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affiliée à l'Université de Montréal

**Quantitative and Qualitative Data Analytics in Ergonomics: Case Studies in
Forest and Technology Industries**

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Département de mathématiques et de génie industriel

Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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Cette thèse intitulée:

**Quantitative and Qualitative Data Analytics in Ergonomics: Case Studies in
Forest and Technology Industries**

présenté par **Sahar ARAB**

en vue de l'obtention du diplôme de Philosophiæ Doctor

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DEDICATION

In memory of my beloved grandfather, Nematollah Alaei, who desired to see this day.

To my parents for their endless love, support, and encouragement.

To my husband, Hossein, who inspired me all the time.

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Any significant achievement is a reflection of more than one person. I would like to acknowledge many people for their support, guidance, assistance, friendship, and most importantly love.

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RÉSUMÉ

Au cours des dernières années, un large éventail d'outils d'analyse de données ont été proposés et largement appliqués par des scientifiques des données dans divers domaines de l'ingénierie. Cependant, ce paradigme n'a pas été largement utilisé dans le domaine de l'ergonomie, qui est l'une des principales et des plus anciennes disciplines majeures du génie industriel. L'analyse de données est définie comme l'ensemble des méthodes et des techniques de collecte, de nettoyage, de transformation, d'exploration, de modélisation et d'analyse de données qui visent à découvrir des informations précieuses pertinentes pour les objectifs des décideurs. Les deux principaux domaines de l'analyse de données sont l'analyse de données quantitative et l'analyse de données qualitative. Dans cette thèse, nous avons l'intention de démontrer les avantages de l'utilisation d'approches avancées d'analyse de données quantitatives et qualitatives dans le domaine de l'ergonomie physique et cognitive. Les trois essais de cette thèse sont des études de cas dans les industries technologiques et forestières qui sont menées pour améliorer les conditions de travail des employés d'un point de vue physique et cognitif.

Dans les deux premières recherches de cette thèse, nous nous sommes concentrées sur l'application de méthodes d'analyse de données quantitatives dans le domaine de l'ergonomie physique. Dans ces études, nous avons analysé les données quantitatives de travailleurs forestiers de la province de Québec, Canada. Dans la première recherche, nous comparons les modèles existants dans la littérature pour la prédiction du métabolisme du travail (WM), qui est un indicateur de santé très important pour les travailleurs physiques. Dans la seconde recherche, nous avons proposé une série de nouveaux modèles de prédiction pour le métabolisme du travail (WM) dans des emplois physiques très exigeants tels que ceux en foresterie. Ces travaux contribueront à l'augmentation des connaissances dans le domaine de l'ergonomie physique en aidant les employeurs à maintenir la santé et la sécurité physiques des travailleurs. Suivant l'objectif général

de cette thèse, la troisième recherche vise à évaluer l'applicabilité et l'efficacité des approches d'analyse de données dans le domaine de l'ergonomie cognitive. Dans la troisième recherche, nous avons l'intention de fournir une évaluation cognitive des travailleurs qui utilisent un outil logiciel ergonomique virtuel et de réduire leur pression psychologique dans le processus de conception. Nous avons analysé les données d'entrevues d'utilisateurs d'une entreprise technologique, Dassault Systèmes à Montréal, et avons extrait des données qualitatives pertinentes des entrevues. À l'aide d'approches d'analyse de données qualitatives, nous avons reconnu les différentes catégories d'utilisateurs de l'ergonomie virtuelle pour créer des personnages qui soutiennent le développement de produits.

Dans la Recherche 1, présentée au Chapitre 4, nous avons comparé neuf modèles de MT basés sur la fréquence cardiaque (FC) en utilisant des données obtenues auprès de 39 travailleurs forestiers pendant le travail. La FC mesurée dans ces modèles peut surestimer la MT réelle puisque l'augmentation de la FC associée à l'accumulation de chaleur corporelle n'est pas métabolique. Par conséquent, nous avons évalué la précision de la prédiction MT pour toutes les combinaisons possibles de modèles en utilisant la HR brute et corrigée (lorsque la composante thermique est supprimée). Dans ces évaluations, nous avons pris en compte cinq estimations différentes de la capacité de travail maximale (CME) pour les modèles que l'ont requise comme entrée. Les 50 combinaisons de modèles ont produit un large éventail d'estimations de la MT. Trois modèles utilisant un étalonnage individuel ont produit le RMSE le plus bas et le LoA le plus étroit avec une FC corrigée ($rRMSE \leq 13\%$; LoA [$rBias < 5\% \pm 25\%$]). L'un des modèles que ne nécessitait ni détermination de la composante thermique ni étalonnage individuel a très bien fonctionné ($rRMSE = 18\%$; LoA [$rBias = 1\% \pm 36\%$]).

Dans la Recherche 2, présentée au Chapitre 5, nous avons proposé de nouveaux modèles d'arbre de décision de régression (ADR) pour prédire la FT basés sur une formulation de programmation

en nombres entiers. Au total, 41 travailleurs forestiers ont participé à la collecte de données dans diverses régions de la province de Québec, au cours de laquelle la fréquence cardiaque (FC) et la $\dot{V}O_2$ ont été mesurées. Tous les modèles ADR proposés (RMSE = < 3,08 ml/kg/min) y compris le modèle moyenné (ADR_AV) (RMSE = 2,67 ml/kg/min) ont donné de meilleurs résultats que le modèle de Ueno et al. (RMSE = 4,41 ml/kg/min) et le modèle ISO 8996:2004 utilisant la méthode de capacité de travail maximale proposée par Statistique Canada (2013) (RMSE = 4,65 ml/kg/min). Les modèles ADR proposés offrent aux praticiens une méthode pratique, économique et rapide pour l'estimation de MT sans tenir compte de la composante thermique.

Dans la Recherche 3, présentée au Chapitre 6, nous avons appliqué des approches d'analyse de données qualitatives pour l'évaluation cognitive des utilisateurs du logiciel de modélisation humaine numérique (DHMS), qui est l'un des principaux outils d'ergonomie virtuelle. L'objectif principal de cette étude était de déterminer les caractéristiques, les expériences, les besoins, les objectifs et les obstacles des utilisateurs dans l'utilisation des outils DHMS. De plus, nous avons étudié les capacités et les défauts des outils DHMS actuels du point de vue des utilisateurs afin de mieux comprendre les limites des packages DHMS actuels. 33 utilisateurs actuels et potentiels du DHMS, dont des ergonomes, des concepteurs, des gestionnaires, des ingénieurs de fabrication et de maintenance, ont participé à des entretiens qualitatifs semi-structurés. Nous avons analysé tous les entretiens à l'aide d'une analyse de contenu et d'une analyse de comparaison constante pour extraire les principaux facteurs/variables représentant les caractéristiques, les expériences, les besoins, les objectifs, les obstacles et les opinions des utilisateurs sur les outils DHMS. Afin de mieux caractériser les utilisateurs du DHMS, nous avons également effectué l'analyse de personnalité en développant un nouveau modèle de programmation en nombres entiers qui a abouti à trois principales catégories d'utilisateurs ayant des caractéristiques similaires au sein de chaque groupe.

Nous avons constaté que les utilisateurs de DHMS attendaient avec impatience une solution soutenant leur processus de prise de décision dans la conception de produits et de postes de travail sûrs, indépendamment de leur niveau de connaissances en ergonomie. Nos résultats ont également indiqué que la faible facilité d'utilisation, la facilité d'apprentissage et le temps nécessaire pour positionner un mannequin jouaient un rôle important dans la résistance des participants à utiliser le DHMS. Nous avons également réalisé que le pouvoir de communication, de visualisation et d'anticipation du DHMS était ses forces les plus influentes.

ABSTRACT

In the past few years, a wide range of data analytic tools have been proposed and vastly applied by data scientists in various engineering areas. However, this paradigm has not been widely used in the area of ergonomics, that is one of the main and oldest majors of industrial engineering. Data analytics is defined as methods and techniques of data collection, cleaning, transforming, mining, modeling, and analyzing to discover valuable information relevant to the goals of decision makers. The two main areas of data analytics are quantitative and qualitative data analytics. In this dissertation, we intend to demonstrate the benefits of using advanced quantitative and qualitative data analytics approaches in the area of physical and cognitive ergonomics. The three essays of this dissertation are case studies in technology and forest industries that are carried out to improve the work conditions of employees from physical and cognitive perspectives.

In Research 1 and Research 2 of this dissertation, we focused on the application of quantitative data analytics methods in the area of physical ergonomics. In these studies, we analyzed the quantitative data of forest workers in the province of Québec, Canada. In Research 1, we compare the existing models in the literature for the prediction of work metabolism (WM), that is a very important health indicator for physical workers. In Research 2, we proposed a series of new prediction models for the work metabolism (WM) in highly demanding physical jobs such as forestry. These works will contribute to the increment of knowledge in the area physical ergonomics by helping employers in maintaining workers' physical health and safety. Following the overall objective of this dissertation, Research 3 aims at evaluating the applicability and effectiveness of data analytics approaches in the area of cognitive ergonomics. In Research 3, we intend to provide a cognitive evaluation of workers that use a virtual ergonomic software tool and reduce their psychological pressure in the design process. In this research, we have analyzed the interview data of users in a technology company, Dassault Systèmes in Montreal, and have

extracted relevant qualitative data from the interviews. Using qualitative data analytic approaches, we have recognized the different categories of virtual ergonomics users to create personas that support product development.

In Research 1, presented in Chapter 4, we compared nine heart rate (HR)-based WM models using data obtained from 39 forest workers during work. Measured HR in these models can overestimate the actual WM since the HR increase associated with body heat accumulation is non-metabolic. Hence, we assessed the accuracy of WM prediction for all possible combinations of models using raw and corrected (when the thermal component is removed) HR. In these assessments, we considered five different estimates of maximum work capacity (MWC) for the models that required it as an input. The 50 model combinations produced a wide range of WM estimates. Three models using individual calibration produced the lowest Root Mean Squared Error (RMSE) and narrowest Limits of Agreement (LoA) with corrected HR ($rRMSE \leq 13\%$; LoA [$rBias < 5\% \pm 25\%$]). One of the models that required neither determination of the thermal component nor individual calibration performed very well ($rRMSE = 18\%$; LoA [$rBias = 1\% \pm 36\%$]).

In Research 2, presented in Chapter 5, we proposed novel Regression Decision Tree (RDT) models to predict work metabolism that is based on an integer programming formulation. A total of 41 forest workers participated in the data collection from various areas of the province of Québec, during which heart rate (HR) and $\dot{V}O_2$ were measured. All proposed RDT models ($RMSE = < 3.08$ ml/kg/min) including the averaged model (RDT_AV) ($RMSE = 2.67$ ml/kg/min) performed better than Ueno et al.'s model ($RMSE = 4.41$ ml/kg/min) and ISO 8996:2004 model using maximum work capacity method proposed by Statistics Canada (2013) ($RMSE = 4.65$ ml/kg/min). The proposed RDT models offer practitioners with a practical, cost- and time-efficient method for WM estimation without considering the thermal component.

In Research 3, presented in Chapter 6, we applied qualitative data analytics approaches for the cognitive evaluation of the users of Digital Human Modeling Software (DHMS), which is one of the main virtual ergonomics tools. The main purpose of this study was to determine users' characteristics, experiences, needs, goals, and obstacles in the use of DHMS tools. Moreover, we investigated the capabilities and flaws of current DHMS tools from users' viewpoint to better understand the limits of current DHMS packages. Thirty-three current and potential DHMS users including ergonomists, designers, managers, manufacturing, and maintenance engineers participated in qualitative semi-structured interviews. We analyzed all interviews using content analysis and constant comparison analysis to extract the main factors/variables representing the users' characteristics, experiences, needs, goals, obstacles, opinions about DHMS tools. To better characterize the DHMS users, we also performed the persona analysis by developing a new integer programming model which resulted in three main categories of users with similar characteristics within each group.

We found that DHMS users were looking forward to a solution supporting their decision-making process in designing products and safe workstations, independent of their ergonomics knowledge level. Our results also indicated that the poor usability, learnability, and the time required to position a mannequin played important roles in the participant's resistance to use DHMS. We also realized that the power of communication, visualization, and anticipation of the DHMS was its most influential strengths.

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LIST OF SYMBOLS AND ABBREVIATIONS

3D	Three-dimensional.
A_b	Body surface area.
Age	Age of the participant.
AI	Artificial intelligence.
ANN	Artificial neural networks.
BMI	Body mass index.
CNN	Convolution neural networks.
DHM	Digital human modeling.
DHMS	Digital human modeling software.
DNN	Deep neural networks.
DT	Decision tree.
Dube	Work metabolism model presented by Dubé et al. (2015).
Hm	Cumulative height climbed during the test in m/min at each step height (or stage).
HR	Heart rate (beats per min).
HR ₉₉	HR value exceeded during 99% of the duration of the HR recording period.
HR _{corr}	Heart rate without thermal pulses.
HR _{max}	Maximum heart rate.
HR _{raw}	Measured heart rate.
HR _{res}	Heart rate reserve.
HR _{rest}	Heart rate at rest.
HR _{wm}	The average of 1-min intervals of heart rate during the observed period.
IsoForm	Work metabolism model presented by ISO 8996:2004 with maximum work capacity as input.
IsoTable	Work metabolism model presented by ISO 8996 :2004 without maximum work capacity as input.
Jackson	Maximum work capacity proposed by Jackson et al. (1990).
Kamon	Work metabolism model presented by Kamon (1982) with maximum work capacity as input.
Keytel1	Work metabolism model presented by Keytel et al. (2005) with maximum work capacity as input.
Keytel2	Work metabolism model presented by Keytel et al. (2005) without maximum work capacity as input.
LoA	Limits of agreement.
Malch	Work metabolism model presented by Malchaire et al. (2017) with maximum work capacity as input.
ML	Machine learning.
Mrest	Resting metabolism.

MWC	Maximum work capacity.
MwcISO	Maximum work capacity proposed by ISO 8996:2004.
MwcMalch	Maximum work capacity proposed by Malchaire et al. (2017).
NN	Neural networks.
PD	Percentage difference.
RDT	Regression decision tree.
Rennie	Work metabolism model presented by Rennie et al. (2001).
RL	Reinforcement learning.
SD	Standard deviation.
Stage number	Level of effort in the Meyer and Flenghi (1995) step-test.
STAR	Smooth transition auto regression.
Statcan	Maximum work capacity estimate from Statistics Canada (2013).
Steptest	Maximum work capacity at HR _{max} = 220 – Age using the WM-HR relationship per Dubé et al. (2015).
TAR	Threshold auto regression.
Ueno	Work metabolism model presented by Ueno et al. (2014).
VE	Virtual ergonomics.
VO ₂	Oxygen consumption.
VO _{2 max}	Maximum oxygen consumption.
Weight _{ideal}	Lean or fat-free body weight.
WM	Work metabolism.
WM_ISOForm	Work metabolism model presented by ISO 8996:2004 with maximum work capacity as input.
WM_Keytel1	Work metabolism model presented by Keytel et al. (2005) with maximum work capacity as input.
WM_Keytel2	Work metabolism model presented by Keytel et al. (2005) without maximum work capacity as input.
WM_Malch	Work metabolism model presented by Malchaire et al. (2017) with maximum work capacity as input.
WM_Ueno	Work metabolism model presented by Ueno et al. (2014).
WMstep	Work metabolism for each stage of the Meyer and Flenghi (1995) step-test, calculated with the equation from Dubé et al. (2015).

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CHAPTER 1 INTRODUCTION

Ergonomics is a scientific discipline that is about the application of physical and psychological principles in designing work and products. The main goal of this field is to modify the relation between elements in a system (e.g., humans and machines) such that human well-being is improved, while respecting the required efficiency of the system. This discipline has widely changed in the past few decades. Enhancing the “Human well-being” is still the main goal of this discipline. However, the computational tools that ergonomists have access to these days are not comparable to those were available decades ago. More specifically, “data analytics approaches” are the main computational tools that have emerged in the past few years and their applications in engineering are growing exponentially.

Data analytics refers to the systematic process of cleaning, transforming, and modeling data in order to extract valuable insights about the original data and help users make more informed and reliable decisions. In the area of data analytics, researchers pursue two main streams of quantitative and qualitative approaches. Quantitative data analytics involves examining the statistical relationships within data to test hypotheses, assess cause and effect, and provide predictions for the future. In this approach, the data includes numerical values and statistics either measured using validated devices or collected by sampling and observation. The outcomes of quantitative analysis are often generalized to other populations or contexts.

On the other hand, qualitative data analytics is used in situations where data are not available in terms of numbers. For example, the aesthetic of a new piece, or the difficulty of working with new software. The mentioned features do not have any intrinsic quantitative nature. Qualitative data analytics is subjective and inductive in assessing a situation, while the quantitative approaches are objective and deductive. Qualitative data analytics pursues the relationship between categories,

themes, and features of data seeking to increase the understanding of the phenomenon. Data can be words, images, or objects from interviews, open-ended responses, and participant observations. The results of qualitative data analytics are less generalizable compared to those in quantitative data analytics.

This dissertation consists of three research studies on the application of qualitative and quantitative data analytics on three ergonomics problems which aim at improving the physical and cognitive health of employees. In Researches 1 and 2, we study the application of quantitative data analytics approaches on health indicators of forestry workers. Following the overall objective of this dissertation, which is to investigate the data analytics in the area of physical and cognitive ergonomics, in Research 3, we have applied data analytics on the qualitative data of users' interviews in the area of virtual ergonomics. The aim of this research is to decrease the cognitive pressure on the users of virtual ergonomics software tools used for product and workstation design, which also will indirectly contribute to the improvement in the physical work conditions of technicians that make the products in the shop floor. Therefore, this dissertation is a convolution of data analytics approaches for ergonomics problems with the goal of improving human work conditions from both physical and cognitive perspectives.

The coherency of this dissertation originates from the three following points:

- 1- Application area: All these three studies are defined in the area of ergonomics and intend to improve the health-related work conditions of employees.
- 2- Approach: In all these three studies, data analytics approaches have been proposed to tackle the problems faced by ergonomists.
- 3- Case study: All these three studies are defined based on real case studies with real data and our outputs are useful and applicable by practitioners, which are mainly ergonomists.

Research 1 and 2 were defined based on the research gaps detected from the literature review on data analytics in physical ergonomics. Also, Research 3 was defined based on a two-year internship that I spent in Dassault Systemes company in Montreal during which I participated to their daily meetings within this period.

