their body discomfort/pain using Borg CR-10 scale. The same scale was used for all participants before and after each session, to see if their body discomfort/pain changed. The practice session was performed so that they could familiarize themselves with the tasks. Then, a break was provided, during which a calibration procedure of the system was performed, which is described more in detail in section 4.3.1. Thereafter, the system was started to record when the participants performed three work cycles in the baseline session. Next, a short break was provided. They were informed that the vibrotactile feedback would be initiated in the

coming session, and they should try to reduce flexed trunk or raised upper arm as hinted by the feedback. Thereafter, the participants performed six work cycles with vibrotactile feedback, which was divided evenly into two sessions for the data analysis, named as intervention session 1 (INS-1) and intervention session 2 (INS-2). Next, a short break was provided and they were informed that the feedback would be stopped. Thereafter, the participants performed another three work cycles without vibrotactile feedback in the post-intervention session. Lastly, the participants were interviewed and filled in questionnaires regarding their experiences and perceived usability of the system (described more in detail in section 4.3.5).

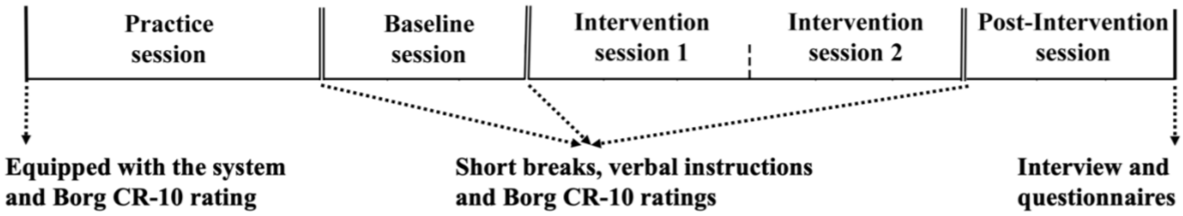

Figure 5. The session design of study IV for evaluating the intervention effects on improving work postures using the smart workwear system 2.0 with vibrotactile feedback. The feedback was provided during intervention sessions 1 & 2. The practice session consisted of at least three work cycles, and the other sessions consisted of three work cycles each.

4.3 Assessment methods

4.3.1 Postures and movements of body segments

In study I, the upper arm elevation angle and angular velocity were measured by an iPhone application using the embedded accelerometer (ACC) and gyroscope. A sampling frequency of 20 Hz was used, which is considered adequate to capture upper arm motions and in agreement with Hansson and colleagues (2006). Two models, i.e. iPhone 5s and 6, were used in the study in different test scenarios. The iPhone 6 was fixed using a neoprene sport armband (Belkin, USA), and the iPhone 5s was fixed using an elastic nylon sport armband (Griffin, USA). The iPhones were placed on the dominant upper arm, with its upper edge at the insertion of deltoid and its long axis parallel to the humerus (see Figure 6a), which corresponds to other similar studies (Bernmark and Wiktorin, 2002; Dahlqvist, Hansson and Forsman, 2016). An optical tracking system (OTS) (Elite, version 2.8.4380, BTS, Milano, Italy) was used as the criterion measurement of the upper arm posture and movement. Three reflexive markers were placed on the same arm: on the humeral head, the lateral epicondyle (Bernmark and Wiktorin, 2002) and the middle of wrist between the radial and ulnar styloid processes (see Figure 6a). A calibration procedure was performed by asking the participants to hold a 2-kg weight and lean to the side with the arm hanging straight (see Figure 6b).

In study IV, the upper arm elevation and trunk inclination were measured by three IMUs (LPMS-B2, LP Research, Tokyo, Japan) with a sampling frequency of 25 Hz. The IMUs were hosted in pockets of a functional t-shirt. The two IMUs on the upper arms were placed with the upper edge approximately at the insertion of the deltoid muscle, see Figure 6c. The IMU on the trunk was place approximately at the level of the T1–T2 vertebrae (Korshøj *et al.*, 2014). Individual calibration was performed by asking the participant to stand straight and look forward with relaxed arms hanging down and palms facing the body (Robert-Lachaine *et al.*, 2017a). Deviation angle from the reference arm posture were calculated as arm elevation angle. Deviation angle from the reference trunk posture on the sagittal plane were calculated as forward (positive) and backward (negative) trunk inclination angle.

Figure 6. Illustration of the (a) placement of the iPhone and three reflexive markers on the arm, (b) calibration procedure of the upper arm in study I, and (c) placement of the IMUs in the pockets of a functional t-shirt on the upper arms and vibration units fixed with straps in study IV.

4.3.2 Work metabolism

Energy expenditure at work is also referred to as work metabolism, which can be accurately assessed by oxygen consumption (VO_2) (Dubé *et al.*, 2015). HR monitoring has been used for estimating VO_2 in field studies based on that there is a strong positive relationship between HR and VO_2 (Shephard and Aoyagi, 2012). However, using HR alone to assess VO_2 in practice has some difficulties: (i) The relationship between HR and VO_2 varies between persons depending on their endurance capacity, which can be tackled by performing individual calibrations; (ii) The slope of the relationship changes depending on how and what muscle groups are utilized, e.g. arm or leg muscle groups, and static or dynamic motion; and (iii) HR

is also affected by other factors, such as stress, food intake and environmental conditions (Haskell *et al.*, 1993; Faria and Faria, 1998; Åstrand *et al.*, 2003; Leonard, 2003).

In study II, three models using HR alone, or in combination with ACCs were evaluated against the criterion measurement using a computerised metabolic system (Jaeger Oxycon Pro, Hoechberg, Germany). The model structures are illustrated in Figure 7. The HR-Flex model was based on HR alone. It applied an individually calibrated linear HR–VO_2 relationship when the HR was above flex-HR point, and the REE value when the HR was below flex-HR (Spurr *et al.*, 1988). The branched equation model was based on HR and one hip-worn ACC (Brage *et al.*, 2004). It used a quadratic HR–VO_2 and a bi-linear ACC–VO_2 equation obtained during individual calibrations. These two equations could be applied by different weightings, and the weightings used in this study were the same as the *a priori* parameters in the original study (Brage *et al.*, 2004). The HR + arm-leg ACC model was based on HR and two ACCs, with one placed on the wrist and the other on the thigh (Strath *et al.*, 2001). It used two linear HR–VO_2 equations obtained during an arm ergometer test and a treadmill test, named as 'linear HR equation – arm' and 'linear HR equation – leg' accordingly. Briefly, a threshold *a* of the ACC output was set to differentiate periods of inactivity, which used REE, and activity with arm or leg, which used the linear HR–VO_2 equations accordingly. When both wrist and leg ACC outputs exceeded the threshold, a ratio between the wrist and leg ACC was used to decide if the arm or the leg activity was dominant, and then the model used the HR–VO_2 equation from arm or leg accordingly.

In study III, due to the limited resources and availability for performing calibration procedures, the HR-Flex model calibrated by the Chester step test was used to estimate the VO_2 at work. The REE was calculated from the Oxford equation using the individual's age, gender, weight and height (Henry, 2005). The individual's maximal aerobic capacity (VO_{2max}) was estimated by the Chester step test with the age-predicted maximal heart rate using $HR_{max} = 208 - 0.7 \times age$ (Tanaka, Monahan and Seals, 2001). The relative aerobic strain (RAS) level was calculated as the ratio of VO_2 at work and the individual's VO_{2max}.

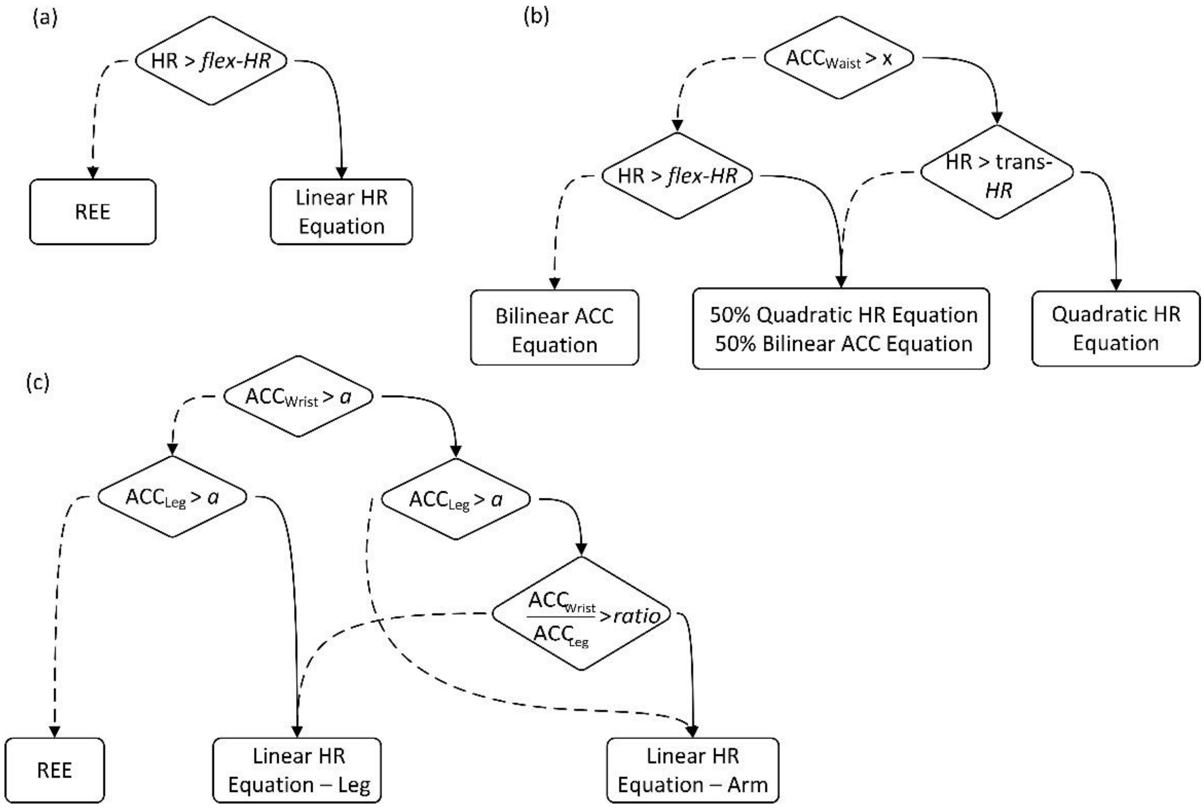

Figure 7. Structure illustrations of the three models for estimating work metabolism based on accelerometry (ACC) and heart rate (HR). The flow goes to the dashed branch if the decision condition is not met. (a) The HR-Flex model (Spurr et al., 1988). (b) The HR branched equation model (Brage et al., 2004): the parameter x was set at 0.027g, and the flex-HR and transition-HR were individual calibrated. (c) The HR+ arm-leg ACC model (Strath et al., 2001): the parameter *a* and ratio were set at 0.013g and 1.5. The parameters were adapted to our study. The HR and ACC equations were obtained from individual calibration tests. HR: heart rate; REE: resting energy expenditure; ACC_{body}: output from the accelerometer worn at the body part accordingly.

4.3.3 Sitting and standing

One inertial measurement unit (IMU) (LPMS-B2, LP Research, Tokyo, Japan) was attached on the mid-thigh using an elastic strap and used for assessing the sitting and standing activities (study III). The algorithm from Skotte and colleagues (2014) was applied for the classification of sitting, standing and other activities, with the same sampling frequency of 30 Hz. The standard deviation of acceleration in the vertical axis was used to classify sitting and standing from other activities. Then, sitting and standing were classified with a threshold of 45 degrees in the inclination.

4.3.4 Subjective rating of tiredness and exertion

In study III, the subjective ratings were used to assess the perceptions of the work characteristics of the work period which were measured by the wearable system. Self-rated physical tiredness level (10-degree scale from 0 “not tired at all” to 9 “totally exhausted”), from Engkvist and colleagues (2010), and the Borg’s ratings of perceived exertion (RPE 15-degree scale, from 6 “No exertion at all” to 20 “Maximal exertion”) (Borg, 1990) were used. The physical tiredness scale was filled in both before and after the work task. The Borg’s RPE scale was filled in after performing the work tasks.