This dissertation consists of seven more chapters. Chapter 2 reviews the literature describing different methods and approaches in qualitative and quantitative data analytics. Chapter 3 better highlights the research gaps and explains the general outlines of the research essays and their originalities. Chapter 4 presents Research 1 that provides a comparison of nine heart rate-based models to predict the work metabolism of forest workers. Chapter 5 presents Research 2 where we developed novel regression decision tree models with k-fold cross-validation to predict work metabolism based on heart rate in forest workers. Chapter 6 presents Research 3 that investigates the use of qualitative data analytic approaches in categorizing the users of a well-known virtual ergonomic tool by analyzing their needs and expectations extracted from their interviews. Chapter 7 provides a discussion on the main findings of this dissertation. Finally, Chapter 8 presents the conclusions, limitations, and future research avenues.

This dissertation is presented in a hybrid format, where Research 1 is presented as a published paper in Chapter 4 while Research 2 and 3 are presented as complementary Chapters 5 and 6.

CHAPTER 2 LITERATURE REVIEW

This chapter provides a literature review on quantitative and qualitative approaches. In Section 2.1, we review the literature of quantitative data analytic approaches, that is relevant to the methodologies used in Research 1 and 2, presented in Chapters 4 and 5. In Section 2.2, we provide the literature review on qualitative data analytic approaches, that is corresponding to the data analysis approaches used in Research 3, presented in Chapter 6. We have provided the literature review on forestry and technology applications separately in the introduction sections of Chapters 4 and 6.

2.1 Quantitative analytics

Quantitative analytics consists of descriptive, diagnosis, predictive, and prescriptive analytics. These analytics are explained in detail in Sections 2.1.1 to 2.1.4.

2.1.1 Descriptive analytics

Descriptive analytics is the first step of quantitative analytics. It helps researchers show, describe and summarize data in a meaningful way which allows simpler interpretation of data. For example, using descriptive analytics, researchers can detect outliers and typos (Laurikkala et al., 2000; McCoach et al., 2010), identify patterns in data (Hammersley, 2006; Asadollahi Kheirabadi and Mirzae, 2019), recognize associations among variables (Mitton and Grant; 1984; Bhattacharya, et al., 2012), and find the distribution of data (Reimann and Filzmoser, 2000.; Bellavista et al., 2012). However, descriptive analytics does not provide any other output beyond the description of the data. It is an approach to describe the data that is very useful especially when researchers deal with

big data (Delen and Demirkan, 2013). Descriptive analytics help researchers present raw data easily where data visualization is difficult.

Generally, there are four approaches to describe the data through statistics and graphs:

- I) Measures of frequency such as counting and percentage that show how often some particular contents (e.g., words, themes) occur.
- II) Measures of central tendency such as mean, median, and mode which are indicators of the central position of a frequency distribution for a group of data.
- III) Measures of dispersion or variation such as range, variance, standard deviation which identify the spread of data by intervals. Measures of dispersion are used when researchers desire to show how “spread out” the data are.
- IV) Measures of position such as percentile ranks, quartile ranks which describe how data fall in relation to one another. Measures of position are used when researchers need to compare data to a norm.

In fact, the descriptive analytics phase asks the question of “what happened” in our data and help to summarize the data using a combination of tabulated description (e.g., see Newton, 1994), graphical description (e.g., see Chambers, 2018), and statistical commentary (e.g., see Arab et al., 2020). Skipping the descriptive analytics could result in losing a lot of valuable insights about data.

2.1.2 Diagnostic analytics

Diagnostic analytics is the second step of data analytics which interprets and analyzes the data to discover why X happened in the past. Often, diagnostic analytics is referred to as root cause analysis. Hence, after asking “what happened” in the descriptive analytics phase, it is time to dive deeper and ask, “why it happened”. For example, the customer service of a company suddenly

realizes that the customer complaints have decreased (Hui and Jha, 2000). The question which arises in this step is why this happened? Diagnostic analytics may find out that it happened due to a new online interface, adding an instruction manual to the product, or hiring new employees who provide better service compared to the previous ones. Therefore, diagnostic analytics reveals the correlation between the potential causes and existing data. There are three key steps for performing the diagnostic analytics:

- I) Identifying anomalies: this step helps researchers identify and interpret data and find the causes which cannot be detected by simply looking over the data because they are uncommon events. An example is the detection of behavioral fraud in a credit card transaction (Bolton and Hand, 2001).
- II) Discovery: this step is about finding the original sources of data causing a certain anomaly. Here, the experts focus on the data from external sources to find the correlation and examine if any of them are casual or not. For example, the reason for decreasing car flow and increasing bike flow can be road closures (Zhang et al., 2018).
- III) Determining causal relationships: The goal of this step is to perceive the hidden relationships between several anomalies. The questions in this step are “how can that be? how could there be many ways to understand causality?” Determining causal relationships will aid analysts to estimate what will happen in the future, with a certain margin of error. For example, Allen et al. (2009) designed a tool to detect and analyze anomalies and their relationships for leaking information by an embassy employee.

2.1.3 Predictive analytics

Predictive analytics is the third step of data analytics that answers the question of “what will happen next?” Predictive analytics uses historical data and analytical techniques such as statistical modeling (e.g., see Wu and Coggeshall, 2012), scenario planning (e.g., see Lindgren, and Bandhold, 2003), and machine learning (e.g., see Samanpour et al., 2018) to forecast future outcomes with a significant degree of precision. Predictive analytics models enable analysts to predict trends and behaviors in the future. Picking the right predictive model depends on several factors such as the size, quality, and availability of historical data, the desirable level of prediction accuracy, and also available time for performing the analysis. In general, the forecaster should choose a technique that makes the best use of available data.

The predictive models are either parametric or non-parametric. When the number of parameters with respect to the sample is fixed, the model is called a parametric model (e.g., see Rothenberg, 1971). On the other hand, the model is called a non-parameter if the number of parameters increases with the sample size (e.g., see Smith et al., 2002). Figure 2.1 shows the top eight predictive analytics models that are regression, classification, clustering, outliers, time series, decision trees, neural networks, and optimization. All these models are described in Sections 2.1.3.1 to 2.1.3.8.

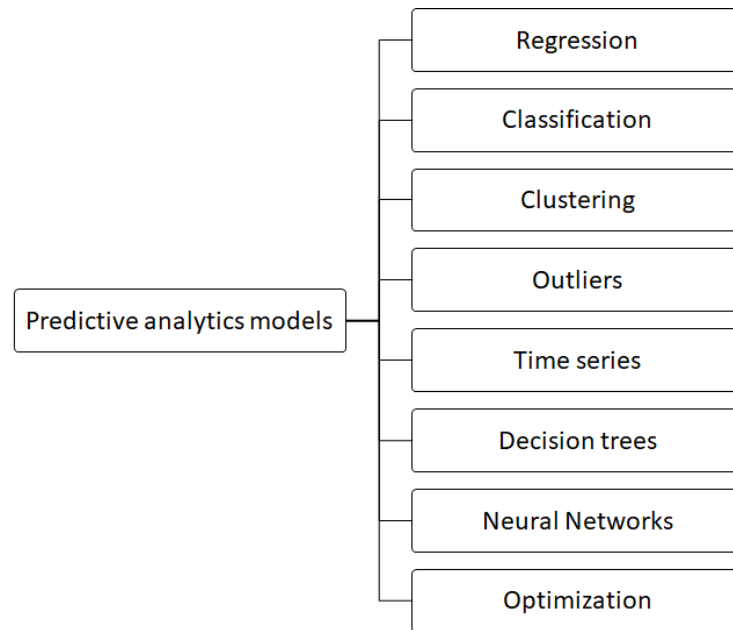


Figure 2.1 Eight types of predictive analytics models

2.1.3.1 Regression models

Regression models are the most common predictive models. It estimates the numerical values of new data by learning from historical data. Regression models are popular because they are capable of handling multiple input variables. Moreover, one of the greatest strengths of predictive analytics is that these models are extremely versatile. For example, Nastiti et al. (2019) proposed a linear regression method for the prediction of smart shopping based on shopping lists of customers. Some types of regression models in predictive analytics are linear, non-linear, and machine learning regression models. As an instance in the context of ergonomics, Matthews et al. (2023) proposed a regression model to assess the associations between job strain and cardiovascular disease mortality among 1870 physical workers in the US.

2.1.3.2 Classification models

Classification is one of the simplest predictive analytics models that categorizes new data based on historical data. It means that classification models determine to which group a new data instance

belongs. These models are easily trained and therefore they are very common in various fields such as health sectors (Khan et al., 2001; Sideris and Papagrigoriadis, 2014.), education (Cortez et al. and Silva, 2008; Grey et al., 2014), construction industry (Wang et al., 2012; Afsari and Eastman, 2016), and call centers (Hernandez et al., 2011; Saewong and Mongkolkeha, 2019). As an example, Hollmén (2000) proposed classification models to detect fraud calls in mobile communications networks. The most common types of classification algorithms are logistic regression, naïve Bayes, stochastic gradient descent, k-nearest neighbors, decision tree, random forest, and support vector machine. As an example in the field of ergonomics, Mendelek et al. (2013) proposed a classification for predicting low back pain prevalence among hospital staff.

2.1.3.3 Clustering models

Clustering models create several groups of data instances where the cases in each group share similar characteristics and attributes. The main difference between classification and clustering is that in the former one the data instances are assigned to predefined groups, while in the latter one, groups and their data members are formed by clustering.

As Figure 2.2 indicates, clustering can be performed by considering hard or soft borders for the groups. In hard clustering, each data either belongs to a cluster or not. Soft clustering is about grouping the data items such that an item can exist in multiple clusters. In soft clustering, instead of putting each data point into a separate cluster, a probability or likelihood of that data point to be in each cluster is assigned (Lin and Kondadadi, 2001). The most common clustering algorithms are density-based (Kriegel et al., 2011), density-based spatial (Ester et al., 1996), ordering points (Ankerst et al., 1999), hierarchical density-based spatial (McInnes et al., 2017), hierarchical (Johnson, 1967), and fuzzy (Zie and Beni, 1991). As an example in the area of ergonomics, Holmer

and Havhed (2007) developed a method for the classification of metabolic and respiratory demands in firefighting activity with extreme workloads.

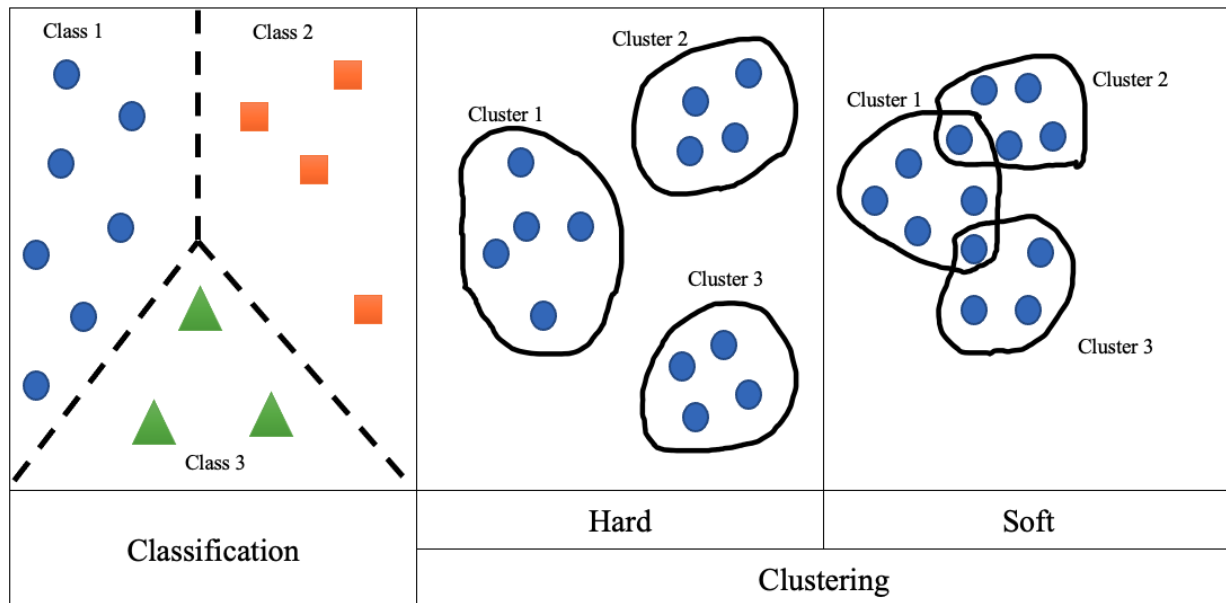


Figure 2.2 Classification vs soft and hard clustering

2.1.3.4 Outliers models

An outlier is an extreme data instance that deviates significantly from other observations in the dataset. It may reveal variability in a measurement, or experimental errors. In other words, an outlier is an observation that diverges from an overall pattern. The most common causes of outliers on a dataset are data entry errors, measurement errors, experimental errors (data extraction or experiment planning/executing errors), intentional (dummy outliers made to test detection methods), data processing errors (data manipulation or dataset unintended mutations), and sampling errors (extracting or mixing data from wrong or various sources) (Beckman and cook, 1983).

Outliers are either univariate or multivariate. When outliers are far from other data instances because of variability in only one of the dimensions/features, then the outliers are univariate. In the case that outliers are far from other non-outliers in several dimensions, the outliers are multivariate

(Ben-Gal, 2005). For multivariate outliers, a model has to be trained since observations of distributions in n-dimensional space distributions are difficult for scientists. From another viewpoint, outliers can be categorized into three types:

- I) Point outliers (global outliers) that are single data points laying far from the rest of the distribution (Achter et al., 2010).
- II) Contextual outliers that are known as conditional outliers because they are conditional on the selected context. For example, if the snowfall happened in the middle of summer and you normally don't get any snow outside of winter (Liu et al., 2017).
- III) Collective outliers that can be subsets of novelties in data such as a signal that may indicate the discovery of new phenomena (Han et al., 2012).

The most common methods to detect outliers are Z-Score or extreme value analysis (Gosh and Vogt, 2012), probabilistic and statistical modeling (Aggarwal, 2017), linear regression models (Rahman et al., 2012), proximity-based models (Idé et al., 2009; Aggarwal, 2017), information theory models (Wu and Wang, 2011), and high dimensional outlier detection methods (Aggarwal and Yu, 2001).

One of the differences between classification, forecast models, and outlier models is the type of data that these models work with. While classification and forecast models work with historical data, outlier models work with anomalous data that deviates from the norm. Outlier models are incredibly valued and used in industries since these models detect the incidence of fraud (a deviation from the norm) before it occurs and consequently, they can save millions of dollars for industries (Valderrama et al., 2007; Li et al., 2012; Blažková and Dvouletý, 2018). As an example, with the help of outlier models, a fraudulent transaction can be detected, and the models can evaluate the amount of money lost, time, location, and purchase history (Yu and Wang, 2009;

Bansal et al., 2016; Malini and Pushpa, 2017). In the context of ergonomics, Hawley et al. (2023) offered an outlier model for a method for detecting fatigue-related changes in repetitive tasks requiring kinematic lifting.

2.1.3.5 Time series models

The time series models work with time series data that are a set of observations collected consecutively over time. Hence, in time series models, time is an input parameter. In fact, time series models develop a numerical metric that will predict trends within a specified period in the future. In time series modeling, the ordering of data matters since changing the order of data can change the meaning of the data (Chatfield, 2003; Wei, 2006; Hamilton 2020). Time series have been applied successfully in different areas such as bridge monitoring (Omenzetter and Brownjohn, 2006), gas pricing (Mishra, 2012), stock market (LeBaron et al., 1999), and health sectors (Pincus and Goldberger, 1994).

A time series model answers the question of “how a particular variable changes over time”. The primary objective of time series analysis is to develop a model which describes the pattern of the time series. The time series models are also used to describe how the past affects the future or how two time series can “interact”, and to predict future values of the series. In addition, visualizing time series data is crucial since it helps us detect if there is a trend, seasonality, outlier, long-run cycle, constant variance, and abrupt changes in the data.

Table 2.1 The definitions of time series data components

Components of time series data	Definition
Trend	The general tendency of the data to increase or decrease over time
Seasonality	The presence of variations such as repeating pattern or fluctuation of highs and lows related to time (seasons, months, days of the week), a fixed and known frequency
Long-run cycle	The variation in data without a fixed frequency
Constant variance	Constant or non-constant variance over the time
Abrupt changes	Any unexpected changes of level of the series (structural breaks) or the variance
Outlier	The data points which outliers are far away from other data

Time series models are categorized into univariate time series models and multivariate time series models. Univariate time series models are used when the dependent variable is a single time series. As an example, Nazaripouya et al. (2016) developed a univariant time series to predict solar power. They used only historical solar power time series data. The univariate time series models consist of univariate generalized autoregressive conditional heteroscedasticity (Degiannakis and Xekalaki, 2004), seasonal autoregressive integrated moving average (Zhang et al., 2011), univariate unit root tests (Pesaran, 2012).

Multivariate time series models are used when there are multiple dependent variables. In addition, each variable not only depends on its past values but also on each series may depend on the past and present values of the other series. For example, Preez and Witt (2003) proposed a multivariate time series model for predicting tourism demand considering personal income, the price of holiday to the destination, etc. Multivariate time series models include vector autoregressive models (Zivot and Wang, 2006), vector error correction models (Anderson et al., 2002), multivariate unit root tests (Harvey and Bate, 2003).

Time series modeling can be developed by either the time-domain approach or the frequency-domain approach. The time-domain approach predicts future values based on past and present values using the time series regression. The time-domain approach includes auto-correlation and cross-correlation analysis (Brandes et al., 1968; Ljung and Glover, 1981). On the other hand, frequency-domain models are based on Fourier representations where the time series is represented as a function of sines and cosines of variables over time. Frequency-domain models use regressions on sines and cosines, rather than past and present values. The frequency-domain approach includes spectral analysis (Berger et al., 1986) and wavelet analysis (Torrence and Compo, 1998).

A structural break refers to the case that a sudden change happens in a time series or a relationship between two time series. In fact, structural breaks reduce the reliability of time series models which assume the model is constant over time. Hence, from this point of view, time series models can be categorized into linear (Sims et al., 1990) and nonlinear models (Franses and Van, 2000). The nonlinear time series analysis is required to deal with the nonlinearities caused by structural breaks. This type of analysis focuses on detecting the structural breaks, predicting the timing of structural breaks, and modeling data behavior before, after, and between breaks. There are different types of nonlinear time series models such as Markov switching, threshold auto regression (TAR), and smooth transition auto regression (STAR) (Potter, 1999). These models are used for the different characteristics of nonlinearities. For example, Markov-Switching models are utilized when an underlying stochastic Markov chain causes a change in the underlying pattern of data. TAR models are used when a threshold variable reaches a specified level. STAR models are extended versions of auto regressive models with more flexibility in modeling parameters through a smooth transition. There are various examples of using time series models in the area of ergonomics. As an instance, Cai (2022) proposed a Long Short-Term Memory (LSTM) model on time series data to detect and prevent work-related musculoskeletal disorder related hazards among construction workers.

2.1.3.6 Decision tree models

The decision tree is a common technique for predictive modeling. This technique is a decision/prediction support tool with a tree-like model. The tree has a root node, branches, and leaf nodes. In each node of the tree, an attribute/predictor is evaluated. Then, based on the evaluated value, one of the branches in the tree is followed. At the bottom of the tree, an outcome exists for each leaf node. One of these outcomes is chosen as the prediction depending on where we end up

at the bottom of the tree for a given data instance. The quality of prediction in decision trees can be enhanced by combining it with other methods (e.g., see Dey, 2002; Zhou and Chen, 2002; Farid et al., 2014).

The decision tree models are categorized into two types: classification (Friedl and Brodley, 1997) and regression trees (Fayyad and Irani, 1992). When a decision tree is used to classify a dataset into different groups based on qualitative data, it is called a classification tree. For example, Azar and El-Metwally (2013) proposed a classification decision tree for medical diagnosis based on various symptoms in patients. In the case that a decision tree is used to predict continuous quantitative data to predict a number, it is called a regression tree. As an example, Chang et al. (2005) proposed a regression decision tree method to schedule reserved load when generator outage incidents happen. A decision tree divides the dataset into subsets based on the most significant predictor in the dataset. The algorithms decide how to identify the most significant predictor and how to split it. Usually, the most significant attribute is considered at the root node. The advantages of decision trees are

- I) They require less effort for data preparation since they do not require normalization and scaling of data. Also, missing values and outliers in data do not affect the process of building a decision tree.
- II) Decision trees do not need the linearity assumption. It means that non-linear relations between input variables do not affect the performance of the tree.
- III) Decision tree models are very intuitive and easy to read, explain, and interpret to technical teams without requiring statistical knowledge.

However, it has to be considered that a minor change in the data can trigger a large change in the final decision offered by the tree. Decision trees require more time for training since the

calculations are more complex in comparison with other methods. Many ergonomics in the literature have used decision tree models for predictions. As an instance, Yang and Zhao (2011) developed a decision tree classification model for the ergonomic evaluation of firefighter's motion.

2.1.3.7 Artificial neural network models

An artificial neural network (ANN) is mostly used to model data with the non-linear relationship. It is also used to find patterns in data or as a decision-making tool. An ANN uses mathematical or computational models for data processing based on the connection between neurons. In fact, an ANN recognizes the main relationships between data and imitates the manner that a human brain works (Lippmann, 1987; McCullocha and Pitts, 1961).

An ANN includes hidden layers, an input layer, and an output layer, where each layer includes a set of neurons. ANN is also known as a Feed-Forward NN since inputs pass only in the forward direction and the connections between the nodes do not form a cycle. An ANN processes information in one direction from input nodes to output nodes. The two learning steps are forward-propagation and back-propagation. In the first step, the algorithm predicts the answer and in the second step, the algorithm minimizes the error between actual and predicted answers.

An ANN selects the features automatically, but for some parameters, called hyper parameters, we have to enter them manually or tune them. The three most crucial hyper parameters are:

- I) Learning rate: it shows how slow or fast algorithms reach results. In fact, the learning rate controls model modifications when model weights are altered to obtain lower estimation errors. It is the most crucial hyper parameters since if it is too small, even after long-time training, it will be far from the optimal results. If it is too high, we will get a wrong result very soon (Li et al., 2009).

- II) Activation function: it is referred to as a power of ANNs. In fact, it decides which information should have to pass to the further layer by activating neurons. Without this function, ANNs lose their representation learning power. The activation functions can be linear, binary step, piecewise, sigmoid, Gaussian, etc (Sibi et al., 2013).
- III) Cost function: it is a measure of “how good” an ANN performed as a whole. It depends on the training sample, the expected output, weights, and biases. The cost function calculates the loss between real and predicted results and the goal of ANNs is to minimize this loss. The most well-known cost functions are quadratic cost (root mean square), cross entropy, and exponential (AdaBoost). The easiest and most used one is quadratic cost (Karnin, 1990).

To have deeper insights from data, researchers use a deep neural network (DNN) which is an ANN with multiple layers between the input and output layers (Sheridan et al., 2015). The two most well-known DNNs are Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN). CNN is a feed-forward ANN with multilayer neurons. which utilizes the connectivity pattern between neurons to minimize amounts of preprocessing. RNN benefits from their internal memory to analyze deliberate series of inputs. Researchers have to be careful when they use DNNs since they need more data to train to minimize the accuracy and their time complexity is higher. In some cases, DNN makes wrong assumptions about the data since it is too deep, or it selects more features. As an example, DNN is used in chat bots which are conversational software agents used to interact with a human agent through text or speech (Nuruzzaman and Hussain, 2018). As an example in the field of occupational health and safety, Ladstätter et al. (2008) proposed a novel neural network algorithm to model the burnout process in Chinese nurses.

2.1.3.8 Optimization models

Optimization is a solid paradigm in mathematical science that has significantly grown in past decades. Mathematical programming is one of the main subcategories of optimization models (Winston, 2002). In mathematical optimization, the decision maker looks for the best values of decision variables such that one or several objective functions are minimized or maximized, while all constraints are satisfied. For example, many researchers have proposed mathematical programming models to determine the optimal production level in production plants to minimize the total cost or maximize the total profit, while production capacities are respected (Pochet and Wolsey, 2006; Hung and Hu, 1998; Chen and Ji, 2007).

The simplest class of mathematical programming is linear programming where the constraints and a single objective function are formulated linearly by continuous decision variables. Mathematical programs are more complicated when either some decision variables are integer (Wolsey, 2020) or some components of the model are nonlinear (Bertsekas Bertsekas, 1997). Nonlinear models are also categorized into convex and non-convex optimization problems. In convex optimization problems, gradient-based methods can be used to find the optimal solution (Boyd et al., 2004).

From another perspective, mathematical optimization can be categorized into deterministic, stochastic, and robust optimization models. In deterministic problems, all parameters are uncertain. However, in stochastic and robust optimization problems, some parameters are uncertain and need to be taken into account while making decisions (Birge and Louveaux, 2011).

In data analytics, optimization models can be used either in predictive or prescriptive data analytics. When using in predictive analytics, the objective function is to find the value of some coefficients in a prediction model such that the prediction output becomes as close of possible to the value of target variables (Gkioulekas and Papageorgiou, 2021). From this perspective,

mathematical programming models for predictive analytics can be considered as goal programming models (Jones and Tamiz, 2010). As an instance using optimization model in the area of ergonomics, Adem and Dağdeviren (2021) proposed a job rotation-scheduling model for employees in a manufacturing firm with the goal of minimizing ergonomics risks.

2.1.4 Prescriptive analytics

While descriptive and predictive analytics respectively answers the questions of “what happened” and “what will happen next”, prescriptive analytics tells us “what should be done”. This methodology is the most advanced and complex step in data analytics and is the one helping users make the best possible decisions based on the available data. In this step, the decisions are made based on the predictions obtained from predictive analytics. Prescriptive analytics can also benefit from machine learning where it uses its forecast ability to make decisions. In other words, in the prescriptive analytics phase, a machine learning algorithm is trained to prescribe what to do next and recommends actions (e.g., see Deshpande et al., 2019). Hence, it can be said that prescriptive analytics is an upgrade compared to predictive analytics.

The main four mathematical-based disciplines for prescriptive analytics are operations research, machine learning, natural language processing, and applied statistics. Each one of these disciplines includes various techniques. For example, operation research includes optimization, simulation, and decision analysis. Moreover, there are two different approaches that data analysts use in the prescriptive analytics phase. The first one is exact optimization models (Lepeniotti et al., 2020) and the second one is heuristics-based automated decision making (Delen and Ram, 2018). The first approach was described in Section 2.1.3.8.

The heuristics are some rules of thumb aiding users to solve problems and make judgments rapidly and proficiently. The advantages of heuristics are to reduce decision-making time and

mental load by allowing people to move forward to the next step. It means that, in the occurrences of unexpected events, the system will decide for the next step based on a set of predefined rules governing the system.

In fact, automating the design of heuristic-based decision-making processes aids organizations to reduce the need for a human expert for the design of algorithms to answer a search problem. Burke et al. (2010) classified heuristics-based decision-making approaches into two main groups: heuristic selection, and heuristic generation. In heuristic selection approaches, algorithms automatically combine pre-existing simple heuristics to solve the problem, whereas in heuristic generation approaches, algorithms automatically create novel heuristics fitted to the problem.

2.1.4.1 Artificial intelligence

Artificial intelligence (AI) is the ability of a computer or a robot controlled by a computer to simulate the problem-solving and decision-making capabilities of the human mind (Barr and Feigenbaum, 2014). In fact, AI is the science of making intelligent machines, especially intelligent computer programs. Figure 2.3 shows that the top seven AI techniques that are machine learning, natural language processing, expert system, vision, speech, planning, and robotics.

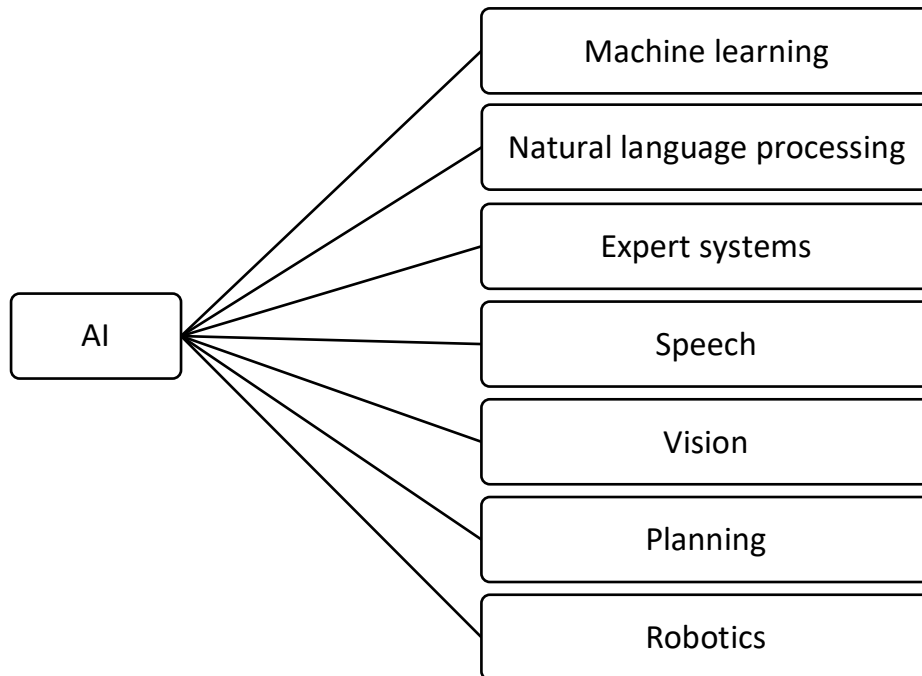


Figure 2.3 AI techniques.

2.1.4.1.1 Machine learning

Machine learning (ML) is a specific subset of AI relying on the idea that machines can learn from data, identify patterns and make decisions with minimum human intervention (Jordan and Mitchell, 2015). As Figure 2.4 shows ML can be categorized into supervised, unsupervised, reinforcement learning, semi-supervised, deep, and deep reinforcement learning. In the next subsection, we explain the four main ML techniques.

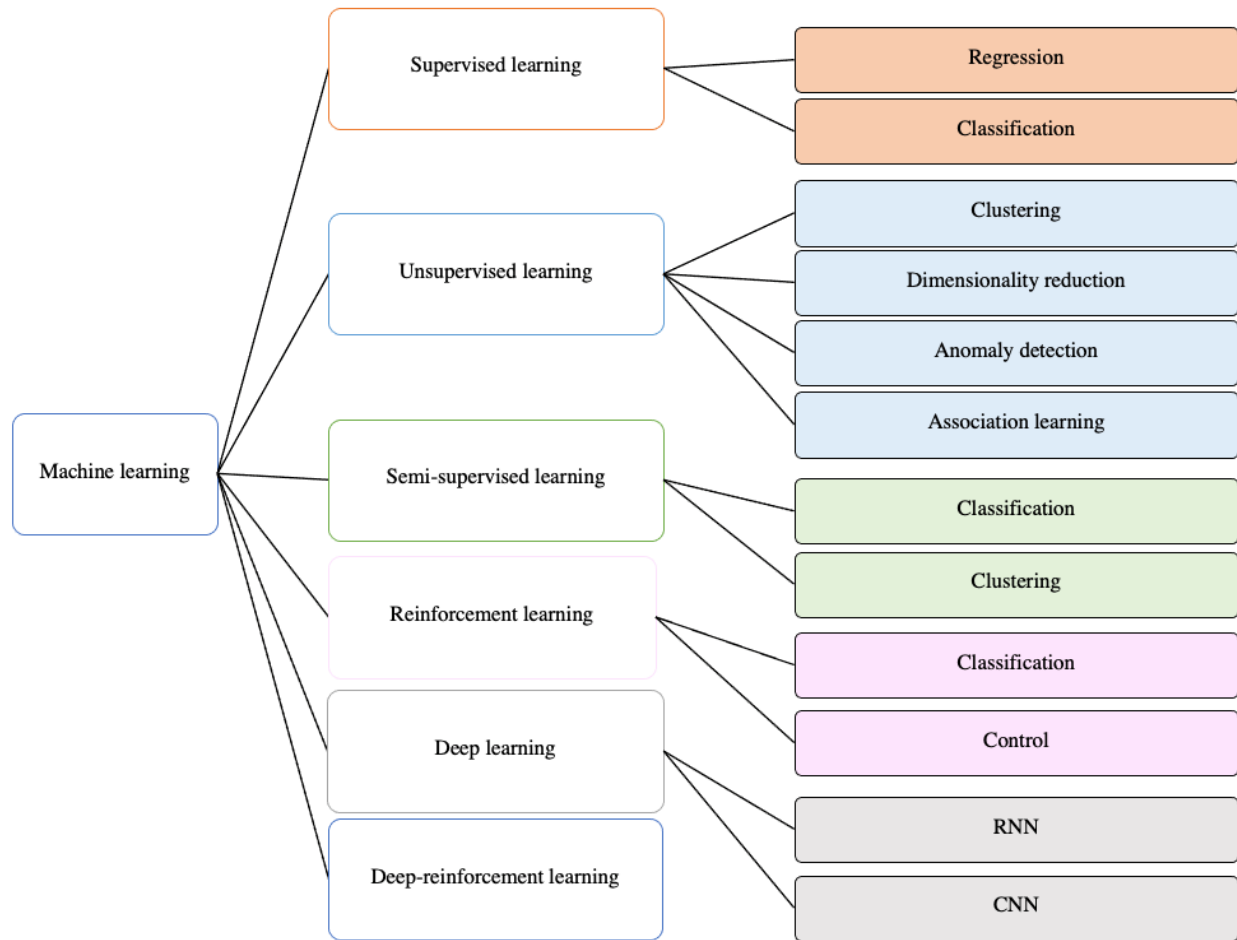


Figure 2.4 Machine learning techniques.

2.1.4.1.1.1 Supervised learning

In supervised learning, models try to learn a mapping between input and target variables. Supervised learning is categorized into two groups which are regression problems (Doan and Kalita, 2015) and classification problems (Freitas, 2014). In regression problems, the model predicts numerical values, whereas in classification problems, the model predicts a class label. Input variables of supervised learning problems can be any data type such as categorical or numerical. In these problems, input and target variables can be one or more variables. As an example of a regression model, Tziridis et al. (2017) proposed a model for the pricing of airplane

tickets based on the number of intermediate stops, number of free luggage, days left until departure, etc. An example of classification problems is the work by Tixier et al. (2016) that developed a model to find a class label for different types of injuries in construction sites. Decision trees and artificial neural networks are two common techniques that are designed for supervised learning problems. As an example in the area of ergonomics, Yang et al. (2021) proposed a supervised learning model cognitive activity recognition from Electroencephalography (EEG) Signals.

2.1.4.1.1.2 Unsupervised learning

Unsupervised learning models extract or discover the relationships between data. The model learns from input variables and there is no target variable. The two main techniques of unsupervised learning problems are clustering (Celebi and Aydin, 2016) and density estimation (Dinh et al., 2016). Clustering models find groups in the dataset with fairly similar attributes. As an example of clustering, Chicco et al. (2003) studied finding different types of electricity customers. On the other hand, density estimation models find the distribution of the data such as anomaly detection. There are also hybrid learning models, also referred to as semi-supervised models, that combine unsupervised and supervised learning (e.g., see Zhu and Goldberg, 2009).

2.1.4.1.1.3 Reinforcement learning

Reinforcement learning is useful where sequential decisions must be made in uncertain environments. In this approach, there is a probabilistic reward function referred to as the Q function. Reinforcement learning aids the users to choose the best policies such that the expected value of the reward function is maximized. RL algorithms do not use a fixed dataset since they interact with an environment and there is a feedback loop between the learning system and its experiences. Reinforcement learning has been vastly used by research in different industries such as the insurance industry (Krashenninnikova et al., 2019), petroleum industry (Aissani et al., 2009),

traffic control (Hu et al., 2021), and manufacturing industries (Kuhnle et al., 2021). An example is the self-driving tasks such as parking can be achieved by learning automatic parking policies (An and Jung, 2019). Also, as an instance in the context of ergonomics, Xie et al. (2022) proposed a reinforcement learning approach for mitigating the risk of musculoskeletal disorders in human-robot interactions.

2.1.4.1.1.4 Deep learning

Deep learning (DL) is an ML method based on artificial neural networks which can be supervised, unsupervised, or semi-supervised. DL uses multiple hidden layers to extract higher-level information from the input variables. DL is applied to computer vision (Voulodimos et al., 2018), speech recognition (Deng et al., 2013), and natural language processing (Otter et al., 2020) to produce results comparable to and in some cases surpassing human expert performance. The difference between deep learning and reinforcement learning is that the first one learns from a training dataset and then the model is tested on a new dataset, but in reinforcement learning, the algorithm is trained by sequentially adjusting the decisions in a feedback loop to maximize the reward function. As an example in the context of ergonomics, Mitsuya et al. (2019) developed an unsupervised deep learning algorithm for the analysis of body pressure distribution on car seats.

2.1.4.1.2 Natural Language Processing

Natural Language Processing (NLP) is another subset of AI that can read text files, withdraw pertinent information or words, allocate value to the information or words, and intelligently analyze structured and unstructured text (Indurkha and Damerau, 2010). For example, Siri and Alexa applications are great examples of NLP which are based on question-and-answer systems, speech-to-text, and text-to-speech. As one of the few examples in the field of ergonomics, Goomas and Ludwig (2023) used natural language processing for voice recognition in order selection in large

industrial settings which resulted in the elimination of time-consuming voice enrollment and setup for each worker and therefore more efficient ergonomic training for the employees.