In study IV, assessment of body part discomfort/pain was obtained using the Borg CR-10 scale (Borg, 1990) before and after each session through the whole tests.

4.3.5 Assessment of system usability

In study III, a modified questionnaire consisting of seven items on the system usefulness and wearability (7-point Likert scale, from 1 “totally disagree” to 7 “totally agree”) was used. The items were adapted from Aaltonen and Laarni (2017) to suit our system. The participants filled in the questionnaire after performing their work tasks for two to three hours wearing the system.

In study IV, two standardized questionnaires, i.e. the Comfort Rating Scale and the System Usability Scale were used (Brooke, 1996; Knight and Baber, 2005). The participants filled in these two scales after performing the whole test sessions. In addition, semi-structured interviews were conducted with each participant for about ten minutes. The interviews coverer items on the participant experiences of the wearable system, their learnings from using the vibrotactile feedback regarding their work technique and how they reflected on redesigning and improving the work.

4.4 Risk assessment criteria of the physical workload

Ergonomic risk assessment criteria of the work were defined based on literature research and consensus discussion between project members. The literature was identified by snowball method and personal knowledge of the group (Greenhalgh and Peacock, 2005). Two aspects of the physical work were included in the smart workwear system 1.0, i.e. too high workload assessed by energy demand, and too low workload assessed by the pattern of sitting and standing activities. Color-coded risk levels were used to show the evaluation results: *green* representing no or low risk, *yellow* representing potential risk which requires further inspection, and *red* representing high risk.

4.5 Statistical analyses

In study I, data from the iPhone system and the OTS (the criterion) were compared by calculating the Pearson correlation coefficient and the root-mean-square errors (RMSEs). Bland-Altman plots were used to assess the bias and limits of agreement (LoA) between the systems. Mean absolute differences and standard deviations of the angular velocity measured by the two systems were calculated, and data from the sensor fusion signal and solely accelerometer were compared.

In study II, three models for estimating WM were compared against the criterion measurement by calculating the bias and RMSEs for all participants of each work task. Bland-Altman plots were used to show the bias and LoA between the criterion and the estimation from the three models by two calibration procedures.

In study III, the risk assessment results obtained from the smart workwear system 1.0 were presented for all participants in a summative form. Questionnaire data on the perceived workload and the system usability were analyzed and presented by descriptive statistics.

In study IV, the postures of the dominant upper arm and trunk recorded by the smart workwear system 2.0 were compared within each participant across the four test sessions, i.e. the baseline, the intervention sessions 1 & 2, and the post intervention session. Since the data were not normally distributed, the Wilcoxon Signed Rank test was used to test the pairwise differences. The ratings from two standardized questionnaires were calculated according to the respective manual, and analyzed using descriptive analysis. The semi-structured interviews were analyzed by extracting meaningful entities from each participant and each question, as a basis of a descriptive analysis.

5 Results

This chapter summarizes the results of the included studies. A newly developed tool for upper arm postures and movements measurement (study I) and three existing models for estimating work metabolism (study II) were evaluated against the respective standard measurement. Newly developed wearable systems were evaluated in a field study for ergonomic risk assessment (study III) and in a factory lab for work posture intervention (study IV).

5.1 Study I

5.1.1 The ErgoArmMeter

An iPhone application (ErgoArmMeter) was developed using the development tool Xcode (version 6.2, Apple Inc., USA). The application uses the built-in accelerometers and gyroscopes of the iPhone with a sampling frequency of 20 Hz. The arm elevation angle is calculated directly after a measurement session and results are shown in the application interface. Recommended action limits expressed in the 50th and 90th angular percentiles, time percentage above 30°, 60° and 90°, as well as the 50th and 90th percentiles of generalized angular velocities, based on Hansson et al. (2016), are presented for risk evaluation. An illustration of how the application is used is shown in Figure 8.

5.1.2 The validation of the application

The iPhone application was validated against the OTS in three conditions: static postures, dynamic swings and simulated work tasks. Both iPhone models 5s and 6 had similar levels of accuracy in the validation experiment. Results using iPhone 6 are presented in the thesis.

For the static arm postures in the sagittal and frontal plane, the limits of agreement (mean ± 1.96 SD) between the iPhone system and the criterion measurement OTS were −4.6° and 4.8°, with a mean difference of 0.095° (Figure 9). For the dynamic arm swings in the sagittal plane, the mean sample-to-sample RMSEs of nine participants between the iPhone and OTS across arm swings ranged from 4.0° to 6.0°. Slightly larger mean RMSEs were observed as the swing speed level increased from slow to fast, and the maximum RMSEs doubled comparing the slow swing (5.2°) to fast swing (10.4°). For the simulated work tasks of postal sorting and blow-drying hair, the mean RMSEs were 5.5° and 4.8°, respectively (Table 4).

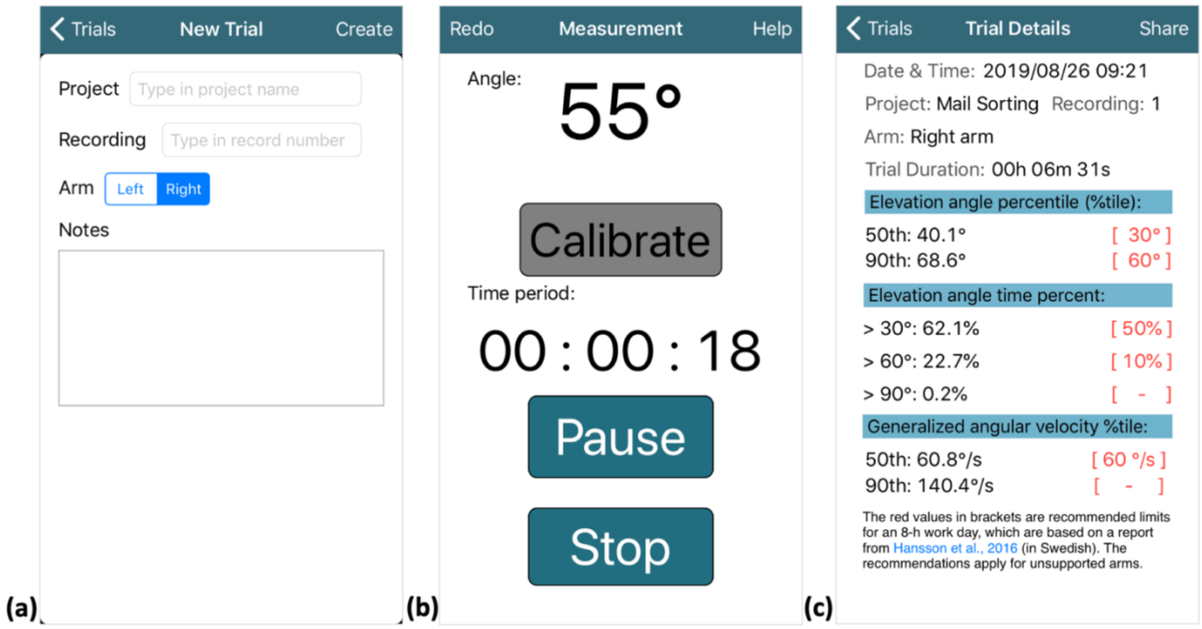

Figure 8. User interfaces of the iPhone application (ErgoArmMeter) for: (a) creating a trial; (b) performing a measurement after calibration, with current angle and time shown on the screen, and (c) the measurement results with suggested action limits in red brackets for risk evaluation.

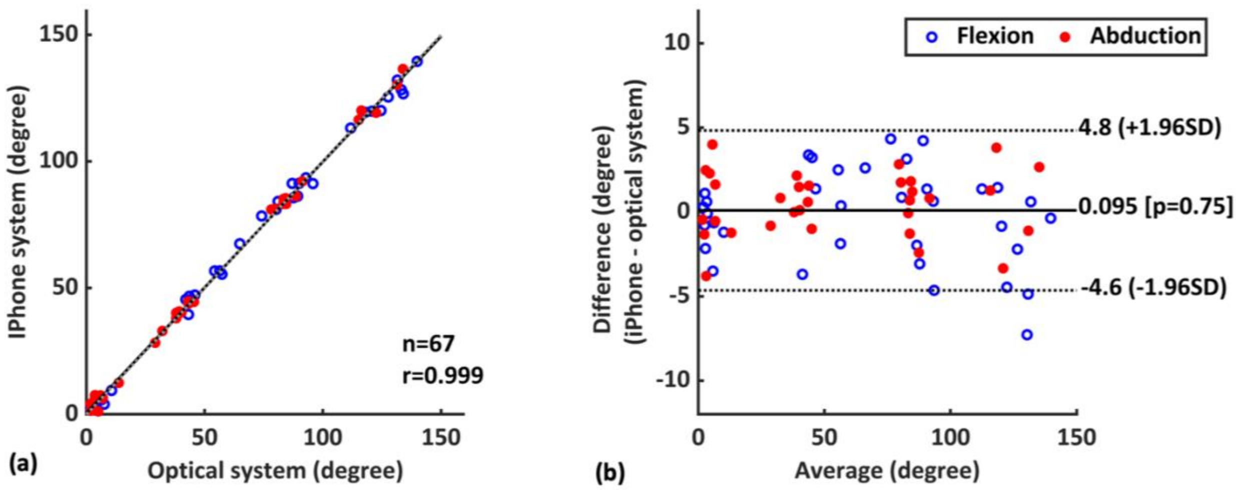

Figure 9. Validation of the iPhone application system against optical tracking system for measuring upper arm elevation in static posture test. (a) Linear correlation scatter plots. (b) Bland-Altman plot. Results from 67 data points from nine participants (other data were missing due to missing markers in the OTS).

Table 4. Mean and maximum sample-to-sample root-mean-square errors (RMSEs) and the mean and minimum correlation coefficients of upper arm elevation between the optical tracking system (OTS) and the iPhone application system, in dynamic arm swings and simulated work tasks. Fewer than 10 participants were included in this table due to missing markers in OTS.

	Arm swings (N = 9)			Simulated work tasks	
	Slow (0.1 Hz)	Medium (0.4 Hz)	Fast (0.8 Hz)	Mail sorting (N = 6)	Blow-drying hair (N = 7)
RMSE (°)					
Mean	4.0	5.1	6.0	5.5	4.8
Max	5.2	8.0	10.4	8.2	6.2
Correlation coefficient (r)					
Mean	0.996	0.991	0.987	0.986	0.986
Min	0.988	0.975	0.951	0.978	0.966

5.1.3 The improvement on accuracy using sensor fusion

As the iPhone application utilizes both built-in accelerometer and gyroscope for the angular measurement, a comparison of the measurement accuracy was made between the sensor fusion signal, i.e. the accelerometer and gyroscope integrated signal, and the accelerometer signal, which is used in standard inclinometry. The results of the upper arm elevation velocity (at the 50th and 90th percentiles) from the sensor fusion signal and the accelerometer signal were compared against the standard measurement using OTS (Table 5). Large improvement on the measurement accuracy was observed, especially in medium to fast arm swings and simulated work tasks. An illustration of the arm elevation of one participant performing the arm swings at three speed levels measured by these two signals compared against the OTS is shown (Figure 10). Distinctive improvement can be observed in median and fast movement.

Table 5. Mean absolute differences (mean ± SD) of the upper arm elevation velocity (°/s) between the iPhone system and the optical tracking system (OTS) in arm swings and simulated work tasks. Data from the gyroscope and accelerometer integrated signal and accelerometer signal were presented. The values from the OTS are given in brackets. Fewer than 10 participants were included in this table due to missing markers in the OTS.