2.1.4.1.3 Expert systems

Another AI technique is the Expert System (ES) which mimics a human expert's decision-making ability. ES is represented mainly as simple if-then rules to solve complicated problems by interpretation of knowledge. Therefore, ES users do not need to be an expert in AI. The components of ES:

- I) Knowledge Base: it represents data, information, facts, and rules combined together.
- II) Inference Engine: it applies logical rules and known facts to deduce a correct and flawless solution.
- III) User Interface: The user interface builds communication and interaction between the user and ES.

The ES development process includes problem domain identification, system design, prototype development, prototype test and refinement, and finally ES development and completeness (Hayes-Roth et al., 1983). The benefits of ESs are the availability due to mass production of software, less production cost, speed, less error rate compared to human errors, and reducing risk. On the other hand, ES limitations are the technology limitation, difficult knowledge acquisition, maintenance difficulty, and high development costs. As an instance in the context of ergonomics, Harih and Vujica-Herzog (2020) proposed an expert system for assigning optimal workplaces to workers with disabilities

2.1.4.1.4 Computer vision

Computer vision is a subset of AI that acquires, processes, analyzes, and understands digital images and visual information from one or more video cameras to produce numerical or symbolic information without the need for human intervention. Hence, it makes repetitive tasks faster to simplify the work for humans. For example, Kakani et al. (2020) showed the role of computer vision techniques in the food and agriculture industries. Also, as an instance in the context of ergonomics, Jung et al. (2022) proposed a computer-vision-based model for recognizing the lifting tasks to minimize the low-back musculoskeletal injuries.

2.1.4.1.5 Speech recognition

Another AI technique is speech recognition which converts spoken language or sound vibration into a digital format that the computer can understand. The algorithms recognize the speech data and convert them into a text or another form. For example, Siri takes the sound data and gives voice results or Google Voice converts spoken words into text. Automatic speech recognition converts audio into text, whereas NLP processes the text to determine its meaning. Srinivasamurthy et al. (2017) developed automatic speech recognition models to control pilot communication in Vienna (Germany). Then, to obtain optimal performance, they customized the speech recognition systems to local audio conditions and vocabularies at each airport.

2.1.4.1.6 Planning

AI planning technique is one of the main areas in AI which aims at finding planning and scheduling for performing tasks through an autonomous search process (Wilkins, 2014). This technique is also used when people are interested in finding a solution in a short time and when the problem changes frequently. In this case, the whole solution will not change, but the model must be tweaked base

on the changes. In the field of ergonomics, Mueller et al. (2021) have studied the boundaries of using AI planning models for human-machine collaborations.

2.1.4.1.7 Robotics

Robotics is a subset of AI used for the designing and manufacturing of robots. Robots are programmable machines performing sequences of tasks automatically or semi-automatically. Performing these tasks consistently is difficult for people. Intelligent robots can complete a sequence of actions with their intelligence using AI algorithms. For example, in assembly lines of automobile manufacturing, intelligent robots are used for moving large objects in space (Talukder et al., 2003). The other example of an intelligent robot is Sophia robot which is a human-like robot. She has potential services and entertainment applications. Sophia can also recognize human faces and sees emotional expressions. She can evaluate humans' feelings during conversations (Hanson Robotics, 2021). Di Marino et al. (2021) have provided a systematic review of the collaborative robotics and ergonomics.

2.2 Qualitative analytics

Qualitative data analytics uses the data from the interview, talk, conversation, documents, observations, and drawing, photographs, and videos. In the literature, researchers have proposed many qualitative research analytics methods that are listed in Table 2.2. The following paragraphs provide an overview of these qualitative research analytics methods.

Table 2.2 Qualitative data analytics methods with the types of data used

Analysis type	Talk/Conversation /Interview	Drawing/Photographs /Videos	Observations	Documents
Word count	✓	✓	✓	✓
Content	✓			✓
Text mining				✓

Table 2.3 Qualitative data analytics methods with the types of data used (cont.)

Qualitative comparative	✓	✓	✓	✓
Constant comparison	✓	✓	✓	✓
Ethnographic	✓		✓	
Micro-interlocutor	✓			
Conversation	✓			
Discourse	✓			
Keywords-in-context	✓		✓	✓
Membership categorization	✓			
Persona analysis	✓	✓	✓	✓
Semiotics	✓			✓
Narrative	✓			

2.2.1 Word count analysis

Word count is one of the simplest qualitative analytics that is based on counting the number of times that a word is repeated in the text (Carley 1993). The more a word is repeated, the more important that word is for the writer/speaker. This analysis accurately determines the frequency of using words and then makes some reasoning about the opinion of the writer/speaker based on it.

Word count analysis can be performed on different text data such as posts on social networks, customer reviews, and surveys. In word count analysis, either the words to be counted are selected based on a previous knowledge of the topic, or they can be identified by counting all words and considering the most repeated ones. The counting process can be done manually or by software tools.

Word count analysis can be performed on two different text data sets so that at the end, the results can be compared for reasoning. For example, one may count the number of times that “defected” is repeated in the reviews of two similar products on Amazon and accordingly decides which one is a better one. Also, word counting must be performed cautiously as it sometimes can

be misleading. For example, the frequency of repeating “warranty” in the google reviews of a store does not specify whether or not the seller respects “warranty” conditions. It just shows how critical and important the topic of “warranty” is for the customers that have purchased from the store.

As an instance in the context of ergonomics, McKendrick et al. (2014) evaluated the effect of using word count analysis in assessing the team performance in a networked supervisory control of unmanned air vehicles.

2.2.2 Content analysis

Content analysis is a qualitative analytics method that was initially used by Barcus (1959). It can be performed on various kinds of data types including text, audio, video, etc. In this analysis, the researcher codes particular words, meanings, or themes in a text (or other qualitative data types such as interview and video) and then counts the number of times that each code is repeated. Then the generated data can be further analyzed by quantitative analytics methods to understand the main messages of the text. In content analysis, the categories/codes are often pre-defined based on the research question and the goal of the analysis. For example, in feedback from first-home buyers that have recently purchased a house, the categories can be about the mortgage rate, the size of the house, the neighborhood of the house, the quality of schools around the house, etc. Content analysis can be applied in different areas of science such as psychology, sociology, communication studies, and marketing research.

Content analysis is superior to the word count method because it analyzes meanings and themes in addition to counting the words. There are two forms of content analysis that are referred to as manifest content and latent content analyses. In the manifest method, the coding and the analysis is performed on observable elements of the qualitative data, while the hidden and implied concepts are the subject of latent analysis (Potter and Levine-Donnerstein, 1999). As an example in the area

of ergonomics, Roach and Duffy (2021) applied content analysis for analyzing the emerging applications of cognitive ergonomics.

2.2.3 Text mining

Text mining extracts the meanings, concepts, and themes by analyzing multiple unstructured text documents (Tan, 1999). Text mining, that is also referred to as text analytics, works based on machine learning algorithms to identify the patterns and extract the information.

The algorithms for text mining have several main steps. Text mining starts with Information Retrieval (IR) that finds reasonable matches for the user's query in a database with many documents. Then, text mining reads the selected documents using Natural Language Processing (NLP) that analyzes the grammatical structure of texts. In this step, text pre-processing is performed on the text to transform the raw text data into structured data that can be more easily analyzed later. Next, text representation is applied that converts the structured data to a format that can be processed by machine learning.

Next, there is a data mining step that identifies patterns in the text read by NLP. This step includes two sub-steps of text classification and text clustering. In text classification, machine learning algorithms classify the summarized data into different pre-determined categories. In text clustering, some categories of text are merged into the same group with respect to their similarity. In the context of ergonomics, Kim et al. (2019) demonstrated that text mining techniques are useful in detecting and addressing the customers' health and safety requests in the product design process.

2.2.4 Qualitative comparative analysis

Qualitative comparative analysis can be applied to any kind of input data to find a logical relation between some input variables and an outcome (Legewie, 2013). This analysis looks for necessary

and sufficient conditions, defined based on input variables, for a specific outcome to happen. Qualitative comparative analysis is often applied in the social science areas such as political science and sociology.

This analysis includes three main steps of truth table analysis, boolean minimization, and logical reasoning. In truth table analysis, each data record (e.g., a photo) is evaluated as a separate case and is converted into numbers in a single row of a “truth table”. In this table, the predefined columns are referred to as conditions or variables indicating different possible features of the cases. This table shows how various possibilities in input variables lead to specific outcomes. In the next step of qualitative comparative analysis, boolean minimization is performed to merge very similar rows and columns for the sake of reducing the complexity of the analysis. In the end, this analysis finds a logical relation (e.g., a mathematical formula) to express the output of each case based on the values of input variables. This logical formula is used for predicting the output of future cases.

Generally, qualitative comparative analysis is useful for detecting the patterns and relations between variables that cannot be easily well understood by conventional statistical analysis methods. The disadvantages of this approach is that 1) the obtained results may not be generalizable to other areas with different records, and also 2) the analyst must have good understanding of the input variables to obtain reasonable results. For example, the analyst may need to avoid merging two columns as they are totally independent and irrelevant. As an instance in the area of ergonomics, Marx and Hootegeem (2007) applied qualitative comparative analysis for the organizational analysis of the occurrences of ergonomic injuries.

2.2.5 Constant comparison analysis

Constant comparison technique is one of the earliest qualitative data analytics techniques conceptualized by Glaser and Strauss (1967). In cases where researchers aim to find similarities

and differences in the data, constant comparison analysis helps them. The overall goal of this method is to identify new categories/patterns by progressively comparing each data record with those categories/patterns that have been recognized so far. Constant comparison technique includes the following steps. In the first step, that is referred to open coding, researchers group similar data together as a keyword, category, or code. The aim in this step is to reduce source(s) to codes inductively. In the next stage, researchers compare each new data to previous data and place it into the most relevant group. This procedure will continue until all the data have been reviewed. Finally, researchers find patterns and themes in the data based on the groups that they created (Smulowitz, 2017). This method can also be used in grounded theory research which aims at proposing new theories based on the collected data instead of using the existing ones. In this case, there might be an additional step for extra sampling of new data until the researcher can extract a new theory out of the categorized data.

Constant comparison technique is an enormously multipurpose analytical technique since it can be used for talk, observations, drawings, photographs, video, and documents (Ratcliff, 2003; Coghlan and Filo, 2013). Various computer-assisted qualitative data analytics software such as NVivo can be used to analyze qualitative data step by step. (Leech and Onwuegbuzie, 2008). The main disadvantage of constant comparison analysis is that it is time consuming, especially when there is a large amount of data. In the context of ergonomics, Cheung et al. (2016) used the constant comparison analysis for exploring the views of women with upper limb repetitive strain injury about changing housework habits.

2.2.6 Ethnographic analysis

Ethnographic analysis is another approach for analyzing qualitative data. Ethnographic was first presented by Spradley (1979) in non-engineering contexts, but it can be applied in engineering

areas as well. The main goal of ethnographic analysis is to understand the detailed cultural relations among members of a particular social group. Ethnographic analysis has applications in various areas such as marketing, education, and healthcare, to better identify the expectations and opinions of different communities.

The first step of ethnographic analysis is domain analysis that aims at understanding the culture of a context by examining the relations between symbols. In terms of engineering language, domain analysis is used to roughly understand a system (or subsystems of a large system such as a country's health system) and the way that it works by analyzing the relationship between its elements. This analysis is usually helpful for the newcomers such as consultants. This step is often referred to as field work and data collection, since it requires the researcher to get engaged with the community/system to collect data by observation and field interviews. After performing the domain analysis on subsystems of a large system, a researcher can perform the second step that is referred to as taxonomic analysis to understand the relationship between domains (i.e., subsystems) with more details. Spradley (1979, 1997) refers to taxonomic analysis as a classification approach to draw flowcharts and diagrams for discovering the relationships of domains (i.e., subsystems).

The next step of ethnographic is a componential analysis that systemically searches for appropriate attributes for the components of the subsystems (or domains). These attributes should map the function of components as accurately as possible. The main disadvantage of ethnographic analysis is that the researcher could be bias about the results and finding based on his/her own cultural background. As an instance in the area of ergonomics, Munro and Mogford (2018) applied ethnography analysis in a cognitive analysis of the work for airline dispatchers.

2.2.7 Micro interlocutor analysis

In a focus group, several team members share their opinions about a specific topic. Micro interlocutor analysis is the approach that researchers use for collecting and analyzing the data in focus groups (Onwuegbuzie et al., 2009). In discussions of focus groups, some members may hesitate to share their beliefs because of low-level self-confidence and also the opposite comments of other members. The goal of this approach is to understand individual opinions and examine how individuals in a group influence and interact with each other within the focus group. In fact, micro interlocutor analysis aims at understanding all members' opinions and finding the consensus by canceling the effect of humanitarian factors such as hesitance between the team members. To this end, micro interlocutor analysis collects and analyzes the following data related to the focus group: which member answered which questions, how many members answered each question, the order of answering questions by members, who was the first person that answered each question, and the personal characteristics of each team member.

2.2.8 Conversation analysis

Conversation analysis, proposed by Schegloff (1968), is one of the main qualitative approaches for analyzing talk/conversation data. This method concentrates on the structure of daily conversation and how people communicate and interact with each other. In conversation analysis, researchers focus on the motivation of the speaker instead of the subjective statements. Conversation analysts search for the similarity of reasoning in talks to link conversations to speakers. This method has application in analyzing the dynamics of interaction in family, doctor-patient consultations, classrooms, and workplaces. There are several features of talks that are examined in conversation analysis. Some of these features are as follows:

- I) Turn taking: It refers to the moments in conversation that the speaker participates in a dialogue by taking a turn expressions such as “Uh, yeah”. Such expressions help both speakers maintain the flow and coherency of conversation.
- II) Adjacent pairs are two related parts of conversations from two different speakers where the second part is expected as a response to the first part. Some examples are question-answer, compliment-thanks, and request-acceptance or refusal.
- III) Formulation: This feature refers to the part of the dialogue that a speaker summarizes the conversation up to that point.
- IV) Repair: It refers to the set of expressions that a speaker may use to correct himself/herself. For example, sometimes a speaker exaggerates and then right away say “I mean ...” which shows he/she is going to clarify what he/she just said. Also, repair happens when a speaker tries to correct/clarify the other speaker by expressions such as “What do you mean?”
- V) Overlap and interruption: This feature of conversation refers to when speakers’ speech coincides and how they interrupt each other to identify their similarities and differences and understand each other more quickly.

For conversation analysis, researchers often record a video or audio file and then transcribe it carefully and analyze the patterns of conversation between speakers accordingly. As an instance in the context of ergonomics, Heath and Luff (1991) studied the use of conversation analysis for studying work, interaction and technology from a social ergonomics perspective.

2.2.9 Keyword-in-context analysis

Keyword-in-context is another qualitative method that assumes words have different meanings that can be perceived depending on how they are used in the text. This method lets researchers perceive

the meaning of words in different contexts based on the meaning of other words that appear around them in the text (Fielding and Lee, 1998).

To perform this analysis, the researchers first determine the most relevant keywords that they want to analyze. Then, they locate them in the text and count the frequency of other words appeared around these keywords in the text manually or using software tools. In the next step, the main keywords together with the other words are displayed on the screen. In this presentation, the main keywords are set at the middle surrounded by the other words that are re-sized based on the number of frequency of their repetitions. This presentation is done for each keyword separately. Using this way of presenting, the researcher can better understand the meaning of the main keyword using the surrounding words and interpret it.

2.2.10 Discourse analysis

Discourse analysis, proposed by Potter & Wetherall (1987), is used for analyzing a written text about its social context. In this analysis, some representing parts of a transcript are chosen and then are analyzed from a social perspective. In contrast to conversation analysis, discourse analysis does not focus on the structures of conversation or transcript but aims at understanding the social position of a person/persons and also the way that values and beliefs are communicated. For example, discourse analysis can reveal whether the person that is asking a question is an expert such as a teacher or novice person such as a student.

In another example, discourse analysis can examine the interactions of medical professional and patients in online forum and reveals the following fact: 1) Doctors in this forum often use technical expressions to convince the patients to follow their practical advice, 2) Doctors usually confirm each other's medical advice even if they do not disagree about a specific treatment and try to be very gentle in disagreement and mostly offer their treatment advice as a better one rather than the

only right option in order to protect their social positions that is being judged in the forum by patients, 3) In some cases, patients challenge the doctors by sharing alternative treatment options, or stating their dissatisfaction with similar previously prescribed medications. By such analysis, researchers can better understand how doctors and patients interact with each other based on their social positions. As an instance in the context of ergonomics, Caid et al. (2016) applied discourse analysis of Uninhabited Aerial Vehicle (UAV) operators to understand the operational issues resulting in fatigue.

2.2.11 Membership categorization analysis

Sacks (1992) proposed membership categorization analysis to describe people's behaviors based on their membership in different categories. Here, categories usually refer to the social position of individuals, e.g., whether a person is a baby, sister, brother, mother, or a father in the family. Other categories could refer to their ethnicity, religion, age group, etc. Another example is that participants in a school conference can be categorized into teachers, parents, and students. These memberships could help researchers in predicting someone's reaction in specific events in interaction with others. In the following, based on the example of school conference, we explain the main concepts studied in membership categorization:

- 1) Role expectations: This refers to the expectations that people in different categories may have from each other. For example, teachers may highlight their professional expertise to justify their advice for parents and students. On the other hand, parents may disagree with teachers' advice based on their personal knowledge of their kids.
- 2) Category-bound activities: This refers to the actions that are related to a specific membership category. For example, to demonstrate their supports for students, parents and

students might mention their efforts as follows: teachers may mention offering extra office hours to support students, while parents could highlight their help with homework.

- 3) Negotiating responsibilities: This refers to conversations between members of different categories to negotiate responsibilities. For example, teachers may express that parents should involve more the students' home work, while parents state that teachers must provide extra support in the school for students.

As an example in the field of ergonomics, Kärkkäinen et al. (2018) applied a membership categorization analysis to study how to manage the sickness absence and supporting return to work of employees with burnout.

2.2.12 Persona analysis

Personal analysis is an organized approach that researchers use to understand and represent the behavior of their target audience through a few chosen users/candidates. These users are selected from the pool of the target audience such that each one of them can reasonably represents a portion of the audience and provide insights to the researchers. The chosen candidates are referred to as personas and are used in the future analysis and decision making of the researchers about the various groups of the target audience. Persona analysis can be considered as a qualitative approach when the input data about the target audience is qualitative such as interviews. This approach usually consists of the following steps:

- 1- Collection of qualitative data: This step usually requires interviewing the audience or collecting qualitative data through focus groups and observations. This step aims at recording the behaviour and experiences of the users.

- 2- Analysis of the data: In this step, various approaches such as content analysis are used to better understand the motivation and viewpoints of different users.
- 3- Categorization of users: In this step, researchers focus on categorizing users such that those with the most similar profile (behaviour, motivation, experiences, viewpoints, etc) fall in the same category.
- 4- Creation of personas: After categorization of the audience, for each group, a user is chosen such that this person represents his/her own group better than anyone else. This person is referred to as a persona. It is also possible to create imaginary characters with fake profiles to represent different groups of the audience.
- 5- Validation of personas: Normally, after creation of the personas, they are validated by a group of experts. Sometime, the experts ask for modifying the categorization of the audience or choosing other personas, which may require revisiting the two previous steps.

In the literature, researchers have used persona analysis in various areas. Some examples are the works done by Rasca et al. (2022), Khir et al. (2020), Salminen et al. (2017), and Agee et al. (2021). Rasca et al. (2022) applied persona analysis for identifying the work-commute travel behaviors of people. Khir et al. (2020) studied the goals, expectations, and attitudes of children that play video games through persona analysis. Salminen et al. (2017) created personas to analyze the behavior of middle-eastern social networks users from a cultural perspective. In the context of building smart houses, Agee et al. (2021) interviewed the occupants of various types of houses in the United States performed a persona analysis to identify their expectations and attitudes about smart houses. As an instance in the field of ergonomics, Dai and Xu (2013) performed a persona analysis for human factors design of furniture for kids in Shanghai middle-class family.

2.2.13 Semiotics analysis

Semiotics analysis, developed by Greimas (1966), examines talks and documents as a series of interrelated signs. In this analysis, each sign does not have any meaning, but a series of signs together can be interpreted as a specific meaning. As an example, a researcher may use semiotics analysis to examine the portrayal of different genders in television advertisements. In this case, the signs and symbols include items showed in the advertisement, the written and the verbal communications in the advertisement, and even the music. All these elements together contribute to the portrayal of different genders in the advertisement. As an example in the context of ergonomics, Bhutkar et al. (2011) combined Semiotic analysis with usability and ergonomic testing for the assessing icons in medical user interface.

2.2.14 Narrative analysis

Narrative analysis, developed by Riessman (1993), investigates individuals' stories such as autobiography, journals, field notes, letters to understand how people interpret and narrate their personal lives. This approach helps the researcher reveal the understanding of an individual from himself/herself through the analysis of stories. Narrative analysis is based on the idea that humans' experiences and their understanding of the world is hidden in their stories. For narrative analysis techniques, online software tools such as Delve lets the researchers examine individuals' stories. As an instance in the area of ergonomics, Das et al. (2018) provided a narrative review on ergonomics in dentistry.

CHAPTER 3 SYNTHESIS OF THE WORK AS A WHOLE

The main purpose of this chapter is to synthesize the three research studies performed in this dissertation and highlight the addressed research gaps. In this regard, two closely related research themes were followed in this dissertation.

In the first research theme, we present Research 1 and Research 2 which are defined on the application of quantitative data analytics in the area of physical ergonomics for forestry workers in Quebec. More specifically, the research gap addressed in Research 1 (Chapter 4) was an extensive statistical-oriented data analysis of 50 existing methods for the prediction of work metabolism of forestry workers. Before carrying out Research 1, the researchers in this area did not know which method is the most accurate one, which one is more reliable than others in the absence of individual calibration, how good or bad other approaches are compared to the best ones, and how accurate these prediction approaches are in other environmental conditions. Thanks to Research 1, which is published in the *Ergonomics* journal, the practitioners and ergonomics researchers know the answers to all above questions, as we will discuss in Chapter 4.

Based on the findings of Research 1, in Research 2 (Chapter 5), we intend to address the following questions: “Is there any other advanced data analytics approach that can predict the work metabolism of physical workers more accurately? If so, how should we design it? How more accurate this approach is? What input are required for such an advanced data analytics approach?” We answer all above questions in Research 2 by developing several mixed-integer-programming-based regression decision tree models for the prediction of work metabolism for forestry workers in Quebec. We also provide extensive numerical results on the proposed algorithm and widely discuss its accuracy and reliability compared to the most-accurate existing methods studied in Research 1.

Research 1 and 2 demonstrate the effectiveness of data analytics in physical ergonomics. However, excessive cognitive/psychological load is another work-related issue that employees deal with and is becoming more and more crucial than ever before, especially with the growing utilization of emerging technologies in the digital era, and Industry 5.0 as a human-centered solution. The question that arises here is whether data analytics can be used effectively to address the psychological load of employees in a similar way as it helped us in Research 1 and 2? This question cannot be answered based on the findings of Research 1 and 2 for two reasons. First, the data related to cognitive ergonomics are mainly interviews which are qualitative and not numerical as in Research 1 and 2. Second, this question is usually relevant to employees that work with computers on a daily basis and not for physical workers such as the forestry workers studied in Research 1 and 2. Therefore, to investigate the applicability and effectiveness of data analytics in cognitive ergonomics, we followed a second research theme which is defined based on applying data analytics on the daily users of a virtual ergonomics software tool. This research is conducted in a different environment compared to Research 1 and 2, but is in line with the overall objective of this dissertation which is to evaluate the applicability of data analytics approaches in enhancing the health and work condition of workers with daily physical or cognitive loads.

More specifically, the main research gap that Research 3 (Chapter 6) addresses is to answer the following questions: How can data analytics be applied to decrease the psychological workload experienced by virtual ergonomics users? How can data analytics deal with the qualitative nature of users' data including their concerns and requests about the corresponding software tools? On the way to answer the above questions, Research 3 also answers the following side questions about the virtual ergonomics software tools: What are the different categories of users applying these software packages? What are the different expectations of the various groups of users from these digital tools? What are the main limitations and advantages of these software tools for different

groups of users with different backgrounds? It is noteworthy that Research 3 also indirectly contributes to the area of physical ergonomics since the virtual ergonomics tools that we study in this work are used by designers and engineers for designing products and workstations with respect to ergonomics and safety rules. Therefore, the findings of Research 3 are expected to result in improving the safety and work conditions of a wide range of physical workers that deal with such products (e.g., manual tools) and workstations (e.g., cockpit of an airplane) designed by the virtual ergonomics tools.

In the following sections 3.1, 3.2, and 3.3 we explain the general outlines and originalities of the three ergonomic-centered data analytics research studied in this dissertation.

3.1 General outline and originality of Research 1

The quantitative research studies in this dissertation, presented as Research 1 and Research 2, are based on the data from the forest industry in Quebec. In these studies, we have provided descriptive and predictive analytics to improve the physical work condition of the forestry workers.

In the literature, there are many different methods for predicting the work metabolism (WM) of physical workers based on their heart rate (HR) data. However, there is no research that has compared the accuracy and the reliability of different HR-based work metabolism (WM) estimation models. In Research 1, for the first time, we compared nine regression HR-based WM prediction models. These models can be used in different settings with different combination of inputs parameters, resulting in a total of 50 models. In Research 1, we have studied all these 50 models and have concluded which one is the most accurate, which one is the more reliable, which input parameters contribute more in the obtained accuracy, etc. This research helps practitioners with varying levels of ergonomics expertise choose the best model according to their needs and available input parameters.

In Research 1, we have used statistical analysis as the quantitative data analysis approach to analyze the accuracy and the reliability of different models. In this context, the statistical indicators that we considered in our analysis included the bias, relative bias, root mean square error, and relative root mean square error. For our statistical analysis, we depicted the LoA for the differences between predicted and measured WM for different models. We assessed the normality in the differences from the distribution histograms by performing a Shapiro Wilks test. We also used linear regression and Pearson's coefficient of correlation to detect trends of biases in the scatter plots of the differences against averages. Also, we tested heteroscedasticity by regressing the absolute residuals against averages based on Bland and Altman (1999).

The originality of Research 1 is that it is the only work in the literature that vastly studies the accuracy and reliability of the existing WM prediction models by various statistical analysis methods.

3.2 General outline and originality of Research 2

The results of Research 1 indicate that the more accurate models need either individual calibration or thermal pulse determination. Individual calibration means that the WM-HR relationship must be determined by taking a step-test. Also, thermal pulse determination is another approach that requires workers to take several seated rest pauses following work periods to assess the effect of the temperature on their HR. Both individual calibration and thermal pulse determination must be performed for each worker separately and are considered as very timely and costly approaches in practice. Therefore, in Research 2, we investigate the possibility of developing a more accurate WM prediction model, especially without any need for individual calibration and thermal pulse determination. In this research, we proposed six novel regression decision tree models (RDT) to

predict WM for Canadian forest workers. These models were developed based on a new integer programming formulation that we have proposed in this work.

The originality of Research 2 is that it offers a series of novel integer-programming-based regression decision tree prediction models that provide significantly more accurate estimates for the work metabolism of physical workers compared to the existing models in the literature. The other advantage of the proposed models is that their input variables can easily be measured in workplaces and hence they can be used quickly by practitioners. Contrary to many other models in the literature, our proposed models do not require individual calibration, physical characteristics, and ambient conditions as input variables.

3.3 General outline and originality of Research 3

In Research 3 of this dissertation, we have focused on the application of qualitative data analytics in the area of cognitive ergonomics. In this research, from a cognitive ergonomics perspective, we have studied the users of DHMS, a virtual ergonomic software tool used on a daily basis in Dassault Systèmes company. The goal of this study is to better understand the expectations of the users and the cognitive challenges that they experience in using different components of DHMS tools. This research does not only contribute to lower the cognitive workload of the software users, but is also expected to result in more ergonomic designs of industrial parts for physical workers that are involved in their production in the shop floor.

In this research, we applied qualitative data analytics to analyze the interviews of the users and categorized the users based their needs, limitations, and capabilities into three persona groups. The main qualitative data analytics approaches used in this research included content analysis and constant comparison analysis. The constant comparison analysis approach enabled the creation of

meaningful comparisons within the data, which leads to deeper insights and interpretations. This approach allowed the identification of similarities and differences across data segment. Content analysis approach also enabled the uncovering of latent meanings and revelatory depth within the data. It facilitated going beyond surface-level observations and explore the underlying messages.

We have already vastly reviewed these qualitative data analytics approaches in Section 2.2. Also, it is worth mentioning that, to perform the clustering step of the persona analysis, we developed a new integer programming model that more accurately formulates the objective function of this problem.

The originality of Research 3 is that it is the first comprehensive work that applies qualitative data analytics approaches to characterize the needs, goals, and opinions of a wide class of DHMS users with various work backgrounds. It is also the only work that uses persona analysis to characterize difference groups of DHMS users. Also, as mentioned earlier, a side contribution of this research is that we have developed a novel integer programming model for the clustering step of persona analysis. This research is expected to help DHMS developers to design and improve new/existing tools that will enable DHMS users to access the required software components more easily and design human-centered parts with reduced risk of physical harm to shop-floor workers.

CHAPTER 4 RESEARCH 1: COMPARISON OF NINE HEART RATE-BASED MODELS TO PREDICT WORK METABOLISM OF FOREST WORKERS¹

Abstract

Predicted work metabolism (WM) from 9 heart rate (HR)-based models were compared to measured WM obtained during work in 39 forest workers. Using measured (i.e., raw) HR in these models can overestimate actual WM since the HR increase associated with body heat accumulation is non-metabolic. Hence, accuracy of WM prediction was assessed on all possible combinations of models using raw HR and corrected HR (thermal component removed) and with five different estimates of maximum work capacity (MWC) for the models that require it as an input. The 50 model combinations produced a wide range of WM estimates. Three models using individual calibration produced the lowest RMSE and narrowest LoA with corrected HR ($rRMSE \leq 13\%$; LoA [$rBias < 5\% \pm 25\%$]). One of the models that requires neither determination of the thermal component nor individual calibration performed very well ($rRMSE = 18\%$; LoA [$rBias = 1\% \pm 36\%$]).

Practitioner Summary: These results provide a better understanding of the accuracy of various HR-based work metabolism (WM) estimation models. This information should prove particularly useful to ergonomics professionals wishing to select a method that provides accurate estimation of WM from HR measurements during work in varied thermal environments.

Keywords: Work Metabolism, Energy Expenditure, Heart Rate, Methods Comparison, Maximum Work Capacity, Field Measurements

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4.1 Introduction

Work metabolism (WM, or energy expenditure) informs on the physical workload as well as on the heat production by the body during physical work (Wu and Wang, 2002; ISO 8996:2004). The forestry, mining and construction sectors among others are known for the high WM they often impose on workers (Abdelhamid and Everett, 1999). Together with insufficient recovery, WM can cause undue fatigue that will reduce work quality and productivity, and possibly affect worker health and safety (Chengalur, Rodgers, and Bernard, 2004). Ergonomics experts and industrial engineers thus need to assess WM to organize work-rest regimens for physical work and also when using thermal stress indices such as the Thermal Work Limit (TWL), Predicted Heat Strain (PHS), Wet-Bulb Globe Temperature (WBGT), Predicted Mean Vote and Predicted Percentage Dissatisfied (PMV-PPD), or Required clothing insulation (IREQ) to determine the importance of heat stress or to assess thermal comfort in the workplace (Chengalur 2004; Parsons, 2014; ACGIH, 2018; Brake and Bates, 2002; ISO 7933:2004; ISO 11079:2008; ISO 7730:2006; Bouchard and Trudeau, 2008). WM estimation is also a key parameter in mobile health and wearable system applications for monitoring cardiac rehabilitation programs in patients with cardiovascular disease (Falter 2019; Abtahi 2017; Lind 2019; Yang 2019).

WM can be assessed accurately by measuring oxygen consumption ($\dot{V}O_2$) during the work activity, but ergonomics and work physiology textbooks as well as the International Organization for Standardization (ISO) also propose heart rate measurement (HR) as a relatively easy, reliable, unobtrusive and cost-effective method of assessing WM for dynamic work that uses major muscle groups (ISO 8996:2004; Åstrand 2003; Louhevaara and Kilbom, 2005; Chengalur 2004; Wilson and Corlett, 2005; Levine 2005; Mairiaux and Malchaire 1990). More specifically, ISO 8996 models HR as a sum of several components, i.e., resting heart rate, dynamic physical work, static

muscular work, mental or psychological stress, thermal stress, circadian rhythms, and some residual variation. Mental stress, circadian rhythms, and residual variation can generally be ignored as the intensity of the dynamic work increases. In dynamic muscular work involving large muscle groups with no thermal strain and little static muscular work, WM can be accurately assessed through HR measurements since the relationship is mostly linear between both variables. Numerous studies have demonstrated the strong correlation between HR and WM (Sunagawa et al., 1985; Preisser 2016; Baker 2017) and several models that can readily be used to assess WM from HR measurements during work have been published (e.g., ISO 8996:2004; Keytel 2005; Malchaire 2017; Buttussi and Chittaro 2008; Seoane 2014; Mohino-Herranz 2015; Dubé et al., 2015).

ISO 8996:2004 further indicates that the relationship between the two variables can be significantly affected by a number of factors, among which the hot thermal environment is known to have a significant impact (ISO 8996:2004; Meyer 2001; Dubé 2016). Dubé et al. (2015 and 2016) reported a 30% average WM overestimation error when using measured (raw) HR to assess WM of forest work when a thermal strain is present. These authors have shown that correcting HR by subtracting the thermal strain component from measured HR yields an accurate WM estimation. Bröde and Kampmann (2018) came to the same conclusion and reported that after removing the thermal component from HR, the overall prediction error of 43% decreased to 10-15%. Two methods have been published to date to assess the thermal component of HR (or thermal pulses); one developed by Vogt et al. (1970, 1973) and the other by Kampmann et al. (2001). Dubé et al. (2019) compared the two methods in forest work, and although both methods produced accurate WM estimations (LoA: $0.2 \pm 3.4 \text{ ml.kg}^{-1}.\text{min}^{-1}$ for Vogt et al.'s, and $0.0 \pm 5.4 \text{ ml.kg}^{-1}.\text{min}^{-1}$ for Kampmann et al.'s), they indicated that Vogt et al.'s method which uses a short seated rest pause following a work period to assess the thermal pulses is the simplest and most practical way to

implement in many industrial work environments, and therefore of great interest to ergonomics experts.

Among the published HR-based models that can readily be used to assess WM, several require the worker's maximum work capacity (MWC) as an input variable (ISO 8996:2004; Chengalur 2004; Malchaire 2017). MWC, also called maximum oxygen consumption or $\dot{V}O_2$ max or maximum aerobic capacity or MAC, is often expressed in Watts or in Watts.m⁻² of body surface area or ml of oxygen per kg of body weight per min (ml.kg⁻¹.min⁻¹). The direct measurement of $\dot{V}O_2$ max or MWC entails risk to the participant whose cardiac health is unknown and hence it has often been restricted mostly to athletes or to studies where medical personnel is present, which is rarely the case in field interventions conducted by ergonomics experts (Björkman 2016). A number of submaximal tests thus have been designed to indirectly assess a participant's MWC safely (e.g., Meyer and Flenghi 1995; ACSM 2014). Various studies have also presented regression equations to estimate, or charts that provide values for, MWC based on the personal characteristics of the participant such as gender, age, weight, height, body mass index (BMI) and physical activity level to name a few (ISO 8996:2004; Eizadi 2011; Dubé 2015; Malchaire 2017; Statistics Canada 2013). Hence, to assess WM using the published HR-based models, one must measure HR during the work activity, correct for thermal pulses when necessary, and specify the worker characteristics to determine her or his MWC when it is required by the model.

To our knowledge, only Kolus et al. (2014) has compared HR-based WM prediction methods with data collected in actual work settings. They showed that an adaptive neuro-fuzzy system approach that does not require the determination of an individual's WM-HR relationship (i.e., individual calibration) produced better WM estimations than three calibration-based methods. However, no study seems to have compared methods that are more commonly available and within

the reach of the ergonomics experts such as the equations from ISO 8996:2004 or from Malchaire et al. (2017), that is methods that do not require calibration. Hence the ergonomics experts who want to use HR measurements during work for its many practical advantages cannot know which method or model will provide the best estimation, nor how the WM prediction can be affected by the MWC figure used as input in some models. Moreover, although Dubé et al. (2015 and 2019) as well as Bröde and Kampmann (2018) indicated that taking into account the thermal pulses yielded better WM estimation with the models they used, the effect of the thermal pulses in other WM models has not been reported on.

This study compares nine HR-based WM estimation models that are easy to use and accessible, and therefore likely to be used by non-researchers with varying levels of ergonomics expertise: Malchaire et al.'s (2017), Dubé et al.'s (2015), Ueno et al.'s (2014), Rennie et al.'s (2001), Kamon's (1982), Keytel et al.'s (2005) two models, ISO 8996:2004's equation set (or formulation) provided in section 6.2 of the standard and the simplified equations table in Appendix A of the standard. These models were all applied to a same large physiological data collection from forest work, which included actual measurements of WM that were used as a reference for comparisons purposes in this study. The aim of this paper was: (1) to assess the accuracy and bias of the different models' WM estimations, (2) to compare the WM estimates when the HR input includes and does not include the thermal pulses, and (3) to compare the WM estimates when using one of five different MWC input figures to the models that require that parameter (Meyer et Flenghi 1995; Jackson et al., 1990; Statistics Canada, 2013; ISO 8996:2004; Malchaire 2017).