Velocity (°/s)	Arm Swings (N = 9)			Simulated work task	
	Slow	Medium	Fast	Mail sorting (N = 6)	Blow-drying hair (N = 7)
Gyroscope and accelerometer integrated signal					
50^{th}	1.2 ± 0.6 (34.3)	5.2 ± 4.3 (135.7)	13.1 ± 7.8 (262.1)	2.2 ± 2.1 (39.7)	1.7 ± 1.2 (34.2)
90^{th}	1.4 ± 0.9 (51.0)	11.1 ± 6.3 (208.7)	24.6 ± 11.5 (424.5)	24.3 ± 10.7 (152.7)	3.9 ± 2.8 (82.7)
Accelerometer signal					
50^{th}	3.3 ± 1.0 (34.3)	6.3 ± 4.1 (135.7)	43.5 ± 37.7 (262.1)	40.1 ± 22.2 (39.7)	9.5 ± 7.6 (34.2)
90^{th}	14.6 ± 5.7 (51.0)	48.5 ±32.4 (208.7)	451.5 ±179.3 (424.5)	32.0 ±38.4 (152.7)	14.1 ± 11.6 (82.7)

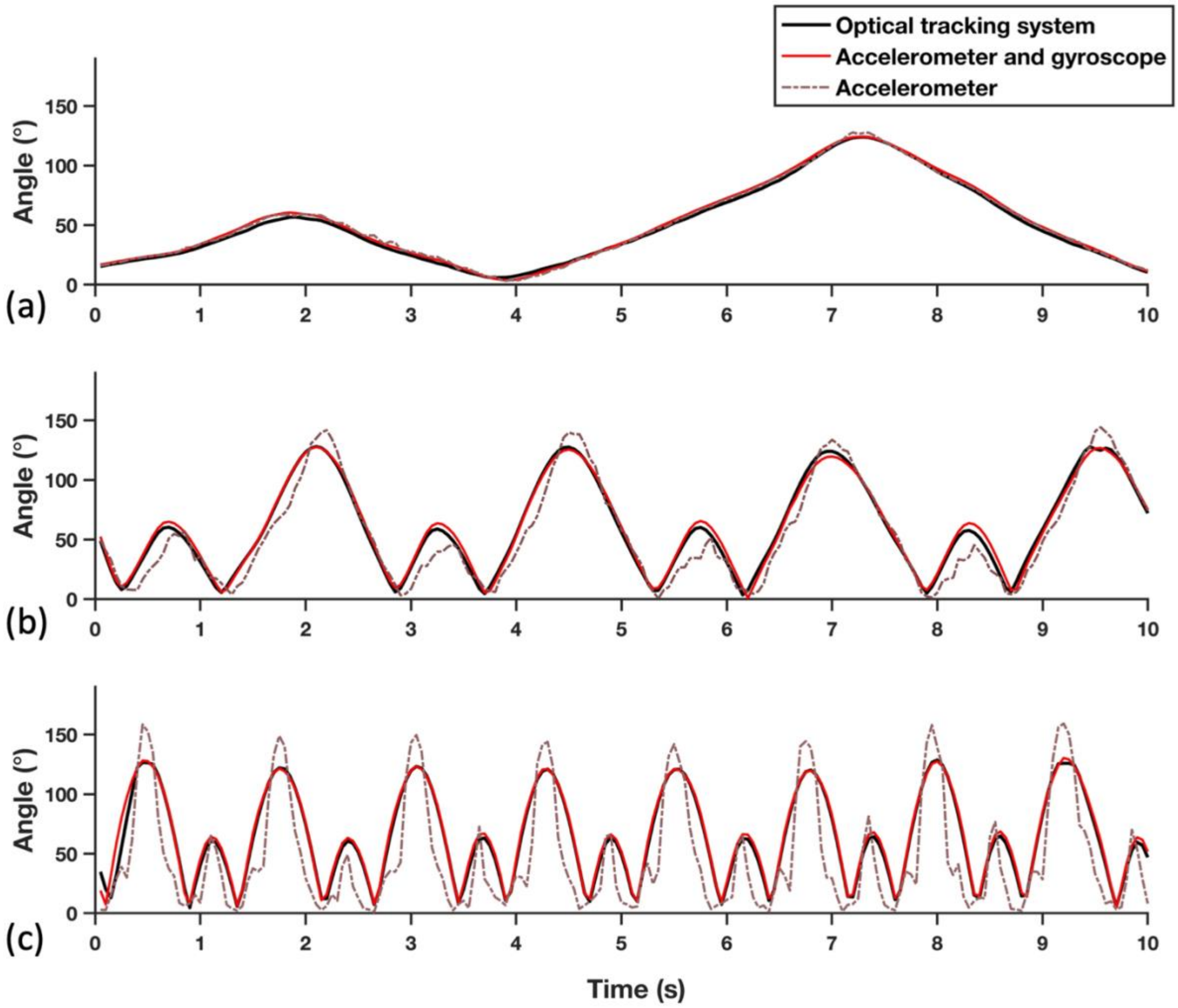

Figure 10. Illustration of the upper arm elevation angle measurements by the optical tracking system, the signal integrating the accelerometer and gyroscope, and the accelerometer only, during arm swings at three speed levels: (a) slow pace at 0.1 Hz, i.e. 6 swings per minute, (b) medium pace at 0.4 Hz, i.e. 24 swings per minute, and (c) fast pace at 0.8 Hz, i.e. 48 swings per minute.

5.2 Study II

5.2.1 Evaluation of three models for work metabolism estimation

Three modeling techniques using heart rate (HR) monitor and accelerometers (ACCs) for estimation of oxygen consumption (VO_2) at work were compared against the criterion measurement during five simulated work tasks (Table 6). All three models performed well during the office work, with a mean RMSE ranging from 0.7 to 1.0 mL/min/kg compared to criterion measurement. The HR + arm-leg ACC model showed the best accuracy in most work tasks, except in office work and painting. The HR-Flex model showed a small bias for the average of all tasks, and the best accuracy in painting. The HR branched equation model showed large underestimations in most tasks, with a bias ranging from -2.7 to -3.5 mL/min/kg, except in office work.

In addition, individual differences were observed regarding the effect of different types of work on HR–VO_2 relationships (illustrated in Figure 11). A clear distinction between the work tasks using mainly arm, leg or mixed muscle groups can be observed for some participants, as illustrated in Figure 11a. The tasks using mainly arm (i.e. painting, meat cutting and construction work with arm) followed the arm calibrated HR–VO_2 relationship, and the other tasks using leg or mix muscle groups (i.e. postal delivery and construction work with mix) followed the leg calibrated relationship. However, the difference of cardiovascular responses between the tasks was not so distinct for some participants, as illustrated in Figure 11b. The observed differences pointed to that the individual cardiovascular responses during work tasks determined by arm or leg motion might not follow the arm or leg HR–VO_2 relationship obtained during submaximal tests.

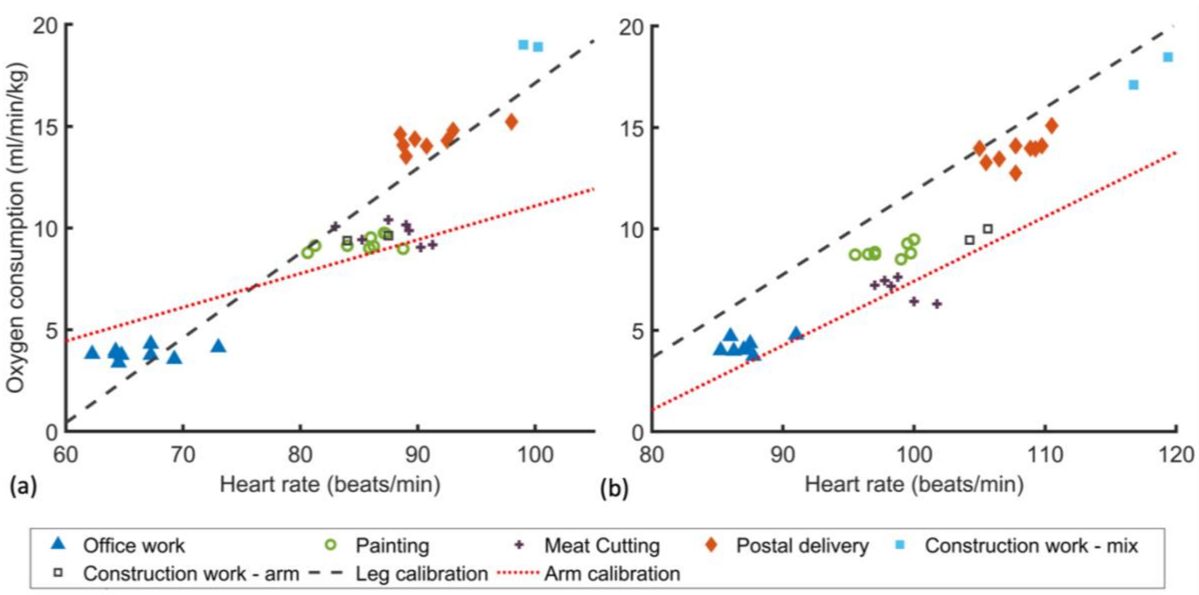

Figure 11. The HR–VO_2 relationships during different simulated work tasks, with two individual calibration lines performed by treadmill (leg calibration) and arm ergometer (arm calibration): (a) example of one participant showing a clear distinction between work tasks with mainly arm or leg muscles on the HR–VO_2 relationship, and (b) example of one participant showing a vague distinction between work tasks. Each data point represents 1-min average value.

Table 6. Estimates of oxygen consumption (mL/min/kg) during five simulated work tasks using three models compared to the criterion measurement using indirect calorimetry. Results with best performance (smallest bias and/or RMSE) are marked in bold.

Estimation models	Office work			Painting			Postal delivery			Meat cutting			Construction work			Average for all work tasks		
	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE
Criterion	4.0 ± 0.8	–	–	8.3 ± 1.1	–	–	14.0 ± 2.0	–	–	7.5 ± 1.7	–	–	12.4 ± 2.5	–	–	9.1 ± 1.2	–	–
HR-Flex	**3.5 ± 0.9**	-0.4	**0.7**	**8.0 ± 2.5**	**-0.3**	**2.1**	11.8 ± 3.5	-2.2	3.2	9.8 ± 3.9	2.3	3.7	13.8 ± 3.5	1.5	2.4	**8.9 ± 2.4**	**-0.2**	1.5
HR branched equation	**3.7 ± 0.4**	**-0.2**	0.8	5.2 ± 1.2	-3.2	3.5	10.5 ± 1.6	-3.5	4.0	4.8 ± 1.0	-2.7	3.2	9.0 ± 2.3	-3.4	4.1	6.6 ± 1.1	-2.5	2.8
HR + arm-leg ACC	3.8 ± 1.2	-0.2	1.0	6.3 ± 1.4	-2.0	2.2	**12.3 ± 2.9**	**-1.7**	**2.2**	**7.5 ± 1.5**	**0.0**	**0.9**	**11.5 ± 2.6**	**-0.9**	**2.1**	**8.0 ± 1.2**	-1.1	**1.2**

RMSE: Root mean square error.

HR-Flex: Heart rate flex model.

HR branched equation: Model combining HR and one accelerometer placed on the hip.

HR + arm-leg ACC: Model combining heart rate and accelerometer data from two accelerometers placed on the wrist and thigh.

5.2.2 Comparison of two calibration procedures

Two calibration procedures, i.e. a Chester step test and a submaximal treadmill test, were compared when used for calibrating the three aforementioned models for estimating WM (Figure 12). For the HR + arm-leg ACC model, an additional submaximal arm ergometer test was performed in order to obtain the arm calibration used in the model.

Overall, the treadmill test showed smaller limits of agreement (LoA) for calibrating the three models compared to the Chester step test. When looking at the model performance with specific calibration procedure, the HR + arm-leg ACC model calibrated with the treadmill test showed the smallest limits of agreement of −3.94 to 2.00 mL/min/kg. The HR-Flex model calibrated with the Chester step test showed the smallest bias (−0.03 mL/min/kg) while quite large LoA of −5.81 to 5.74 mL/min/kg. The HR branched equation had a large underestimation both when calibrated with Chester step test (−2.64 mL/min/kg) and treadmill test (−2.59 mL/min/kg). Thus, the HR + arm-leg ACC model calibrated by a submaximal treadmill test and arm ergometer test had best performance in WM estimation. However, it also required most resources for individual calibration.

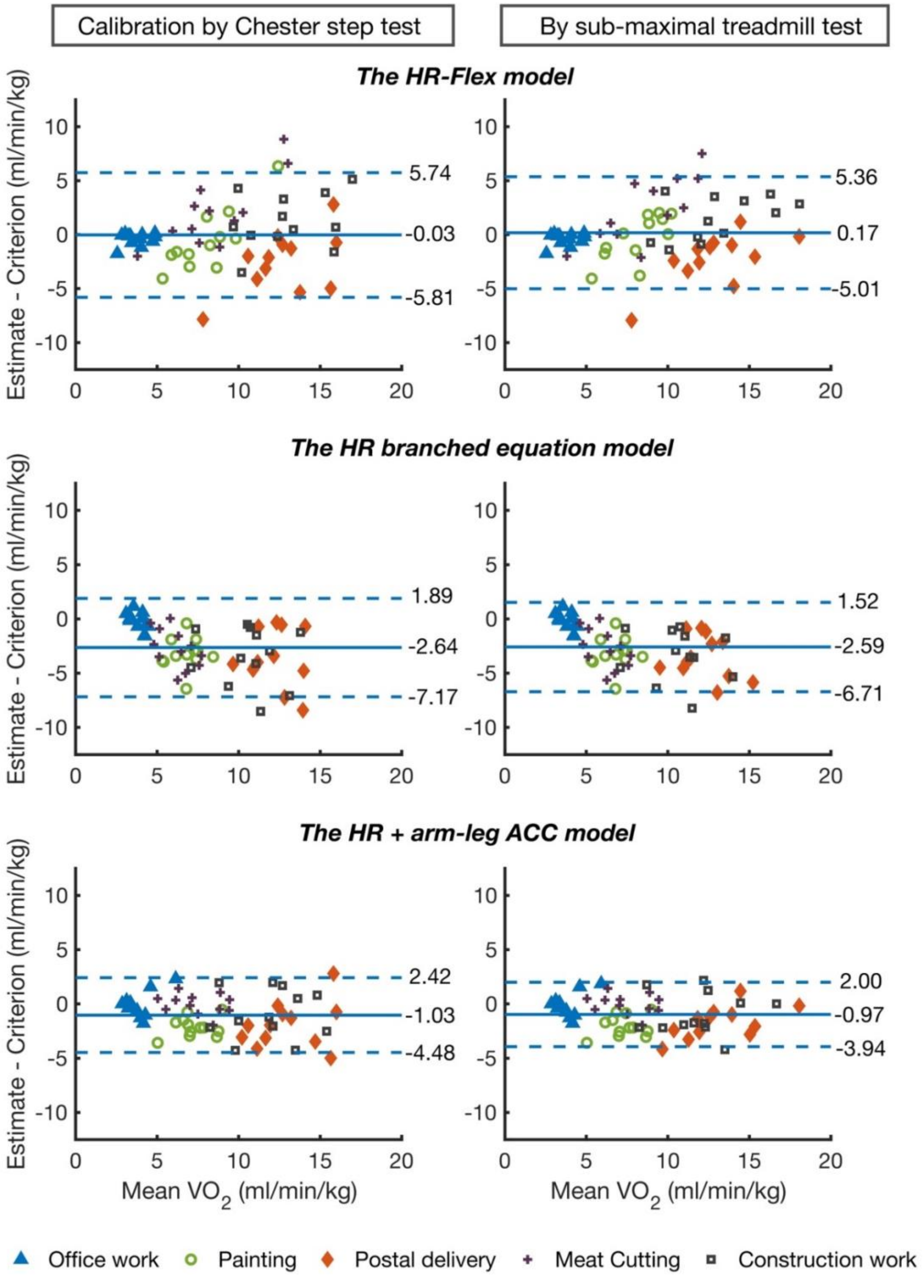

Figure 12. Bland-Altman plots of the oxygen consumption (VO_2) estimated by three models with two different calibration procedures, marked by five simulated work tasks. The two calibration procedures were: Chester step test (to the left in each model row), and a submaximal treadmill test (to the right in each model row); the three estimation models were, from top to bottom row, the HR flex model, the HR branched equation model and the HR + arm-leg ACC model.

5.3 Study III

5.3.1 The Smart workwear system (1.0)

The smart workwear system 1.0 was developed in the project team and it comprised a hardware and a software sub-system. The hardware sub-system consisted of a vest with textile electrodes, a wireless compact recorder (ECGZ2, Z-Health Technologies AB, Borås, Sweden), which recorded and transmitted the electrocardiogram (ECG) and thoracic electrical bio-impedance signals, a wireless IMU (LPMS-B2, LP Research, Tokyo, Japan), and an Android 6.0 tablet (SM-T713, Samsung, Seoul, South Korea) (Figure 13).

The software sub-system consisted of an Android application. It communicated with the aforementioned wireless sensors via Bluetooth and stores the data. At the same time, it also processed the signals and computes two workload parameters, i.e. the relative aerobic strain (RAS) based on the heart rate calculated from ECG and the sitting/standing behaviors based on the acceleration signal from the IMU. Risk assessment was performed in the software, following the criteria as described in section 5.3.2. The assessment results were available both during the measurement, which could be used for analyzing risks and providing feedback in real time, and after completing the measurement, which enabled post-analysis with more details.

Figure 13. The smart workwear system 1.0, illustrated by its hardware components.

5.3.2 The risk assessment criteria

Ergonomic risk assessment criteria used in the system were defined based on literature research and a consensus discussion between project members. Two aspects of the physical workload were included, i.e. too high workload assessed by WM in the form of RAS, and too

low workload assessed by sitting and standing behaviors. Color-coded risk levels were used to show the evaluation results: a *green* light representing no or low risk, a *yellow* light representing potential risk which requires further inspection, and a *red* light representing high risk. For the work metabolism, a RAS limit of 33 % was chosen as the red level, and 25 % as the yellow level (Legg and Myles, 1981; Asfour *et al.*, 1988; Smolander and Louhevaara, 2011). For the occupational sitting and standing, two tentative criteria were used. One was based on prolonged duration, whether it exceeds 55 min in 1-hour episodes, and the other was based on accumulated time, whether it exceeds 50 % of the total time (Toomingas *et al.*, 2012; Callaghan *et al.*, 2015). If both criteria were met, the sitting/standing behavior was considered at the red level. If only one criterion was met, the sitting/standing behavior was considered at the yellow level. The limits were proposed for an 8-hour working day. Consideration should be taken when measuring a shorter period of the work, and the risk levels can apply given that this period represents a normal whole working day.

5.3.3 Illustration of the risk assessment results

The results were made from the 2–3 hours' measurement data and extrapolated to an 8-hour working day, based on the assumption that the measurement period represented a normal working day. However, with the aim to demonstrate the use of the system, the obtained risk levels of the participants should not be applied for the occupation. The mean RAS and the risk assessment are presented for each participant (see Table 7). Here, participant 4 was assessed as red, suggesting that if this level of physical workload continued for a whole working day, the risk of adverse health effects in the long term was high. Participant 3 and 8 were assessed as yellow, suggesting that further analyses were needed.

Table 7. Illustration of the summative risk assessment results regarding work metabolism (WM), with the risk level as red if relative aerobic strain (RAS) exceeding 33 % and as yellow if exceeding 25 %. The RAS was calculated as the ratio between the WM and individual's maximal capacity.

Participant	Occupation	Relative aerobic strain (%)	Risk level
1	Driver	8.6	Green
2	Driver	11.6	Green
3	Postal worker	31.1	Yellow
4	Postal worker	40.5	Red
5	Office worker	8.5	Green
6	Office worker	12.6	Green
7	Construction worker	16.4	Green
8	Construction worker	25.1	Yellow

The assessment on occupational sitting and standing behavior and the risk levels are shown in Table 8. Two drivers and one office worker (participants 1, 2 and 5) were assessed as red regarding their sitting behavior. The other office worker (participants 6) was assessed as yellow due to that the sitting duration exceeded 50% of the total time with no prolonged episodes. One construction worker (participant 8) was assessed as yellow due to that the standing duration was 62.9% of the total time without prolonged standing episode.

Table 8. Illustration of the summative risk assessment results regarding occupational sitting or standing behaviors, with the risk level based on two criteria: whether the percentage of time exceeds 50 % of the total time and whether there are prolonged episodes exceeding 55 minutes in 1-hour episodes.

Participant	Occupational sitting			Occupational standing		
	Time (%)	Prolonged episodes	Risk level	Time (%)	Prolonged	Risk level
1	99.9	Yes	Red	0.0	No	Green
2	97.1	Yes	Red	0.3	No	Green
3	18.6	No	Green	18.1	No	Green
4	5.1	No	Green	27.7	No	Green
5	76.3	Yes	Red	8.8	No	Green
6	57.2	No	Yellow	25.0	No	Green
7	8.4	No	Green	49.3	No	Green
8	6.9	No	Green	62.9	No	Yellow

In addition, self-reported physical tiredness level before and after the measurement, as well as the Borg's RPE scale of the tasks are shown in Table 9. For the two postal workers, self-reported physical tiredness level (0–9 scale) increased from 3 to 5, and 2 to 6, respectively. They also rated the Borg's RPE (6–20 scale) of 13 and 14, as somewhat hard to hard. The construction workers rated their work as extremely light, i.e. 7 of Borg's RPE scale, with no change in their physical tiredness level. This was due to that they had really light work during the day when the measurement was performed. For the office workers and drivers, the ratings on the Borg's RPE scale were low, ranging from 6 to 7, with a slight change of physical tiredness level ranging from -1 to 1.

Table 9. Subjective ratings of physical tiredness level (0-9) before and after the measurement, as well as the ratings of perceived exertion (Borg's 6-20 RPE) of the work tasks.

Participant	Occupation	Physical fatigue level		Borg RPE Scale
		Before	*After*	
1	Driver	2	2	6
2	Driver	1	1	7
3	Postal worker	3	5	13
4	Postal worker	2	6	14
5	Office worker	0	1	6
6	Office worker	2	1	7
7	Construction worker	0	0	7
8	Construction worker	1	1	7

5.3.4 Usability evaluation

Usability evaluation results are shown in Figure 14. Most of the participants (N=6) agreed that the system was usable for assessing risks at work, easy to put on and take off, comfortable to wear at work, and easy to interpret. The majority also agreed (N=7) that the system did not distract or cause any disturbance to them during their work. All participants agreed (of which 50% strongly agreed) that the system was not unpleasant.

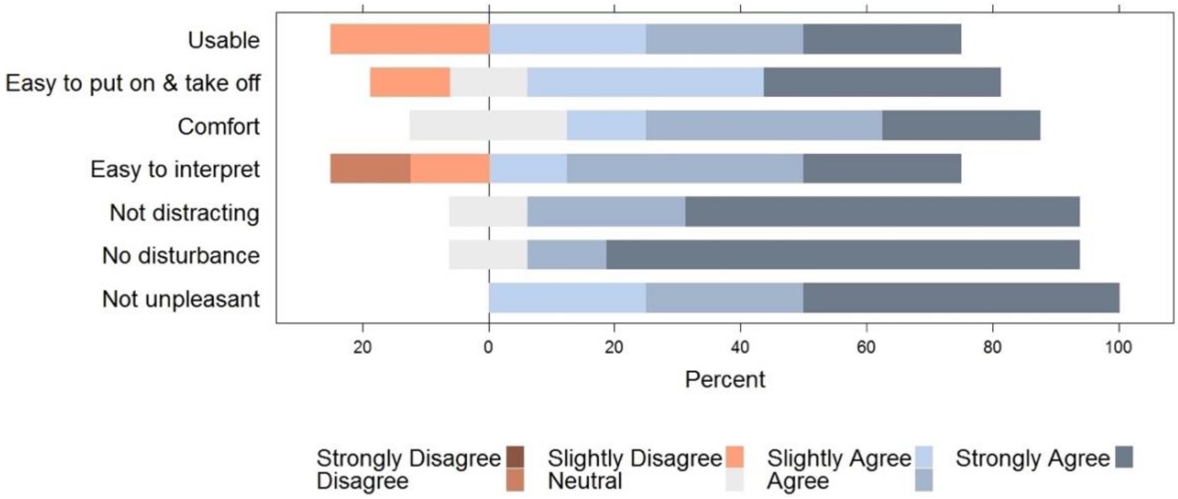

Figure 14. The usability evaluation (7-degree Likert scale) of the smart workwear system 1.0 on seven items from all participants (N=8). Answers on the plot from left, to middle, and to right: strongly disagree, neutral and strongly agree.