4.2 Methods

This study uses data collected on forest workers during four research projects on physical workload and productivity of forest work in the province of Québec (Canada). All data were measured during

the months of July to October between 2008 and 2013. These studies were approved by Polytechnique Montréal's Research Ethics Committee (CÉR-07/08-17, CÉR-08/09-14, and CÉR-11/ 24-04). The data for this study comes from the dataset assembled and used by Dubé et al. (2015, 2016, 2019).

4.2.1 Participants

The 39 healthy male participants included six tree planters and 33 brushcutters from various areas of the Province of Québec. All participants had a minimum three-year experience. They all signed an informed consent form prior to participating in the study and then completed a Physical Activity Readiness Questionnaire (PAR-Q; Thomas et al., 1992). Tree planters (mean $\pm$ SD: 25.2 $\pm$ 2.2 years, range: 23-28 years) were younger than brushcutters (mean $\pm$ SD: 52.5 $\pm$ 9.3 years, range: 22-67 years). Table 4.1 shows the participants' characteristics as well as the widely varying ambient conditions in which the measurements were performed.

Table 4.1 Description of participants' characteristics (N=39) and ambient conditions during data collection.

Variable	Mean $\pm$ SD (range)
Participants:	
Age (years)	47.4 $\pm$ 13.3 (22 – 67)
Weight (kg)	76.7 $\pm$ 10.2 (53.5 – 100.0)
Height (m)	1.75 $\pm$ 0.06 (1.63 – 1.88)
BMI ^a (kg.m ⁻²)	25.1 $\pm$ 2.8 (19.0 – 30.2)
HR _{rest} ^b (bpm)	63.2 $\pm$ 7.4 (42 – 80)
MWC ^c (ml.kg ⁻¹ .min ⁻¹)	42.6 $\pm$ 10.3 (26.0 – 68.7)
Ambient conditions:	
Ta (°C)	17.4 $\pm$ 4.9 (7.2 - 26.5)
Tg (°C)	22.4 $\pm$ 8.4 (8.9 - 36.2)
RH (%)	71 $\pm$ 21 (30 - 100)
Va (m.s ⁻¹)	0.8 $\pm$ 0.8 (0 - 3.0)
WBGT (°C)	16.9 $\pm$ 4.2 (8.5 - 23.6)

^a BMI: body mass index

^b HR_{rest}: seated resting heart rate (beats per min - bpm)

^c MWC: maximum work capacity

Ta = dry-bulb temperature; Tg = globe temperature; RH = relative humidity; Va = air velocity; WBGT = Wet-bulb globe temperature.

4.2.2 Data collection procedure

The procedure is summarized here, but for more detail the reader is referred to the works of Dubé et al. (2015 and 2016). Prior to the data collection day, the forest workers were instructed to not smoke, drink coffee, or engage in an arduous activity during the morning of the day they were scheduled to participate in the study. In the morning before the start of the workday the participants reviewed the experimental procedures with one of the researchers either outside the forest camp building where they lodged or directly on the side of the road near their day's worksite for the participants who did not lodge near the work site. Each participant donned a HR monitor (RS800, Polar Electro Oy, Kempele, Finland) and kept it until the end of the workday. Next, each participant took a seated rest, then underwent a Meyer and Flenghi (1995) submaximal step-test to determine their WM-HR relationship (individual calibration), which can then be used to determine their MWC through extrapolation of the WM-HR relationship to theoretical maximum HR given by $220 - \text{age}$. The Meyer and Flenghi step-test is a bench stepping test with 4 step heights that is simple, cost effective, and practical to conduct in the workplace. The test is safe for older and less active individuals since it does not induce a high cardiac strain right before the beginning of a workday. In the Meyer and Flenghi step-test, a heart rate monitor is used to measure HR at each step height during the test and a simple equation provided by Meyer and Flenghi (1995) is then used to estimate WM for each step height, yielding data pairs of HR and WM (measured HR, estimated WM) from which the WM-HR relationship of the participant can then be obtained graphically or with a simple linear regression. Imbeau et al. (2010) found that the measured energy consumption during typical brushcutting work corresponded well to the highest WM exerted on this step-test for a group of forest workers such that this test assesses well the level of effort for this type of work. After completion of the step-test, the participant took a 10- to 15-min seated rest and was then freed to

start his normal workday. Later during the workday, the participant donned a $\dot{V}O_2$ measurement apparatus (a Fitmate Pro from Cosmed, Rome, Italy for $n=28$ participants, or a K4b2 from Cosmed, Rome, Italy for $n = 11$ participants) and wore it during one complete work phase that included a work period (average: 31.5 min, range: 11-74 min) and an ensuing 10-min seated rest pause (average: 9.9 min, range: 8-12 min). Each participant took four 10-min seated rest pauses during the workday to evaluate their thermal pulses per Vogt et al.'s (1973) method. In this method, the thermal pulses are determined graphically on the HR profile: the HR elevation above resting HR at the fourth minute after the beginning of a seated rest break is assumed to correspond closely to the thermal pulses at the end of the work period. The thermal pulses (or thermal HR component) increase linearly between the beginning and the end of the physical activity period when the heat exposure and work rate are constant, while it slowly decreases during recovery from the 4th minute on, since in the first four minutes of the recovery period the fast HR decrease corresponds to the recovery of the HR motor component (i.e., static and dynamic muscular work) (ISO 9886:2004; Vogt et al., 1973, Mairiaux and Malchaire 1990). Around the 4th minute of the recovery period a transition point can usually be observed on the HR recovery profile marking the end of motor recovery and beginning of thermal recovery (Dubé 2015, 2019).

The $\dot{V}O_2$ measurement apparatuses were calibrated prior to each data collection day according to manufacturers' requirements. $\dot{V}O_2$ was recorded at 1-min intervals. HR data was averaged to 1-min intervals during the work period to match the $\dot{V}O_2$ measurement rate. The WM values measured in this study with the K4b2 were adjusted using the equation provided by Duffield et al. (2004) to equivalence with a metabolic cart since this instrument is known to overestimate WM (McNaughton and Sherman 2005; McLaughlin 2001). Dubé et al. (2015) found that the COSMED Fitmate Pro showed a consistent $1 \text{ ml.kg}^{-1}.\text{min}^{-1}$ overestimation vs a reference metabolic cart, and

hence the Fitmate Pro data was adjusted by subtracting 1. These corrections ensured that the $\dot{V}O_2$ measurements made with the K4b2 and Fitmate Pro were comparable to those from a reference metabolic cart (MOXUS Metabolic System, AEI Technologies, Naperville, IL, USA), and thus comparable to the values predicted by the different HR-based models.

4.2.3 HR-based WM estimation models

Table 4.2 shows the different variables required by each of the nine models that were compared in this study. The 1-min HR data were averaged over the duration of the work period (HR_{wm} in the equations) and then used as input to estimate WM during the work period with each model. In agreement with Westerterp (2019) most models use gender, age (years), height (m), and weight (kg) of the participant as inputs. Some models use body mass index (BMI, $\text{weight} \cdot \text{height}^{-2}$). Four models out of nine require MWC (or $\dot{V}O_{2\text{max}}$) of the participant or population group as an input and thus, the models were categorized into two sets: 1) the four using MWC as an input variable; 2) the five not using MWC as an input. All nine models were tested using raw HR (HR_{raw} i.e., measured HR) and using corrected HR (HR_{corr} i.e., thermal pulses subtracted from measured HR). Figure 4.1 summarizes the different model combinations tested in this study. All WM outputs from the models were expressed in units of oxygen consumption per kg of body weight per min ($\text{ml} \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) per ISO 8996:2004.

The equations for each model compared in this paper are provided in Section 1 of Appendix A, while the equations to convert between different units are provided in Section 2 of Appendix A. The four WM models using MWC (or $\dot{V}O_2 \text{ max}$) as an input are: Keytel1, IsoForm, Malch, and Kamon.

Keytel1: The first HR-based model presented by Keytel et al. (2005) uses gender, weight, age, and MWC as inputs beyond HR. This model was developed with a group of 115 participants who

regularly exercised and were aged 18 to 45 years, weighted 47 to 120 kg, and had an MWC between 27 to 81 ml.kg⁻¹.min⁻¹.

Table 4.2 WM estimation models and their input variables

Model	Name	Input variables											
		HR _{WM}	MWC	Age	Weight	Height	BMI	HR _{rest}	HR ₉₉	HR _{max}	Gender	Body fat %	Dry bulb T°
Keytel et al. (2005); model #1	Keytel1	✓	✓	✓	✓						✓		
ISO Formulation (Sect. 6.2)	IsoForm	✓	✓	✓	✓			✓		✓	✓		
Malchaire et al. (2017)	Malch	✓	✓	✓	✓	✓			✓	✓	✓		
Kamon (1982)	Kamon	✓	✓	✓									
Dubé et al. (2015)	Dube	✓				✓							
Keytel et al. (2005); model #2	Keytel2	✓		✓	✓						✓		
Rennie et al. (2001)	Rennie	✓		✓	✓		✓	✓			✓		
Ueno et al. (2014)	Ueno	✓		✓	✓		✓	✓		✓		✓	✓
ISO Table (Appendix A)	IsoTable	✓		✓	✓						✓		

HR: heart rate (bpm); MWC: maximum work capacity ($\text{ml.kg}^{-1}.\text{min}^{-1}$), BMI: body mass index (kg.m^{-2}); HR_{rest}: seated resting heart rate (bpm); HR₉₉: the heart rate exceeded during 99% of the working time .

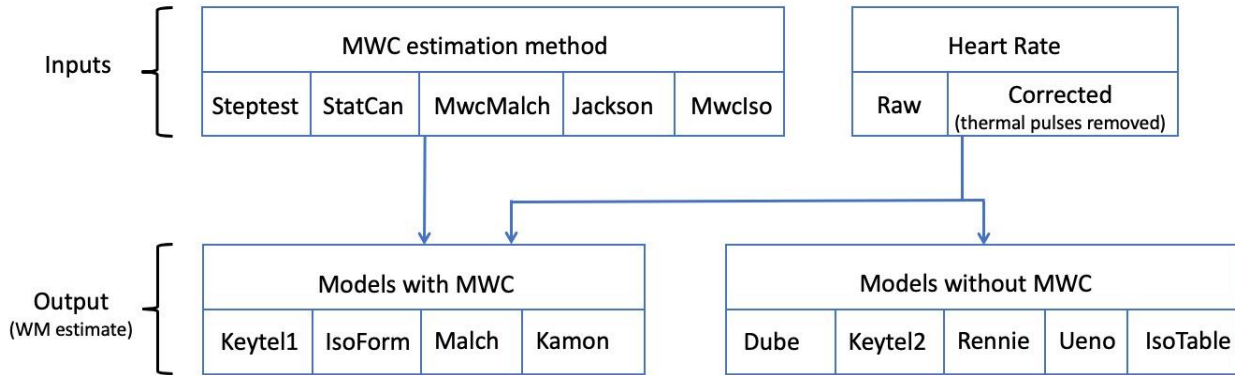


Figure 4.1 Model combinations tested.

IsoForm: According to Malchaire et al. (2017), the first version of ISO 8996 standard was published in 1990 based on work published in 1982 by Spitzer and colleagues, which investigated German workers between 1960 to 1975, and despite a revision in 2004, ISO 8996:2004 was still based on the old data. In section 6.2 of the 2004 version of ISO 8996, a set of equations was proposed to estimate WM from HR, MWC, age, weight, and metabolism at rest (M_{rest}). In the model from ISO, HR_{rest} is measured while the participant is taking a seated rest pause (e.g., before the morning step-test).

Malch: The model proposed by Malchaire et al. (2017) has the same form as IsoForm, but it is based on the more recent literature. In Malch, HR_{rest} is replaced by HR_{99} , which is the HR value exceeded 99% of the time on the HR profile of the participant during the day of data collection. In this model, Height is expressed in cm.

Kamon: Figure 6.4.7 in Kamon (1982) provides graphical WM-HR relationships for different ages for men and women. In this figure, WM is expressed in percentage of MWC and starts at 30%, while the HR range for which the WM-HR relationship is linear begins at 100 bpm and ends at $HR_{max} = 220 - Age$. For instance, a 45-year-old participant performing a dynamic muscular work with a 132-bpm HR would work at 60% MWC (Appendix A).

The above four models (Keytel1, IsoForm, Malch, and Kamon) require an MWC estimate as input. IsoForm and Malch each provide an equation to estimate MWC together with the WM model, however the MWC estimate they yield can be used in other models if the ergonomics professional feels that one of these equations (or any other) better describes the MWC in the worker group she or he is studying. Among the many ways MWC can be estimated, five methods were used in this study to investigate their impact of WM predictions: Steptest, StatCan, MwcMalch, Jackson, and MwcIso.

Steptest: An estimate of MWC can be easily calculated by extrapolating the WM-HR relationship of the participant derived from measurements data obtained during a step-test to her or his maximum HR (HR_{max}). Since HR_{max} cannot be determined unless a maximal test is conducted (an unsafe proposition for workers for whom cardiac health is unknown and in the absence of medical personnel during the test), a number of equations have been proposed over the years to estimate HR_{max} with $HR_{max} = 220 - Age$ being the most common. Dubé et al. (2015) found that using this equation yielded a non-significant (-1.1%) MWC prediction bias when using the WM-HR relationship obtained with the Dube model. Hence, in the Steptest method, the participant's WM-HR relationship is first determined from the step-test data using the Dubé et al. (2015) method (see below), and then this relationship is extrapolated to $HR_{max} = 220 - Age$ to obtain an estimate of the participant's MWC (see Dubé 2015 for more detail).

StatCan: Statistics Canada (2013) reported data on the health of Canadian men and women aged 8 to 79 years. All data were collected between 2009 to 2011 through the Canadian Health Measures Survey. Table 15 of this survey provides percentile values of MWC for different age groups of men and women. For the purpose of this study, the 50th percentile of age group 20 to 39, 50 to 59, and 60 to 69 were used as an estimate of MWC, that is, 44, 34.4, and 26.8 ml.kg⁻¹.min⁻¹, respectively.

MwcMalch: Based on a review of seven studies, Malchaire et al. (2017) proposed an equation to estimate MWC for men and women aged from 20 to 60 years (Appendix A, with the Malchaire model). This equation can thus be used in any WM estimation model above.

Jackson: Based on data from 1543 NASA workers, 150 women (age: 37.6 ± 9.3 years, BMI: $23.3 \pm 3.8 \text{ kg.m}^{-2}$, MWC: $32.4 \pm 8.3 \text{ ml.kg}^{-1}.\text{min}^{-1}$) and 1393 men (age: 43.7 ± 8.6 years, BMI: $25.5 \pm 3.0 \text{ kg.m}^{-2}$, MWC: $39.7 \pm 8.9 \text{ ml.kg}^{-1}.\text{min}^{-1}$), Jackson et al. (1990) published an equation to estimate MWC without the need for exercise testing; this equation uses the self-declared physical activity level of the participant. In this study, forest workers were considered to have a physical activity level of 7 on the NASA/JSC physical activity scale cited by Jackson et al. (1990) because they worked 4 to 5 days a week for extended hours at an aerobic level, which represents longer weekly time but lower intensity than level 7.

MwcIso: ISO 8996:2004 provides an equation to estimate MWC based on Age and Weight (Appendix A, with the IsoForm model), which can also be used in any WM estimation model.

Table 4.3 shows mean and standard deviation of MWC estimates using these methods for the 39 forest workers of this study.

Table 4.3 Mean, standard deviation and range of MWC for the 39 forest workers (ml.kg-1min-1) estimated with each of the five MWC models

Model name	Mean $\pm$ SD (range)
Steptest	42.6 ± 10.3 (26.0 – 68.7)
StatCan	35.3 ± 5.6 (26.8 – 44.0)
MwcMalch	37.0 ± 5.9 (25.2 – 48.5)
Jackson	43.8 ± 5.7 (33.4 – 57.4)
MwcIso	41.3 ± 4.4 (33.9 – 49.6)

The five WM models not using MWC (or $\dot{V}O_2 \text{ max}$) as an input are: Dube, Keytel2, Rennie, Ueno, and IsoTable.

Dube: Dubé et al. (2015) present an extension of the Meyer and Flenghi (1995) method to predict WM using the Meyer and Flenghi step-test. The method requires to calibrate the HR-WM relationship of each participant by measuring HR during the step-test and using a simple equation to estimate WM at each of the five stages (the first stage being a 5-min seated rest) (Appendix A). As in the methods presented by Spurr et al. (1988) and Rennie et al. (2001), the Dube method also uses a HR flex point, that is, the point along the HR axis below which the resting energy expenditure is considered constant, and above which WM increases in proportion with HR at the rate of the calculated slope of the HR-WM relationship. HR_{rest} is obtained during a seated rest (stage 1) and the flex point is determined by averaging the measured HR during stage 1 and stage 2 (stage 2 or lowest step height). The Dube model is derived from $\dot{V}O_2$ measurement obtained on a dataset of 93 Meyer and Flenghi (1995) step-tests comprising 41 experienced Québec male forest workers (age: 46.3 ± 13.2 years, BMI: $25.4 \pm 3.1 \text{ kg.m}^{-2}$) and 26 healthy males attending physical activities in a university training center (age: 34 ± 9.0 years, BMI: $26 \pm 2.5 \text{ kg.m}^{-2}$) and has the same form as the original Meyer and Flenghi equation.

The Dubé model equation is intended to be used by ergonomics experts administering the Meyer and Flenghi (1995) step-test to obtain the WM-HR relationship for a participant by measuring HR only at each step of the test. In this study, this equation was used in the same way, that is, with the HR values measured at each step height during the morning step-test, WM was calculated for each step of the test thus providing the WM-HR data pairs that were used to obtain the relationship between HR and WM. Using this relationship, ergonomics experts can then estimate WM for a given work activity from HR measurements taken during that activity, provided that the work involves large muscle groups dynamically without heat strain.

Keytel2: The second model presented by Keytel et al. (2005) is intended for a more general population and thus easier to use than the Keytel1 model as it does not include MWC as an input variable. The model for males was used in this study.

Rennie: Based on the work of Spurr et al. (1988), the Rennie et al. (2001) model provides a set of equations to predict the intercept, the slope and the flex point of a participant's WM-HR relationship, in lieu of calibrating the relationship using a step-test, for example. HR_{rest} is obtained during a seated rest. The model is based on 789 Caucasian middle-aged participants: 335 men (age: 58.0 ± 7.7 years, BMI: $26.7 \pm 3.2 \text{ kg.m}^{-2}$) and 454 women (age: 57.1 ± 7.4 years, BMI: $26.3 \pm 4.7 \text{ kg.m}^{-2}$).

Ueno: Ueno et al. (2014) presented two linear WM-HR relationships: one derived from seven younger male university students (age: 22.9 ± 0.7 years, height: $173.9 \pm 5.3 \text{ cm}$, weight: $64.1 \pm 6.0 \text{ kg}$, body fat: $17.1 \pm 4.3\%$) and the other derived from seven older male workers (age: 61.7 ± 2.2 , height: $168.1 \pm 8.6 \text{ cm}$, weight: $67.7 \pm 18.0 \text{ kg}$, body fat: $20.9 \pm 6.4\%$). In this study, the WM value obtained with each of the Ueno equations (i.e., one for Young males and one for Older males), were interpolated with respect to age of the participant so as to obtain a WM value for the participants whose age was between 22.9 and 61.7. For the participants aged 22.9 or below the WM value from the Ueno equation for Young males was used, whereas for the participants aged 61.7 or higher, the WM value from the Ueno equation for Old males was used. The Ueno et al. (2014) models differ from the other models investigated in this study by using body fat percentage and a thermal environment parameter (i.e., dry bulb temperature in °C). Ueno et al. (2014) do not indicate how HR_{max} nor HR_{rest} were determined, so the common $HR_{max} = 220 - Age$ was used for the former, and resting HR while seated was used for the latter.

IsoTable: Table C.1 in ISO 8996:2004 shows WM-HR relationships per gender, age and body weight. These equations are very simple to use and thus appealing to ergonomics experts.

In the remainder of this paper, to facilitate reading, the model combinations will be named as follows: WM model + HR type + MWC method. For instance, for estimations from Keytel et al.'s (2005) first model (Keytel1) using HR corrected for thermal pulses (HRcorr) with MWC estimated from Statistics Canada (2013) (StatCan) as input, the combination will be named: Keytel1_HRcorr_StatCan. When the model does not use MWC as input, the combination will include only the model name followed by the HR type (e.g., Ueno_HRcorr).

From all the model combinations (9 WM models; HRraw and HRcorr; 5 MWC values for 4 of the 9 WM models) a total of 50 corresponding WM estimates were generated for each of the 39 workers. Of them, 40 combinations compare MWC values with HRraw or HRcorr (4 WM models x 5 MWC values x 2 HR inputs). The remaining 10 combinations compare only HRraw or HRcorr (5 WM models x 2 HR inputs). The accuracy and bias of these 50 model combinations were then assessed.

4.2.4 Statistical analyses

Predicted WM over the work bout of a participant was computed using the average HR (average HRraw, average HRcorr) over the work bout. This was repeated for every model combination. From the minute-by-minute measured WM, a mean over the work bout was also calculated for each participant. The bias, relative bias (rBias), root mean square error (RMSE), and relative root mean square error (rRMSE) were then computed to assess and compare the performance of the model combination in estimating mean measured WM over the work bout. Hence, these statistics were computed with our sample of N=39 participants.

$$\text{Bias} = \frac{1}{n} \times \sum_1^n (WM_{predicted} - WM_{measured}) \quad (1)$$

$$rBias = \frac{Bias}{mean WM_{measured}} \times 100 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (WM_{predicted} - WM_{measured})^2} \quad (3)$$

$$rRMSE = \frac{RMSE}{mean WM_{measured}} \times 100 \quad (4)$$

Agreement between measured and estimated WM was assessed using LoA analysis as described by Bland and Altman (1986, 1995, and 1999); 95% LoA were calculated on differences ($WM_{predicted} - WM_{measured}$) in $ml.kg^{-1}.min^{-1}$ as $\pm 2 \times$ standard deviation of the differences (SD_{diff}). Normality in the differences was assessed visually from the distribution histograms and by performing a Shapiro Wilks test, which showed no departure from normality in biases in all 50 combinations ($p > 0.05$). Scatter plots of the differences against averages were examined for trends indicating a scale effect of the biases over the range of measurements using linear regression and Pearson's coefficient of correlation. Furthermore, heteroscedasticity was examined by regressing the absolute residuals against averages per Bland and Altman (1999). No heteroscedasticity was found in any of the combinations. Data were tabulated in Microsoft Excel. Statistical analyses were conducted with Microsoft Excel, SAS JMP version 14.1, Python version 3.6 (Jupyter Notebooks), and R version 3.6.0.

4.3 Results

Table 4.4 and Figure 4.2 show the WM estimation results obtained with the models using MWC as an input for the group of 39 forest workers together with the different statistics used to compare model outputs with measured WM. Table 4.5 and Figure 4.3 show the corresponding results and statistics for the models not using MWC. The tables also provide a performance ranking with

respect to RMSE of the different combinations of WM model, MWC estimation method, and type of HR. In the Figures, the black (zero-mean bias) line represents perfect estimation of WM measured and a low spread in the data points indicates a better precision in the estimates.

4.3.1 WM models using MWC as input

Relative bias (rBias) varied widely across the 40 combinations of models using MWC as an input, that is, ranging from an underestimation of -33.6% (Keytel1_HRraw_Statcan) to an overestimation of 46.2% (Keytel1_HRraw_Jackson), but generally rBias was lower when HRcorr was used as input in the model compared to HRraw (Table 4.4). For the five best performing combinations, rBias ranged from -2.1% to 12.6% with HRraw, and from -2.0% to 2.0% with HRcorr. Median rBias was smaller with HRcorr (median bias= $-0.9 \text{ ml.kg}^{-1}.\text{min}^{-1}$, median rBias= -5.1%) than with HRraw (median bias= $3.5 \text{ ml.kg}^{-1}.\text{min}^{-1}$, median rBias= 18.8%). This is well illustrated by the mean bias trend lines for these models being farther from the zero-mean bias (black horizontal) line with HRraw in Figure 4.2, compared with HRcorr. RMSE and rRMSE displayed similar results indicating a generally smaller error when HRcorr is used (HRraw median RMSE= $6.1 \text{ ml.kg}^{-1}.\text{min}^{-1}$, HRraw median rRMSE= 32.6% vs HRcorr median RMSE= $4.4 \text{ ml.kg}^{-1}.\text{min}^{-1}$, HRcorr median rRMSE= 23.5%). This pattern (lower rBias and rRMSE with HRcorr) was present for most combinations of models and MWC methods except with StatCan which showed lower biases and lower rRMSE in 3 out of the 4 models with HRraw. However, these combinations still produced RMSEs that were slightly larger than the eight best performing combinations using HRcorr, among which IsoForm_HRcorr_Steptest and Malch_HRcorr_Steptest produced the lowest mean errors of all (RMSE = $2.3 \text{ ml.kg}^{-1}.\text{min}^{-1}$, rRMSE = 12.2 and 12.4%).

Among the MWC estimation methods, the Steptest produced the lowest RMSE and rRMSE compared to the other MWC estimation methods when HRcorr was used (Steptest ranked 1

column-wise with HRcorr on all four WM models in Table 4.4). When using the Steptest MWC method, the best results were achieved with IsoForm and Malch. When using HRraw, StatCan yielded the lowest RMSE and rRMSE with all four WM models (StatCan ranked 1 column-wise with HRraw with all four models in Table 4.4), whereas Jackson yielded the highest errors (Jackson ranked last column-wise with HRraw in all four models) (Table 4.4).

On a per WM model basis with HRcorr, IsoForm systematically ranked first with any MWC method, while Malch ranked second, Keytel1 third and Kamon last. With HRraw, no such systematic pattern was observable. Among the eight best performing combinations the IsoForm model with HRcorr together with Steptest, or Jackson, or MwcIso produced the lowest rBias (-2.0%, 2.0%, and -3.2%, respectively) and rRMSE (12.2%, 16.0%, 17.1%, respectively) pairs of all 40 combinations in Table 4.4. This is well illustrated in Figure 4.2 by the trend lines for these combinations being closer to the horizontal black line and with tighter LoA boundaries. Some of these best performing combinations produced a lower or comparable rBias but a higher rRMSE (Keytel1_HRcorr_MwcMalch with 0.8% and 24.9%, Malch_HRcorr_Jackson with -0.5% and 17.9%, Kamon_HRraw_StatCan with -2.1% and 26.1%), while the others produced a larger rBias and a comparable rRMSE (Malch_HRcorr_Steptest with -4.8% and 12.4%, Malch_HRcorr_MwcIso with -5.3% and 19.7%).

Table 4.4 WM (ml.kg⁻¹.min⁻¹) estimation results for the models using MWC as input (five MWC estimation methods), with raw (HRraw) and corrected HR (HRcorr), against measured WM (mean $\pm$ SD: 18.5 $\pm$ 4.8 ml.kg⁻¹.min⁻¹; range: 11, 31).

MWC method	Statistic	HRraw				HRcorr			
		Keytel1	IsoForm	Malch	Kamon	Keytel1	IsoForm	Malch	Kamon
Steptest	WM $\pm$ SD	26.7 $\pm$ 6.2	23.4 $\pm$ 6.5	23.0 $\pm$ 6.1	21.3 $\pm$ 7.3	20.1 $\pm$ 4.2	18.1 $\pm$ 4.6	17.6 $\pm$ 4.2	14.7 $\pm$ 5.6
	Bias $\pm$ SD _{diffs}	8.2 $\pm$ 4.6 * [†]	4.9 $\pm$ 3.5 * [†]	4.5 $\pm$ 3.1 * [†]	2.8 $\pm$ 4.6 * [†]	1.6 $\pm$ 3.4	-0.4 $\pm$ 2.3	-0.9 $\pm$ 2.1	-3.8 $\pm$ 3.1
	[95% LoA]	[-1.1, 17.5]	[-2.1, 11.9]	[-1.7, 10.8]	[-6.4, 12.1]	[-5.1, 8.4]	[-4.9, 4.1]	[-5.2, 3.4]	[-10.0, 2.5]
	rBias (%)	44.4	26.6	24.6	15.4	8.8	-2.0	-4.8	-20.5
	RMSE	9.4	6.0	5.5	5.4	3.7	2.3	2.3	4.9
StatCan	rRMSE (%)	50.9 {4, 3}	32.5 {3, 3}	29.7 {2, 3}	29.0 {1, 2}	20.0 {3, 1}	12.2 {1, 1}	12.4 {2, 1}	26.4 {4, 1}
	WM $\pm$ SD	24.7 $\pm$ 6.5	20.0 $\pm$ 5.2	19.8 $\pm$ 5.1	18.1 $\pm$ 6.3	18.1 $\pm$ 4.7	15.7 $\pm$ 3.8	15.4 $\pm$ 3.8	12.5 $\pm$ 5.0
	Bias $\pm$ SD _{diffs}	6.2 $\pm$ 5.6 * [†]	1.5 $\pm$ 3.5 [†]	1.3 $\pm$ 3.7 [†]	-0.4 $\pm$ 4.9 * [†]	-0.4 $\pm$ 4.7	-2.8 $\pm$ 3.1 *	-3.1 $\pm$ 3.3 *	-6.0 $\pm$ 3.9
	[95% LoA]	[-5.0, 17.5]	[-5.5, 8.5]	[-6.1, 8.7]	[-10.1, 9.3]	[-9.8, 9.1]	[-8.9, 3.3]	[-9.8, 3.6]	[-13.8, 1.9]
	rBias (%)	-33.6	8.3	7.2	-2.1	-2.0	-15.2	-16.8	-32.2
MwcMalch	RMSE	8.4	3.8	3.9	4.8	4.7	4.1	4.5	7.1
	rRMSE (%)	45.1 {4, 1}	20.5 {1, 1}	21.1 {2, 1}	26.1 {3, 1}	25.3 {3, 3}	22.3 {1, 5}	24.6 {2, 5}	38.5 {4, 5}
	WM $\pm$ SD	25.2 $\pm$ 6.8	21.0 $\pm$ 5.9	20.8 $\pm$ 5.8	19.2 $\pm$ 7.2	18.6 $\pm$ 4.9	16.4 $\pm$ 4.2	16.0 $\pm$ 4.2	13.2 $\pm$ 5.6
	Bias $\pm$ SD _{diffs}	6.7 $\pm$ 5.8 * [†]	2.6 $\pm$ 3.8 * [†]	2.3 $\pm$ 4.0 [†]	0.7 $\pm$ 5.4 * [†]	0.2 $\pm$ 4.7	-2.1 $\pm$ 2.9	-2.4 $\pm$ 3.2	-5.2 $\pm$ 4.1
	[95% LoA]	[-4.9, 18.4]	[-5.0, 10.2]	[-5.6, 10.3]	[-10.2, 11.6]	[-9.2, 9.5]	[-7.8, 3.6]	[-8.8, 3.9]	[-13.4, 2.9]
Jackson	rBias (%)	36.4	13.9	12.6	3.8	0.8	-11.3	-13.2	-28.4
	RMSE	8.9	4.5	4.6	5.4	4.6	3.5	4.0	6.6
	rRMSE (%)	47.9 {4, 2}	24.6 {1, 2}	24.6 {2, 2}	29.3 {3, 3}	24.9 {3, 2}	19.0 {1, 4}	21.5 {2, 4}	35.7 {4, 4}
	WM $\pm$ SD	27.0 $\pm$ 6.9	24.4 $\pm$ 6.4	24.1 $\pm$ 6.3	22.6 $\pm$ 7.9	20.4 $\pm$ 4.9	18.8 $\pm$ 4.5	18.4 $\pm$ 4.6	15.6 $\pm$ 6.1
	Bias $\pm$ SD _{diffs}	8.5 $\pm$ 5.8 * [†]	6.0 $\pm$ 4.1 * [†]	5.6 $\pm$ 4.3 * [†]	4.1 $\pm$ 6.1 * [†]	2.0 $\pm$ 4.6	0.4 $\pm$ 3.0	-0.1 $\pm$ 3.3	-2.9 $\pm$ 4.5 *
MwcIso	[95% LoA]	[-3.1, 20.1]	[-2.3, 14.2]	[-3.0, 14.3]	[-8.1, 16.3]	[-7.3, 11.2]	[-5.6, 6.3]	[-6.8, 6.6]	[-11.9, 6.1]
	rBias (%)	46.2	32.2	-30.5	22.2	10.6	2.0	-0.5	-15.7
	RMSE	10.3	7.2	7.1	7.3	5.0	3.0	3.3	5.3
	rRMSE (%)	55.6 {4, 5}	39.0 {2, 5}	38.3 {1, 5}	39.4 {3, 5}	26.8 {3, 5}	16.0 {1, 2}	17.9 {2, 2}	28.8 {4, 2}
	WM $\pm$ SD	26.2 $\pm$ 6.5	23.1 $\pm$ 5.5	22.8 $\pm$ 5.5	21.2 $\pm$ 7.0	19.7 $\pm$ 4.6	17.9 $\pm$ 3.9	17.5 $\pm$ 4.0	14.6 $\pm$ 5.5
	Bias $\pm$ SD _{diffs}	7.8 $\pm$ 5.7 * [†]	4.6 $\pm$ 3.9 [†]	4.3 $\pm$ 4.2 [†]	2.7 $\pm$ 5.8 * [†]	1.2 $\pm$ 4.8	-0.6 $\pm$ 3.1	-1.0 $\pm$ 3.6	-3.8 $\pm$ 4.4
	[95% LoA]	[-3.6, 19.1]	[-3.2, 12.5]	[-4.1, 12.8]	[-8.8, 14.3]	[-8.4, 10.8]	[-6.9, 5.7]	[-8.1, 6.1]	[-12.6, 5.0]
	rBias (%)	42.1	25.0	23.5	14.8	6.5	-3.2	-5.3	-20.8
	RMSE	9.6	6.0	6.0	6.3	4.9	3.2	3.6	5.8
	rRMSE (%)	51.9 {3, 4}	32.6 {1, 4}	32.6 {1, 4}	34.2 {2, 4}	26.4 {3, 4}	17.1 {1, 3}	19.7 {2, 3}	31.4 {4, 3}

* Indicates a significant scale effect, that is, regression of differences against mean of predicted and measured WM is statistically significant (p<0.05)

[†] Indicates a significant correlation between the differences (bias) and thermal pulses at p<0.05.

{L, C}: Performance ranking within each row and within each column based on RMSE; 1 is best performance. The bold numbers indicate the best performing combination line wise {1, C}; numbers in italic indicate best performance column wise {L, 1}.

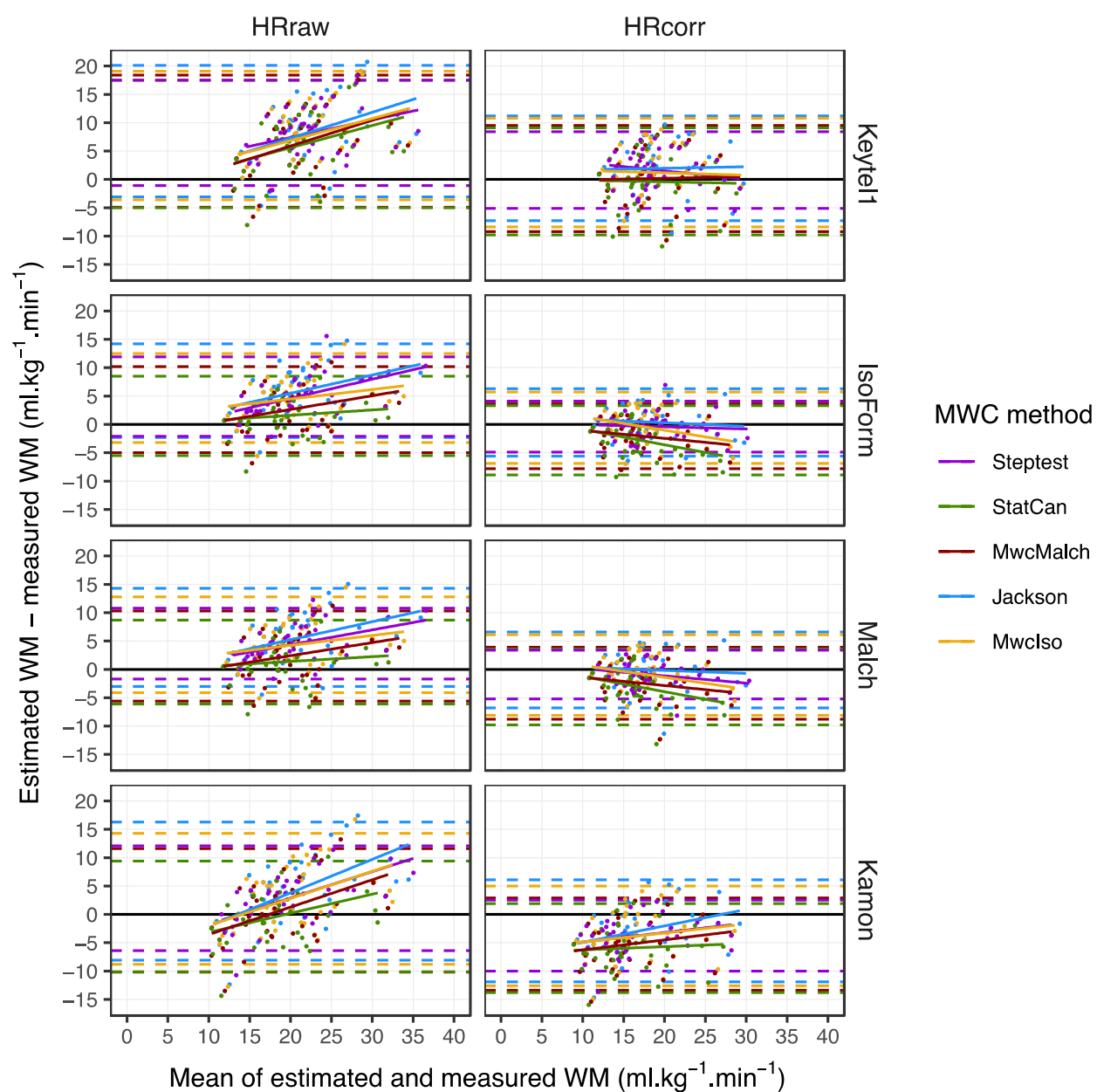


Figure 4.2 Bland-Altman (or difference) plots of estimated vs. measured WM for raw (HRraw) and corrected HR (HRcorr) for models using MWC as input. Mean bias is indicated by a colored solid line and LoA are indicated with dashed lines.