5.4 Study IV

5.4.1 The Smart workwear system (2.0)

The smart workwear system 2.0 was further developed in the project team, with a focus on assessment of upper arm and trunk postures and an additional function of offering vibrotactile feedback. The hardware sub-system consisted of three wireless IMUs (LPMS-B2, LP Research, Tokyo, Japan), a functional t-shirt with embedded pockets hosting the IMUs, two in-house built wireless vibration units, and an Android 8.0 smartphone (Galaxy A5 2017, Samsung, Seoul, South Korea), as shown in Figure 15. The software sub-system consisted of an Android application which communicates with the IMUs and vibration units via Bluetooth. The IMUs were set at a sampling frequency of 25 Hz. The application down-sampled the IMU output into 1 Hz and computed the upper arm and trunk angles in real time. At the same time, it compared the angles with two levels of thresholds to decide if the vibrotactile feedback should be initiated. The first level of vibration was intermittent and lower in power and the second level had continuous vibration with higher power.

Figure 15. The smart workwear system 2.0, illustrated by its hardware components.

Various studies have used different exposure thresholds for assessing risk factors, including work postures, when analyzing the exposure-response relationships with no consensus reached in the research area (Punnett and Wegman, 2004). The choices of the two levels of feedback thresholds in the system were set at 20° and 45° for the trunk inclination (Punnett *et al.*, 1991; Jansen, Morgenstern and Burdorf, 2004), and at 30° and 60° for the arm elevation (Hanvold *et al.*, 2015; Hansson, Arvidsson and Nordander, 2016; Wahlström *et al.*, 2016). Additional

exposure thresholds, i.e. trunk flexion over 30° (Hoogendoorn *et al.*, 2002; Lötters *et al.*, 2003) and upper arm elevation over 45° (Silverstein *et al.*, 2008; van Rijn *et al.*, 2010), and the angular percentiles at 50_{th}, 90_{th}, and 99_{th} of both upper arm and trunk (Hansson *et al.*, 2010; Balogh *et al.*, 2019) were also presented when evaluating the intervention effects in reducing adverse postures.

5.4.2 Intervention effect on work postures

Trunk posture

The trunk inclination angle of the four sessions are presented as the time over 20°, 30° and 45° (Figure 16a) and the percentile at 50_{th}, 90_{th} and 99_{th} (Figure 16b). During the vibrotactile feedback was provided, statistically significant median decreases were observed in all parameters comparing intervention sessions 1 & 2 to baseline ($p < 0.01$). The group median time of trunk inclination over 20° and 30° from baseline (medians of 56 s and 26 s) decreased slightly more than half. The group median time over 45° decreased substantially from baseline (a median of 12 s) to intervention sessions 1 & 2 (medians of 3 s and 1 s). Shortly after feedback withdrawal, statistically significant median decreases were still observed in all parameters comparing post-intervention session to baseline ($p < 0.01$), with a slightly smaller reduction.

In addition, statistically significant median increases in the session duration were observed comparing intervention sessions 1 & 2 (medians of 389 s and 360 s) to baseline (medians of 326 s) ($p < 0.01$). However, when comparing post-intervention session (medians of 335 s) to baseline, the difference in the session duration was no significant (Figure 16c).

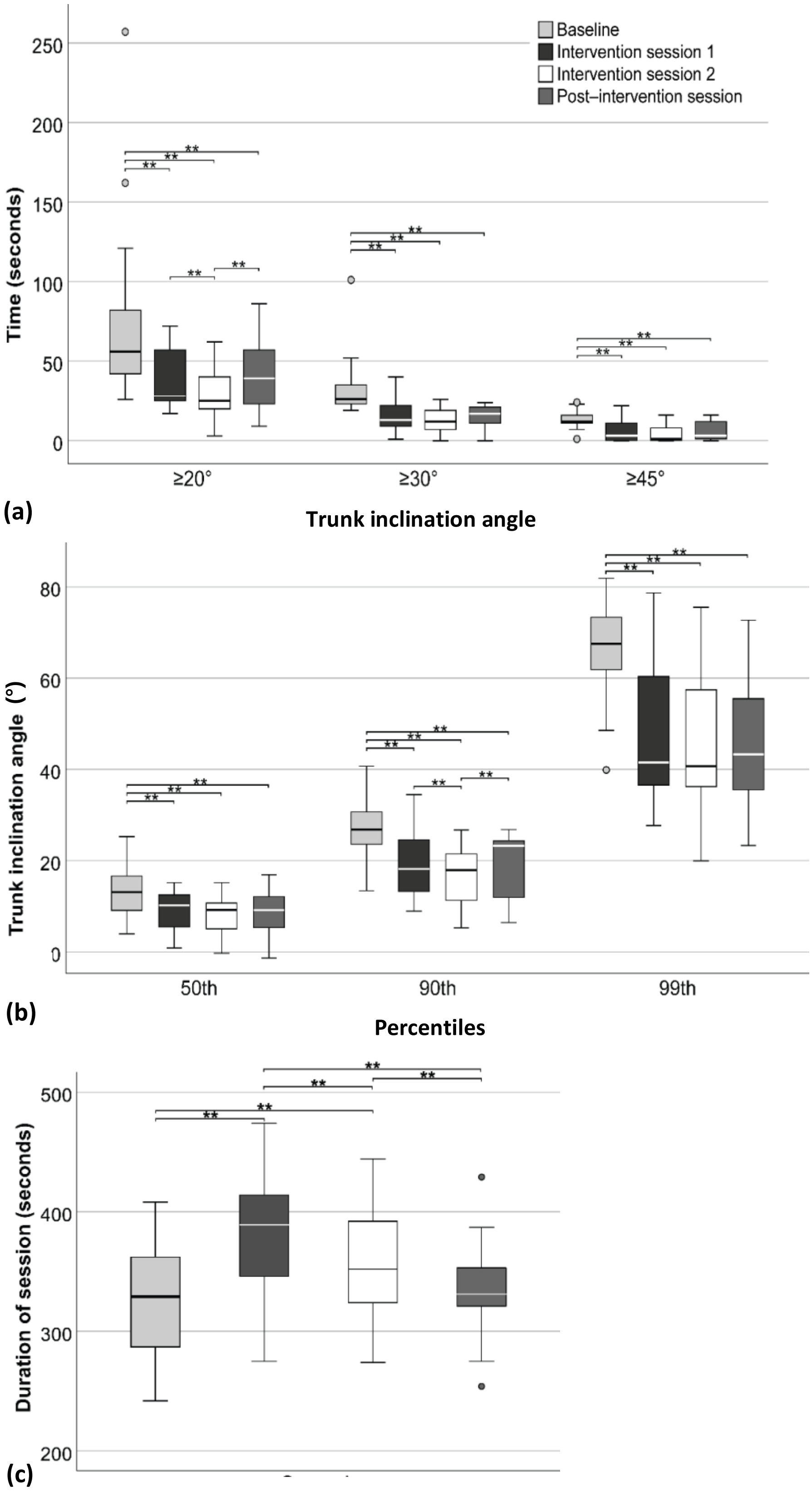

Figure 16. Comparison between the four test sessions of: (a) time in trunk inclination exceeding 20°, 30° and 45°, (b) the 50th, 90th and 99th percentiles of trunk inclination, and (c) the duration of each session. *p<0.05, **p<0.01.

Arm posture

The upper arm elevation angle of the four sessions are presented as the time over 30°, 45° and 60° (Figure 17a) and the percentile at 50th, 90th and 99th (Figure 17b). Statistically significant median decreases were observed in the time in arm elevations over 30° and 45° from baseline (medians of 92 s and 36 s) to intervention session 2 (medians of 64 s and 32 s) ($p < 0.05$). After feedback withdrawal, statistically significant median decrease was only observed in the time in upper arm elevation over 30° comparing post-intervention session to baseline ($p < 0.05$).

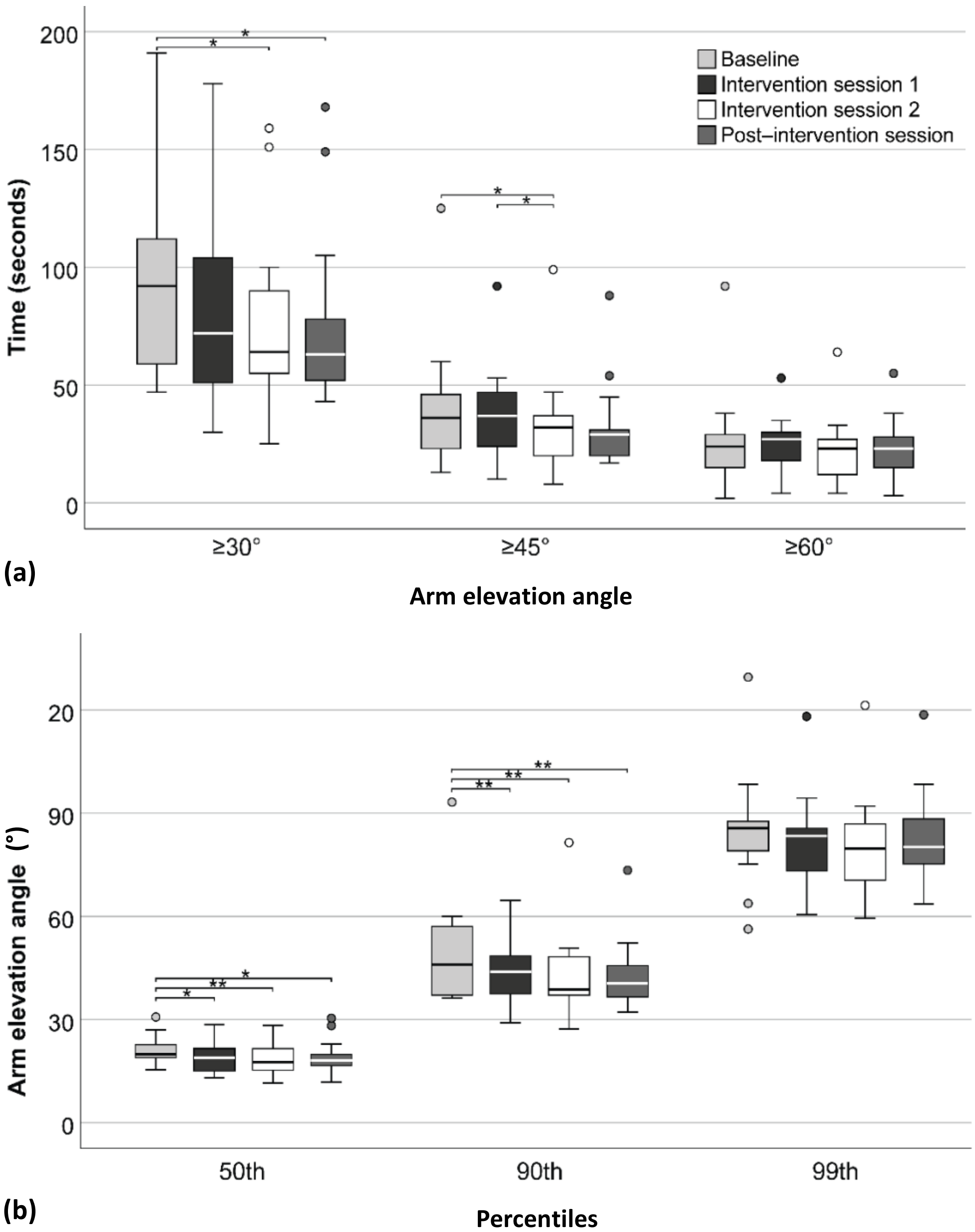

Figure 17. Comparison between the four test sessions of: (a) time in arm elevation exceeding 30°, 45° and 60°, and (b) the 50th, 90th and 99th percentiles of arm elevation. *p<0.05, **p<0.01.

For the percentiles of upper arm elevation, statistically significant median decreases were observed in the 50th and 90th percentile of the upper arm elevation from baseline (medians of 20° and 46°) to intervention session 2 (medians of 18° and 39°) ($p < 0.01$). Statistically significant median decreases were also observed from baseline to post-intervention session in the 50th (a median of 18°, $p < 0.05$) and 90th (a median of 41°, $p < 0.01$) percentile of the upper arm elevation. No significant decrease in the 99th percentile was observed across sessions.

Test on repetition effect

In order to test whether the adverse work postures were reduced due to performing the order picking tasks repetitively over time, additional tests comparing the first three work cycles in the baseline were run for both trunk and upper arm postures. Only one statistically significant median difference was observed in the time of trunk exceeding 30°, which had a small median increase from the first work cycle (a median of 8 s) to the second work cycle (9 s). There was no significant difference in the other parameters during the work cycles in the baseline.

5.4.3 System comfort and usability evaluation

The participants were almost free from discomfort or pain in the body through the whole tests. Their ratings on Borgs CR10 scale had a mean (SD) value of 0.5 (0.8) before starting the baseline, and a maximum of 0.9 (0.9) through the whole tests. The participants had low ratings on the Comfort Rating Scale (0 to 20 scale) suggesting that the system was comfortable to wear. The mean (SD) ratings on the sub-dimensions were: emotion 2.8 (3.9), harm 0.8 (1.1), perceived change 1.5 (2.1), and anxiety 1.5 (4.1). The participants had high ratings on the system usability scale (total score 0 to 100), with a mean (SD) score of 81 (16), which suggests that the system had good overall usability (Bangor *et al.*, 2009). In particular, the participants felt confident about how to use the system, and rated that it was easy to use and easy to learn, with a mean rating ranging from 4.3 to 4.7 (items on a 5-point scale).

Results from the interview showed that the participants considered the vibrotactile feedback positively contributed to better postures of the trunk (N=14, out of 15) and the arm (N=12). A majority of the participants stated that the vibrotactile feedback reminded them to adopt better postures (N=10). Most of them also stated that they learned better work techniques (N=13). The participants gave examples of how they changed their work technique because of the vibrotactile feedback: e.g. to load and unload from the long side of the cart, have a more upright trunk posture, walk closer to the racks, and place the items in the cart closer to the body. Moreover, the participants reflected on the design of the work. A majority of them proposed improvements to the design of the racks, boxes and placement of the items (N=14). Further, several of them mentioned that the vibrotactile feedback was of more importance for them when learning which situations were unsuitable, than the body discomfort

6 Discussion

This chapter first discusses the methodological aspects of this thesis, including material and measurement methods used. Then the main results of the four included studies are discussed, regarding the accuracy of the tool and models (study I & II), the functionality and usability of the workwear systems (study III & IV), and the intervention and learning effect of using the system (study IV).

6.1 Material

In this thesis, a range of participants from various occupations were included. In study I, 10 university students and staff were involved in order to validate an iPhone-based tool for for assessment of upper arm postures and movements at work. The number of participants involved was in agreement with other studies with similar aims. Korshoj and colleagues validated a sensor for arm and upper body measurement with 8 participants (Korshøj *et al.*, 2014), and Schall and colleagues validated an IMU system with 6 participants (Schall *et al.*, 2016).

In study II, 12 university students and staff were involved to evaluate models using heart rate and accelerometry for estimating work metabolism. The number of participants was similar to the original studies that developed these models (Brage *et al.*, 2004; Strath, Brage and Ekelund, 2005). Compared to those studies, the participants in study II had a wider spread in age and fitness level. However, with a limited number of female participants (N=3), the sex difference in the model estimations cannot be investigated.

In study III, a field test with 8 participants from four occupations were performed in order to demonstrate and evaluate a newly developed smart workwear system (1.0) for ergonomic risk assessment. The choice of four occupations was made to include work tasks with light to heavy workload and including static as well as dynamic tasks. However, the two construction workers had really light work tasks during the measurement day. Still, for the aim of testing and evaluating the system, results from the measurements and subjective ratings provided useful information. For studies that aim to assess the occupational exposure, measurement for longer periods with a larger group of participants should be performed, to provide a better picture of the workload (Wahlström *et al.*, 2010).

In study IV, 15 employees in a vehicle factory were involved to evaluate a smart workwear system (2.0) for work postures intervention using real-time vibrotactile feedback. Among them, there were two employees working with logistic applications who had less experience in order picking tasks compared to the others. Therefore, the influence of experience level in the intervention effect was not investigated, which should be looked into in future studies. Still, the number of participants was in agreement with similar studies (Agruss, Williams and Fathallah, 2004; Vignais *et al.*, 2013; Doss *et al.*, 2018), and was sufficient to show an intervention effect in the measured outcomes. To sum up, although rather small numbers of participants were involved in the studies, the results of the involved participants were found valid and relevant.

6.2 Measurement methods

6.2.1 Postures and movements of upper arm and trunk

Calibration

Technical measurement methods were used for assessing the upper arm elevation and trunk inclination in studies I and IV. The calibration procedures of the upper arm vary between studies and research groups, which can affect the absolute assessment results and impede the possibility for between-study comparison. In study I, a calibration procedure in agreement with Bernmark and Wiktorin was used, by asking the participant to hold a 2-kg weight and lean to the side with the arm hanging vertically (2002). This posture was taken as the reference posture for both the new tool and the criterion measurement. The same calibration procedure has been adopted in a few studies in both laboratory and field measurements (Hansson *et al.*, 2006; Wahlström *et al.*, 2010; Jackson, Mathiassen, Wahlstrom, *et al.*, 2015).

In study IV, another single-pose calibration procedure was used to calibrate both upper arms and the trunk, which is considered fast and simple and has been adopted by a few studies (Cutti *et al.*, 2008; Schall *et al.*, 2016; Robert-Lachaine *et al.*, 2017a). The procedure was done by asking the participant to stand straight with relaxed arms and palms facing the body. However, this calibration can have lower accuracy in estimating the upper arm elevation angles (Robert-Lachaine *et al.*, 2017a), since its angular measurement is affected by the individual differences in body shape. For example, individuals with a leaner body will have a smaller upper arm angle relative to gravity in this calibration posture (defined as 0 degree after calibration) compared to individuals with a larger or muscular upper body. In study IV, with the aim to evaluate the intervention effect using vibrotactile feedback in posture training in a within-subjects design, the calibration procedure was chosen due to that the need for convenience outweighed the need for accuracy. The absolute upper arm elevation for each individual might be underestimated, while the intra-individual change of arm elevation across the scenarios could still be captured.

Sensor placement

In addition to the choice of calibration procedure, the placement of sensors is another factor that influences the measurement outcome. The placement also varies between studies and research groups. For upper arms measured by common inclinometry systems, one placement with smaller distance to the shoulder joint over medial deltoid has been used (Trask *et al.*, 2014), which could reduce the errors introduced by dynamic accelerations from upper arm movements (Hansson *et al.*, 2001). However, by placing the sensor over the deltoid, the bulging of the deltoid muscle during arm movement will affect the sensor alinement with the humerus. To reduce the error from soft tissue artifacts, another placement with sensor's upper edge distal to the insertion of deltoid muscle has been used (Bernmark and Wiktorin, 2002; Hansson *et al.*, 2010; Wahlström *et al.*, 2010). Jackson and colleagues reported measurement bias of using ACCs attached at both placements on the upper arm, with mean bias around 10° (Jackson *et al.*, 2015). The measurement bias was discussed that it might be caused by the differences in reference postures as well as the size of the attached surface (Hansson, 2015; Jackson *et al.*, 2015). In study I, the iPhone was fixed on the upper arm at the insertion of the deltoid muscle. In addition, with its built-in sensor fusion using the accelerometer and gyroscope, the errors from dynamic arm movements can also be reduced to a large extent (as shown in Figure 10). By placing the iPhone to reduce soft tissue artifacts and using the sensor fusion signals, the performance of the iPhone application in assessing upper arm movements was improved and better than the common inclinometry using solely accelerometer.

For the trunk inclination, different placement protocols have been used, which vary from on the sternum at the front side of trunk (Van Driel *et al.*, 2013; Schall *et al.*, 2015), or on the back at levels of T1-T2 vertebrae (Korshøj *et al.*, 2014; Labaj *et al.*, 2016), to between scapulae at T6 (Wahlström *et al.*, 2016). In study IV, the IMU sensors were placed in small elastic pockets of a functional workwear t-shirt. The designed placements were, for the upper arms, at the insertion of deltoid muscle, and for the trunk, at the level of T1-T2 vertebrae. The choice for placing the IMU at T1-T2 level was due to practical concern. The other two placements may not follow the trunk so well, due to varied body shape if placed on the sternum/chest or during shoulder extension movement if placed between two shoulder blades. The exact sensor placements, when worn by individuals, would have some variations due to different body shapes, even with four different sizes of t-shirt to choose from. In this study, with the within-subject design to compare changes across the scenarios, the influence is less critical. As shown by the results (Figure 16), the intervention effect on trunk postures could be captured.

Criterion measure and definitions

Although OTS was regarded as the criterion measure for upper arm assessments in study I, it was not obvious how to find the best line representing the underlying humerus. The reflexive markers attached to the skin could be affected by soft tissue artifacts, especially during arm elevation and rotation. Two reflexive markers on the humeral head and the lateral epicondyle, following the protocol of Bernmank and Wiktorin (2002), were used in most test scenarios. The marker on the wrist was used together with the one on the humeral head for assessing

upper arm elevation during static arm abduction tests. This was used to counteract the errors from soft tissue artifacts when the arm was elevated and supinated (with the palm facing up). In future studies, an increased number of markers in combination with the anatomic joint coordinate systems recommended by the International Society of Biomechanics (Wu *et al.*, 2005) may provide a better estimation of the humerus elevation during arm rotations.

In general, work postures including trunk and upper arm angles can be defined in two ways, i.e. the segment angle, which is relative to the gravity, and the joint angle, which is relative to the another body segment (van Dieën and Nussbaum, 2004). Both definitions assume body segments to be rigid links as a simplification of the reality in ergonomic practice. Upper arm elevation angle is defined as the angle of the upper arm relative to gravity, which was used in studies I and IV as well as in common inclinometry systems. The measurement did not differentiate between arm flexion and abduction. This was due to limitations of the current sensor technology including the noise in the gyroscopes. With IMU systems incorporated with magnetometers, orientation in three dimensions can be estimated, but magnetic disturbances still limit the use of magnetometers in many work situations (Robert-Lachaine *et al.*, 2017b). In some other studies, the joint angle of upper arm, also called the shoulder angle, has been used, which is defined as the relative angle between upper arm and trunk and calculated following an Euler angle sequence in three dimensions (Oyama *et al.*, 2017; Robert-Lachaine *et al.*, 2017a). Similarly, the trunk segment angle, which is also referred to as trunk inclination, is defined as trunk orientation relative to gravity. This definition has been used in study IV, in common inclinometry systems (Korshøj *et al.*, 2014) as well as in IMU systems (Oyama *et al.*, 2017). The trunk joint angle can be referred to as trunk bending and twisting angles, and is defined as trunk orientation relative to the pelvis (van Dieën and Nussbaum, 2004). This definition has mainly be used in IMU systems and calculated by Euler angle (Robert-Lachaine *et al.*, 2017a). However, these two definitions might be used implicitly when assessing trunk motions (Schall *et al.*, 2015). Therefore, it is important to be aware of which definition of postural angles is used before comparing data to previous studies or validating methods to a criterion measure.

6.2.2 Work metabolism estimation

Calibration

To estimate work metabolism using HR (with or without ACC), an individual calibration procedure is needed to build the HR and VO_2 relationship. Calibration procedures should resemble the tasks to be performed, in order to get a better estimation (Åstrand *et al.*, 2003). In study II, three submaximal tests were used for the individual calibration. Chester step test is a simpler and more convenient test to carry out. It also has a look-up table and can be used in the field without a need for measuring VO_2. The submaximal treadmill and arm ergometer tests require more resources and need VO_2 measurement to carry out. The Chester step test and submaximal treadmill test are both designed to calibrate the condition involving mainly

leg muscles, while the submaximal arm ergometer test is designed to calibrate the condition involving mainly arm muscles.

When comparing the calibration procedures for the three models' performance in estimating work metabolism, the calibration using a treadmill with measured VO_2 had smaller limits of agreement (LoA) compared to Chester step test without measured VO_2 in all models. This also reflects the trade-off between method convenience and performance when choosing different assessment methods.

When performing the submaximal arm ergometer test, it is also worth noticing that it might be difficult to get an accurate individual calibration. The reasons for this include that some participants may not be used to perform such arm exercise up to a submaximal level, and different individuals may utilize different muscles in order to perform the test.

Technical properties of the sensors

The specifications of the accelerometers, and therefore the thresholds used in the models in study II, differed from previous studies (Strath *et al.*, 2002; Brage *et al.*, 2005). One reason was that in previous studies, the accelerometer outputs were device-dependent and calculated in the form of 'counts'. This calculation used built-in algorithms and differed between manufacturers, which were difficult to compare across studies. Therefore, in order to evaluate and compare the three existing models from different studies, the raw acceleration signals of the accelerometers (in the unit of m/s^2 or g) were used, and the thresholds in the original models were adapted to ours. The choices of the thresholds may need to be modified when applying these models to sensors from other manufacturers.

Other influencing factors

HR can be influenced by several non-physical factors, such as heat, stress, and food or caffeine intake. Therefore, the performance of estimation models for VO_2 based on HR would also be affected by non-physical factors, which are common in real life scenarios. Study II was performed in a laboratory setting where the non-physical factors were controlled. However, in real life scenarios, those factors cannot be avoided and will influence the estimation of VO_2 based on HR. The estimation models using both HR and ACC might have a buffering effect against the influence from non-physical factors, as the ACC-VO_2 relationship will not be affected.

6.2.3 Sitting and standing

In study III, sitting and standing were classified using the thigh-worn IMU, following the algorithm and sampling frequency of 30 Hz as used and validated by Skotte and colleagues (2014). Only accelerometer signals of the IMU were used. Still, some misclassifications were observed, such as kneeling might be classified as standing. The algorithm used in the system should be improved when validation studies with better algorithms are available.

6.2.4 Subjective assessments

Rating of tiredness and exertion

Subjective ratings can be used to supplement physiological measurements and assess subjective responses, such as perceived exertion, fatigue and pain intensities (Borg, 1998). Although they might be influenced by other factors, e.g. individual motivation and experiences, they still provide valuable information. In study III, perceived physical tiredness (0-9 scale) and Borg's RPE scale were used to show participants' perception of workload. Perceived physical and mental tiredness was used by Engkvist and colleagues in assessing the work of several occupations, including nurses and recycling center workers (Engkvist, 2006; Engkvist *et al.*, 2010). As this study focused mainly on physical workload, only the physical tiredness scale was included for a subjective assessment. Borg's RPE scale is commonly used for estimating work task demand. It provided a subjective assessment of the work demand in addition to the workload assessed by the smart workwear system.

Borg's CR10 scale is a commonly used scale to estimate pain intensities (Borg, 1998). In study IV, it was used to assess what the level of body discomfort or pain was and if it increased for the participants wearing the system with vibrotactile feedback through the tests.

Questionnaires on system usability

When evaluating the usability of the smart workwear systems, different questionnaires were used in study III and IV. A modified questionnaire focused on the system wearability and usefulness was applied in study III. The modified questionnaire covered the items that were most relevant to the wearable system evaluated. The disadvantage was that it could not be compared with other studies. Two standardized questionnaires, i.e. the Comfort Rating Scale and the System Usability Scale, were used in study IV. These questionnaires were validated by previous researches and offered a score that can be used for comparison (Brooke, 1996; Knight and Baber, 2005). However, they may include items that were not relevant for the wearable system evaluated, or missing some items that were of interest. Still, for study III and IV, the used questionnaires provided a general assessment of the system usability.

Semi-structured interviews

In study IV, semi-structured interviews were conducted for about 10 minutes with each participant. One limitation was that, due to its semi-structured design, not every participant got the same follow-up questions depending on their responses. One the other hand, the interviews gave opportunities for participants to express their thoughts and reflections on certain aspects of their use of the wearable system, and researchers were able to ask follow-up questions to gain deeper understanding of their responses.

6.3 Result discussion

6.3.1 Criterion validity of the ErgoArmMeter

The developed iPhone application (ErgoArmMeter) showed to be accurate for measuring upper arm elevation under static and dynamic conditions. Its accuracy was similar to results reported by Korshoj and colleagues (2014) with an accelerometer in static arm elevations and slow velocity movements, and better than that in fast movements. In simulated work tasks of mail sorting and blow-drying hair, the RMSE was similar to results reported by Schall and colleagues (2015) with an IMU system during simulated dairy parlor work.

Signals only using accelerometer showed an overestimation on the measured angular velocity in medium to fast movements (see Table 5 and Figure 10). The improved accuracy by integrating gyroscope and accelerometer signals was distinctive in movements with medium or fast velocities (see Table 5). This improvement in the accuracy level is of practical importance for assessing occupational exposures, as an overestimation of the exposure could lead to an underestimated exposure-response relationship.

A similar study was conducted by Chen and colleagues (2018) showing that the upper arm angular assessment errors can be reduced by up to 87% depending on the work rate and sensor fusion of gyroscope and accelerometer signals compared to solely accelerometer signals. One difference worth noticing is that due to a different method used for signal processing and calculation of the arm elevation angle, i.e. calculated from quaternion to Euler angles, their results showed that signals only using accelerometer underestimated angular velocities in medium to fast movements.

6.3.2 Model performances for work metabolism estimation

Three models, i.e. the HR-Flex model, the HR branched model, and the HR + arm-leg ACC model, were evaluated for estimating work metabolism in five work tasks using mainly arm or leg muscles with a dynamic or static component. The HR + arm-leg ACC model performed best in simulated postal delivery, meat cutting and construction work. The HR-Flex model performed best in simulated painting. The HR branched model had large underestimations in four out of five work activities, except in office work. Therefore, the HR branched model may not be suitable for estimating work tasks which have a dynamic component. This was contradictory to the results reported by Brage and colleagues, showing that the HR branched model had a more accurate estimation than the HR-Flex model in daily activities (2015). In their study, the overall activity intensity was low — as stated about 62% of time the HR was below flex-HR point, which might be the reason for the different findings. However, in occupational activities with a need for estimating work metabolism, the intensity level would usually be higher than their tested scenarios and more similar to our findings. A study from Edwards and colleagues also reported that the performance of the HR branched model might be limited by the heterogeneity in daily activities (2010).

Individual differences of the cardiovascular responses on different tasks, shown by the HR–VO_2 relationships, were observed between participants (see Figure 11). Reasons for the observed differences could be that participants performed the tasks with different work techniques, e.g. in how they used the muscles and how much force they exerted. In addition, the work tasks had different workload levels on participants with different fitness levels. When comparing the participants with higher fitness levels than the median value against the participants with lower fitness levels than the median value, slightly larger bias and RMSEs were observed. Still, due to the limited number of participants in the half group, no clear conclusion can be drawn on the factor of fitness level.

Although the HR + arm-leg ACC model had good performance in most tasks, errors were observed during simulated painting. This work task was classified as an arm-mainly activity since the wrist-worn ACC had much higher output than the thigh-worn ACC. However, the VO_2 was actually closer to the estimation based on the leg calibration rather than the arm calibration. One reason could be that participants used their trunk muscles, which have larger muscle mass than arm muscles. Another error was observed for the simulated construction work with mixed muscle groups, i.e. lifting tasks from floor to table. This work task was misclassified for eleven out of twelve participants as an arm-mainly activity since the thigh motion was relatively small and the arm/leg acceleration ratio exceeded the preset threshold. Further improvement of the classification algorithm in the model is still needed to suit various types of work.

The simulated work tasks included were chosen to represent a variety of work involving different muscle groups and dynamic or static components. However, the number and duration of the tasks were still limited, and the tasks were more constrained compared to those in real life. Therefore, the models' external validity regarding occupational activities in real life still needs to be evaluated in field studies.

6.3.3 Functionality and usability of smart workwear system 1.0

The smart workwear system 1.0 was developed as a demonstrator for automated risk assessment using wearable systems. The risks of too high workload and too much prolonged occupational sitting/standing were considered in the system. Risk criteria for too high workload were based on the relative aerobic strain (RAS), and the limits, i.e. 33% and 25%, were set based on literature research and a consensus discussion between project members. The literature mainly consists of psychophysical experimental studies and reviews on acceptable workload. The limit of the red level at 33% has been adopted by the International Labor Organization (Smolander and Louhevaara, 2011), which are in agreement or close agreement with several studies (Jorgensen, 1985; Waters *et al.*, 1993; Wu and Wang, 2002). However, regarding work involving muscle groups with smaller mass or work with static components, the limit values vary from 18.5% to 29%, from studies with various subject populations, tasks and task durations. Therefore, a tentative limit of the yellow level was proposed at 25%, and further inspection of the work is required if the RAS is at yellow level.

The risk criteria of prolonged occupational sitting/standing were proposed based on both the duration proportion and prolonged behavior episodes with a focus on adverse health effects. Still, there is no clear evidence on how often and how long a break can be counted as effective, nor on what activities are most recommended to take as a break. Bergouignan and colleagues (2016) showed that introducing 5-minute breaks each hour can improve mood and vigor as well as reduce fatigue levels and food cravings. For the criteria proposed in the system, accumulated breaks of 5 minutes within a one-hour episode was counted as a way to deal with the lack of evidence. Better and more accurate exposure-outcome relationships, including time patterns of these behaviors, may emerge as research moves forward. Therefore, these tentative criteria used in the system can and will be updated as soon as better evidence underpinned by research is available.

As a study to demonstrate the use of wearable systems for automated risk assessment, limited duration and number of days for the measurements were performed. Four occupations were included to represent a variety of work, from being inactive to having a high workload. However, the construction workers didn't perform heavy tasks during the measurement period, which were revealed by their subjective ratings of physical tiredness and exertion level and the risk assessment results on RAS.

The wearability and comfort of the system was found to be acceptable for most of the users (Figure 14). Although two levels of feedback were designed in the system, the feedback function was not tested on the users in this study. The risk assessment results were not explained to them directly after the measurement. These could contribute to the lower ratings on 'usable' and 'easy to interpret' in the questionnaire results. The limited range of sizes of the vest and lack of sufficient adjustability meant that two of the participants had to wear a very tight vest, which did not give optimal comfort. Still, participants reported that the wearable system did not distract nor disturb them during their work, and that the system was not unpleasant to use.

6.3.4 Work posture intervention effects using smart workwear system 2.0

The smart workwear system 2.0 was developed for improving work postures using its vibrotactile feedback function. It was tested in industrial order picking. Two levels of feedback were designed with the aim to reduce users' adverse postures of upper arm and trunk.

For the trunk, substantial significant reductions in the time in adverse forward trunk inclination over 20°, 30° and 45° and the 50_{th}, 90_{th} and 99_{th} percentile were observed in all sessions compared to the baseline. The 99_{th} percentile of trunk inclination decreased significantly from baseline (median of 64°) to post intervention session (median of 42°), see Figure 16b. This could be compared to and even better than that reported by Doss and colleagues in training nursing students with real-time audible feedback and verbal coaching, where a reduction in peak trunk flexion was 7.6° during a patient transfer task (2018). In addition, for trunk inclination over 20°, a tendency of increased time during the post-intervention session was

observed compared to the intervention sessions-2 (see Figure 16a). This was expected, as the intervention effect might weaken after the feedback withdrawal. Still, part of the effect remained and the improvement was significant compared to the baseline. Long-term effects still need to be tested with different strategies of giving feedback to strengthen the learning. Some studies have shown that intervention programs with the use of direct feedback has the potential to achieve sustained effects in work posture improvement at 1-week or 12-month follow-up (Agruss, Williams and Fathallah, 2004; Bazazan *et al.*, 2018).

For the upper arm, relative smaller proportional reductions were observed in the time in adverse arm elevations over 30° and 45° compared to the baseline. The time in arm elevation over 60° remained similar. This was due to that participants were more constrained in their upper arm movements due to the work design of the order picking tasks. Still, they were able to adjust some of their work technique to reduce the arm elevation, which was also confirmed and exemplified in the interviews. Therefore, in order to reduce the exposure and related risks to a large extent, work technique training should be combined with other risk-reduction strategies, e.g. redesign of work stations or organizational change.

As each participant served as their own control, a test was run within the baseline to examine the potential repetition effect, i.e. whether participants improved their postures by performing the tasks repetitively over time. No significant decrease of the time in adverse trunk or arm postures was observed within the baseline. Therefore, with the observed significant reduction in adverse trunk and upper arm postures after providing vibrotactile feedback, it can be drawn that this improvement was mainly attributed to the intervention. Wilcoxon signed rank test was used in order to show the pairwise difference between sessions and the p-values were presented without a Bonferroni correction. This was chosen since the tests on each pair of four sessions were not independent from each other and the Bonferroni correction would be too conservative in this situation (a higher rate of false negative errors). Still, with an adjusted p-value of 0.01 (which is close to a Bonferroni correction), all of the significant reductions in adverse trunk postures and a small part of the adverse arm postures remained significant (Figure 16a&b).

The session duration increased significantly during the intervention sessions compared to the baseline (Figure 16c). This was expected as the participants need to learn from the feedback and try to change their work technique while performing the work tasks, as also reported by Vignais and colleagues (2013). Still, after a period of learning and practicing, the duration decreased. In the post intervention session, the duration was no longer significantly longer compared to the baseline. Due to the different lengths of session durations, i.e. longer duration after the feedback started, the data of adverse postures were presented and compared by the time, as in seconds, instead of time proportions. Slightly more significant changes could be observed when comparing the time proportions in adverse postures. However, since the participants chose their own work pace during the order picking tasks, the effect of time

constraint, which was reported by Vedsted and colleagues (2011) as one influencing factor, was not investigated.

The usability and comfort of the system were rated high among the participants. However, two participants experienced some discomfort from the pressure over the chest due to the lack of size adjustability of the current workwear system. Two participants stated that the feedback was given too frequently. The workwear system can be improved by introducing more size choices and using self-adaptive feedback algorithms for future applications. As the system can be applied for both risk assessment and intervention of work postures, it has a potential to contribute to improve work technique and work design, and reduce MSD risks in manual jobs.

7 Conclusions

In this thesis, methods using wearable technologies for ergonomic risk assessment and intervention were developed and studied. Revisiting the aims of the thesis, the following conclusions can be drawn accordingly:

- *To develop and validate a smartphone-based tool for assessment of upper arm postures and movements at work*

- The developed iPhone application (ErgoArmMeter) showed similar accuracy in static conditions and improved accuracy in dynamic conditions compared to the standard inclinometry used in field assessments. This improvement was achieved by integrating accelerometer and gyroscope signals.
- The ErgoArmMeter can be used by practitioners and researchers in various scenarios for risk assessment, with convenience and low cost.

- *To evaluate methods using wearable sensors, i.e. heart rate (HR) monitor and accelerometers (ACCs), for assessment of work metabolism (WM)*

- When evaluating methods for assessment of WM, the HR + arm-leg ACC model showed best accuracy in most work tasks, except in office work and painting. The HR-Flex model showed a small bias for the average of all tasks, and best accuracy in painting. The HR branched equation model showed large underestimations in most tasks, except in office work.
- For estimating WM in the field using wearable technologies, the HR + arm-leg ACC model calibrated by a submaximal treadmill test and arm ergometer may be used when the need for accuracy level is high and resources are available. The HR-Flex model calibrated with Chester step test may be used when the resource and possibilities for individual calibration are limited. Still, further improvement of the classification algorithm in HR + arm-leg ACC model is needed in order to suit various types of work.

- *To develop and evaluate a smart workwear system (1.0) for ergonomic risk assessment of light and heavy physical work*

- A smart workwear system using a sensorized vest, an inertial measurement unit and smartphone application was able to detect risks of high physiological workload and

prolonged occupational sitting/standing behaviors. The assessment results were presented in three color-coded risk levels.
- The system was evaluated as usable, comfortable and not disturbing to the work by most participants. Further development of the system is required for automated risk assessment including various aspects of ergonomic risk factors in real work life.

- To develop and evaluate a smart workwear system (2.0) for work postures intervention using real-time vibrotactile feedback in industrial order picking

- A smart workwear system using an instrumented t-shirt, inertial measurement units and vibration units which provided real-time vibrotactile feedback showed to be effective in improving work postures of the trunk and dominant upper arm in industrial order picking tasks, during and shortly after feedback withdrawal.
- Larger effects were observed for trunk postures than for upper arm postures. Extreme upper arm elevation was not reduced since high picks were demanded by the tasks. The intervention needs to be combined with other strategies, e.g. improvement in workplace design, to further decrease the adverse postures.
- The system was evaluated as comfortable and useful. The feedback from the system also triggered individual learning and reflection on the work design. The system has potential to be used for work posture training and work design improvement.

Overall, the research in this thesis showed that wearable technologies can be used both in the laboratory and for field applications. The systems can collect postural and physiological data with information on temporal patterns. Ergonomic risks can be assessed and visualized. The developed smart workwear systems were perceived having good comfort and usability. In addition, feedback can be provided through the systems for preventive actions, e.g. training work techniques and supporting learning. Therefore, wearable technologies and the smart workwear systems as tools for risk assessment and intervention have a potential to contribute to improved work design, better work techniques, and reduced MSD risks in working life.

8 Practical implications and future work

In this thesis, tools and methods using wearable technologies have been developed, evaluated and applied for ergonomic risk assessment and intervention, both in laboratory and field studies. They range from a single smartphone with its embedded sensors to smart workwear systems consisting of mobile applications and work clothes that house wireless sensors and vibrotactile feedback units. The application scenarios range from light to heavy work, static to dynamic work, and various tasks such as mail sorting and order picking.

The smartphone application (ErgoArmMeter) is now being used by ergonomists in industry jobs and university researchers for educational purposes. In fact, it is free to download as an iPhone application (with about 4400 installed units till now). With smartphones being widely used by most people in daily life and the convenience of installing and using the application free of charge, ErgoArmMeter has the potential to be used in short-term risk assessments, e.g. for comparing present and prototype workstations or before and after workplace interventions. When long-term risk measurements for multiple full working days are needed, the smart workwear systems or other wearable sensors of smaller sizes can be used.

The HR + arm-leg ACC model had best performance in most tasks, except in office work and painting. However, errors were still observed during simulated painting and lifting from floor to table. Further improvement of the classification algorithm in the model is needed in order to suit various types of jobs in real life. Another approach is to develop new models using neural networks for WM estimation. One method combining HR, ACC and respiratory signals using a neural network to estimate the WM was investigated in another study from our research group (Lu *et al.*, 2018). Still, in future research, the model needs to be trained and validated in various occupational settings before they can be used in practice.

Two smart workwear systems were evaluated for risk assessment of workload and intervention for improving work techniques. The systems showed good usability and wearability. Visualized results can be presented with color-coded risk levels, based on the pre-programmed risk criteria. Feedback can be provided based on pre-defined thresholds with different vibrotactile modes. The current risk criteria for work postures of trunk and upper arms are based on time percentage of adverse postures, percentiles of angular distribution and angular velocities. Some future improvements can be made regarding the criteria. One aspect is to

assess and present the variation of work postures and loads, which is shown to be an important parameter for the risk assessment and prevention (Mathiassen, 2006; Wells *et al.*, 2007). The temporal pattern of occupational sitting and standing was included and assessed based on accumulated break time in the smart workwear system 1.0. This was made as an attempt to deal with the lack of evidence in the temporal pattern of sitting and standing for the exposure-response relationships. These risk assessment criteria applied in the systems should be updated as soon as better evidence underpinned by high quality researches is available.

The real-time vibrotactile feedback provided by smart workwear system 2.0 showed to be effective in improving work techniques and creating learning in a factory lab. Two levels of feedback were provided based on predefined thresholds. The effects of how and when to give feedback, e.g. the strategies of fading or increasing feedback (Goodman and Wood, 2009), individualized feedback, as well as using various vibrational modes of frequency and amplitude, need to be evaluated in future studies. In addition, the tests were performed during order picking tasks without fixed cycle time. Future research needs to examine whether the effects can last in the long term, transfer into other work scenarios with new tasks and in conditions with fixed cycle time, which are common in production lines.

Still, further development is needed to apply the systems in real work life. If textile electrodes are to be used, it is crucial to keep the moisture and skin-electrode contact and reduce movement artifacts to ensure reliable signals. The wireless connection of current systems is achieved via Bluetooth, which may be limited in the number of units connected, the distance between the unit and data receiver as well as the amount and speed of data transfer. Other wireless communications such as WiFi, fourth generation (4G) or the emerging fifth generation (5G) cellular network may be adopted in future versions of smart workwear system to ensure larger numbers of devices to be connected and larger amount of data to be transferred with high speed in real time. Higher computing capabilities and comprehensive databases for collection, analyses and storage of the data over time may also be developed using cloud platforms or local servers (Vega-Barbas *et al.*, 2019). Such databases can be used for risk assessment of occurring tasks, generating new ergonomic guidelines, and developing interventions targeted at each individual (Romero *et al.*, 2018).

In order to implement and achieve optimal use adherence and outcomes of wearable technologies at workplaces, it is important to fulfill employees' needs, improve acceptance and generate motivation for long-term usage, as discussed earlier in Chapter 2.5. Future research may involve employees, OHS organizations and industrial partners in the development and implementation of smart workwear systems in a participatory approach. How to ensure data privacy, ownership and access as well as share and comparison of data across groups or organizations are also important aspects for future development of wearable systems. These specifications may evolve along with the generation of governmental standards, industry regulations and consensus in the research field. Additionally, the economic challenges may affect the implementation of wearable systems in the workplaces (Khakurel,

Melkas and Porras, 2018). Thus, to quantify the return on investment or cost-benefit ratios may be a strong incentive for both OHS and industrial organizations to apply the systems, which need to be looked into in future research.

In the foreseeable future, smart workwear systems can provide opportunities for automated assessment of risks at work, with sufficiently good accuracy and resource efficiency regarding time, competence demands and equipment costs. Real-time feedback can be provided based on adverse work techniques, accumulated workload, fatigue or other work exposures, which can be used for alerting of risks or training. The assessment results can be provided to different levels of user groups, from individual employees, first-line managers to top management teams. Results on an individual level can be used by employees to evaluate the work exposure impact, consult with OHS experts and get training or instructions to prevent work-related injury and illness. Results on a group or organizational level can be used for organizational risk management including risk assessment and treatment, design and redesign of work, as well as establishing new ergonomic guidelines.

Therefore, with further research and development, smart workwear systems have the potential to contribute to the risk assessment and intervention, the prevention of work-related ill health, and the improvement on the design and overall quality of work.

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Appendix A: Interview guide used in study IV

- How did you experience the task of order picking here compared to ordinary order picking?
- Did you feel discomfort in any body parts?
- How did the discomfort affect your way of working?
- How did you experience the vibrotactile feedback?
- How did the vibrotactile feedback affect your way of working?
- What did you learn from working with vibrotactile feedback?
- How would you like to change the order picking task, the racks and the placement of the items?
- Is there something you would like to change that cannot be changed?