4.3.2 WM models not using MWC as input

Among the WM models not using MWC as an input rBias and rRMSE ranged widely, that is, from -61.9% (Rennie_HRcorr) to 62.0% (Keytel2_HRraw) for rBias and from 12.8% (Dube_HRcorr) to 71.3% (Keytel2_HRraw) for rRMSE. The Dube WM model with HRcorr yielded the best performance of all 10 model combinations not using MWC (Table 4.5) (rBias= -3.6%, rRMSE=12.8%), while the Ueno model achieved the second-best performance with HRraw (rBias= -1%, rRMSE=17.6%). IsoTable with HRcorr performed slightly less well (rBias= -11.7%, rRMSE=23.7%). Figure 4.3 shows that the mean bias trend lines for these model combinations are the closest to the zero-mean bias (black horizontal) line, among the 10 not using MWC.

The Dube_HRcorr RMSE ranked 3rd among all 50 combinations tested in this study, while the Ueno_HRraw was 6th. The WM models producing the largest errors were Rennie_HRcorr, and Keytel2_HRraw.

Table 4.5 WM (ml.kg⁻¹.min⁻¹) estimation results for models not using MWC as input, for raw (HRraw) and corrected HR (HRcorr), against measured WM (mean $\pm$ SD: 18.5 $\pm$ 4.8 ml.kg⁻¹.min⁻¹; range: 11.5, 31.4).

Statistic	HRraw					HRcorr				
	Dube	Keytel2	Rennie	Ueno	IsoTable	Dube	Keytel2	Rennie	Ueno	IsoTable
WM $\pm$ SD	23.3 $\pm$ 5.8	29.9 $\pm$ 7.2	9.1 $\pm$ 1.6	18.3 $\pm$ 4.6	21.8 $\pm$ 6.2	17.8 $\pm$ 3.8	23.4 $\pm$ 5.0	7.0 $\pm$ 1.0	14.5 $\pm$ 3.7	16.3 $\pm$ 4.6
Bias $\pm$ SD _{diffs}	4.9 $\pm$ 3.4 * [†]	11.5 $\pm$ 6.6 * [†]	-9.4 $\pm$ 4.6 *	-0.2 $\pm$ 3.3 [†]	3.3 $\pm$ 4.7 * [†]	-0.7 $\pm$ 2.3 *	4.9 $\pm$ 5.3	-11.4 $\pm$ 4.5 *	-4.0 $\pm$ 2.9 *	-2.2 $\pm$ 3.9
[95% LoA]	[-2.0, 11.7]	[-1.7, 24.6]	[-18.6, -0.2]	[-6.7, 6.4]	[-6.2, 12.8]	[-5.3, 3.9]	[-5.6, 15.5]	[-20.5, 2.4]	[-9.8, 1.8]	[-9.9, 5.6]
rBias (%)	26.4	62.0	-50.8	-1.0	17.8	-3.6	26.6	-61.9	-21.7	-11.7
RMSE	5.9	13.2	10.4	3.2	5.7	2.4	7.2	12.3	4.9	4.4
rRMSE (%)	32.1 {3}	71.3 {5}	56.5 {4}	17.6 {1}	30.9 {3}	12.8 {1}	38.7 {4}	66.4 {5}	26.7 {3}	23.7 {2}

* Indicates a significant scale effect, that is, regression of differences against mean of predicted and measured WM is statistically significant (p<0.05)

{ }: Performance ranking within the row based on RMSE; 1 is best performance. The bold numbers indicate best performing combination based on RMSE or rRMSE.

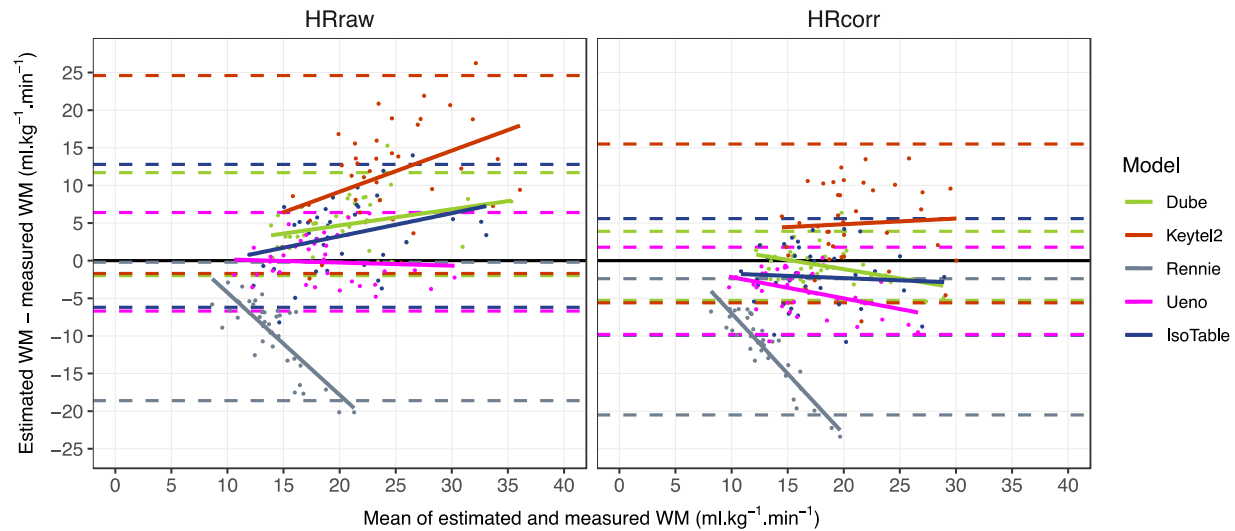


Figure 4.3 Bland-Altman (or difference) plots of measured vs. estimated WM for raw (HRraw) and corrected HR (HRcorr) for models not using MWC as input. Mean bias is indicated by a colored solid line and LoA are indicated with dashed lines.

4.3.3 Biases and agreement

Ten model combinations produced rRMSE at or lower than 20.0% and with an absolute rBias at or lower than 11.3%. Only one of these models used HRraw (Ueno). Among these, the three best performing used HRcorr and produced the smallest rBias and narrowest LoA (i.e., $\leq \pm 4.6 \text{ ml.kg}^{-1}.\text{min}^{-1}$ or $\pm 25\%$: IsoForm_Hcorr_Steptest, Malch_HRcorr_Steptest, Dube_HRcorr), while the other 7 combinations showed fairly similar performance with four showing the narrowest LoA (i.e., $\leq \pm 6.6 \text{ ml.kg}^{-1}.\text{min}^{-1}$ or $\pm 36\%$: Isoform with HRcorr and either Jackson or MwcIso, Malch_HRcorr_Jackson, Ueno_HRraw).

Table 4.4 and 4.5 show that 24 out of the 50 model combinations have a statistically significant regression ($F > 4.1$, $p < 0.05$) of the differences against the mean of predicted and measured WM. This indicates the presence of a significant scale effect that can be readily observed in Figures 4.2

and 3 by a mean-bias trend that is not parallel to the zero-bias line. The scale effect is more frequent with HRraw (18 combinations out of 25 vs 6 combinations with HRcorr) and is most often towards overestimation with HRraw. A further analysis showed a significant correlation and linear trend between bias and thermal pulses in almost all models with HRraw (24 combinations out of 25) vs HRcorr (no combinations). This indicates that WM estimation errors may be affected by the level of thermal pulses present when HRraw is utilized in models, as showed by Dubé et al. (2016).

4.4 Discussion

The nine HR-based models compared in this study produced a wide range of WM estimates, with absolute rBias ranging from 1.0% to 62.0%, and rRMSE ranging from 12.2% to as high as 71.3% with respect to the measured WM (the reference). The models using MWC as an input tended to produce better estimations of the measured WM (e.g., rBias and rRMSE from Keytel1 vs Keytel2). As shown by a number of authors (Vogt et al., 1970, 1973, Dubé 2015, 2016 and 2019; Bröde and Kampmann 2019), the presence of a thermal strain in HRraw degraded WM estimation by increasing the magnitude of errors in 80% of the model combinations. Clearly, the ergonomics expert can expect large variations in her or his WM estimation from HR measurements depending on the model and parameter combinations she or he happens to pick.

Model performance degradation when using HRraw comes from the fact that the thermal pulses (indicative of thermal strain), a non-metabolic HR elevation, reduces the slope of the WM-HR relationship, the higher the thermal pulses, the lower the slope. Hence, to predict measured WM accurately from HRraw a lower MWC value would "theoretically" need to be used to compensate for the thermal pulses in the models that require it. This is well illustrated by the better performance produced by the four WM models with HRraw when the StatCan MWC was used as input (StatCan ranked first column-wise with all four models with HRraw in Table 4.4). This result is associated

with the fact that the StatCan group mean MWC (Table 4.3) was lower than those of the other MWC methods and hence prediction with HRraw was improved. The difficulty with using HRraw is that it is impossible to select the right MWC figure that will compensate an unknown level of thermal pulses that can be expected to vary widely from one work setting to another, unless it is determined with the method from Vogt et al. (1973) for instance in which case HRcorr would be used instead of HRraw. HRraw can thus never be used to accurately predict WM unless one is certain that no thermal strain is present. In this study, the 50th percentile MWC from StatCan data was arbitrarily selected at the start of the study, however if a lower percentile had been used to better take into account the fact that our forest workers were exposed to thermal stress, then the models would all have overestimated less with HRraw and underestimated more with HRcorr. Figure 4.4 illustrates this very well, as with HRraw the 25th percentile MWC StatCan (orange line) predicts WM better than the 50th percentile (green line) and even much better than the 75th percentile (light blue line). Clearly, the 25th percentile does not reflect the well above average physical condition of our forest workers as indicated by the large gap between the mean Steptest MWC and the mean StatCan MWC in Table 4.3. On the other hand, with HRcorr, the 75th percentile line is closer to the zero-bias line than both 50th and 25th percentiles, which both clearly underestimate WM (Figure 4.4). Using the data from this study an average 16 bpm thermal pulses was estimated for the group of 39 participants, which translates to a theoretical equivalent 11 ml.kg⁻¹.min⁻¹ reduction in MWC needed to achieve perfect prediction with HRraw, that is, a 25% reduction of the 42.6 ml.kg⁻¹.min⁻¹ MWC group mean determined with the step-test (Table 4.1). Wingo et al. (2012) have also brought the idea that cardiovascular drift due to heat stress (e.g., thermal pulses) can be translated into a consequent reduction in MWC.

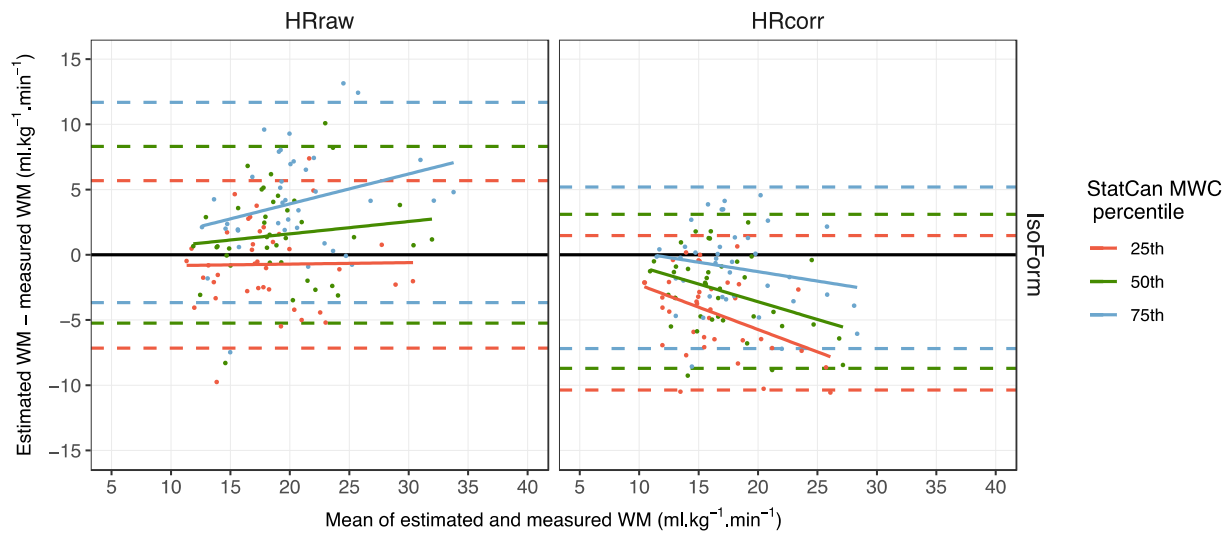


Figure 4.4 Bland-Altman (or difference) plots of measured vs. estimated WM for raw (HRraw) and corrected HR (HRcorr) for the IsoForm model and three different StatCan MWC percentiles (25th, 50th and 75th). Mean bias is indicated by a colored solid line and LoA are indicated with dashed lines.

A similar logic applies, albeit to a lesser extent, with the physical condition of the participants in relation to the population group from which an MWC figure is extracted. In this study, it was suspected that the forest workers likely had a higher MWC than the average Canadian male worker, and hence that the 50th percentile value of the age group of each participant in the StatCan data would likely underestimate the mean MWC for this group of workers. Until the step-test was conducted it was not possible to know what percentile of the Canadian male worker population would best describe the forest workers. The comparison between the IsoForm_HRcorr_Steptest and the IsoForm_HRcorr_StatCan shows that picking an arbitrary 50th percentile changed the rBias from -2.0% to -15.2%, that is, a 7-fold change (Table 4.4). The same logic applies to the Malch WM model with MWC values from the step-test compared to those from StatCan. The use of any equation or tabulated data on MWC from different reference populations (different age, weight,

height, BMI, gender, MWC, etc.) will likely introduce an estimation bias on WM with varying degrees as shown in this study (Table 4.4 and Figure 4.4), and as proposed by others (Colditz and Henderson-Smart, 1990; Sallis, 2000). With HRraw, the thermal pulses and physical condition relative to the reference population both contribute to the WM estimation error with respect to the WM measured value (Table 4.4).

The advantage of the step-test is that it does not force one to formulate assumptions about the MWC of the workers being studied since the slope of the WM-HR relationship is determined directly from the (WM, HR) data pairs collected at the different levels of exertion without further assumptions on rest metabolism nor HRmax. On the other hand, its main disadvantage is that it requires time to administer (approximately 30 min) and equipment (metronome, bench). For the ergonomics expert who does not have the opportunity to calibrate the participants, the IsoForm, and Malch models seem to offer very good alternatives with either the Jackson or MwcIso methods at least for our group of forest workers. Results from Table 4.4 show that these models produced estimates that were very close to those from the Dube WM model. This was to be expected particularly when Steptest MWC was used in IsoForm and Malch; the Dube model uses the data pairs from the step-test to determine the WM-HR relationship, while the Steptest MWC is the result of an extrapolation of that relationship to HR_{max} (with $HR_{max} = 220 - \text{age}$). This in itself shows that when the MWC of the workers to be studied can be determined then WM prediction obtained with Malch or IsoForm are virtually the same as those obtained with the Dube WM model. However, the MWC of the workers is rarely known and to know it requires some kind of calibration. Therefore, if a calibration is performed then a WM-HR relationship can be determined for each participant, and that relationship might as well be used either directly as in the Dube model, or to determine a calibration MWC that can be used in the IsoForm and Malch models.

One difference between IsoForm and Malch is that they do not use the same HR_{max} (see Appendix A), HR_{rest} , and MWC prediction equation. Malch uses HR_{99} which may be slightly different from HR_{rest} used in IsoForm and the Dube model. The results also show that both of these models (IsoForm, and Malch) perform slightly less well when the MWC value is determined with a method other than individual calibration with extrapolation to HR_{max} , as the errors increase slightly with IsoForm and more so with Malch when the other MWC methods are used. Contrary to the assertion of Malchaire et al. (2017) that their model produces the best WM estimates, IsoForm seemed to work slightly better for the forest workers of this study, as shown by its systematically better rankings owing to lower errors and narrower LoA in Table 4.4. It would seem that the WM-HR relationship of our workers was better reflected by the IsoForm_HRCorr_MwcIso combination (ISO 8996:2004) than the updated equations proposed by Malchaire et al. (2017). In summary, the IsoForm and Malch models with Jackson or MwcIso MWC methods represent very easy and appealing alternatives to the use of a step-test.

The Kamon and Keytel1 WM model did not perform as well as the Malch and IsoForm. With HRraw, both models systematically overestimated actual WM except for Kamon with StatCan MWC, while with HRcorr Kamon systematically underestimated, while Keytel1 overestimated except with StatCan MWC (Figure 4.2 and Table 4.4).

The Ueno model is the only one that performed very well with HRraw, that is, without the need to assess the thermal pulses and determine HRcorr. The good estimation performance of the Ueno model with HRraw can be explained by the fact that it includes dry bulb temperature as an input (from 25°C to 35°C), that is, one of the 6 parameters contributing to thermal strain (relative humidity, dry bulb temperature, radiant temperature, air velocity, WM, clothing insulation) (ISO 7933:2004). By including one of the thermal environment parameters, the model is able to capture at least partly the effect of the thermal environment on measured HR. Second, the Ueno model uses

percent body fat, a parameter related to a participant's MWC as captured by the model from Malchaire et al. (2017) through the ideal weight (or lean weight) (Appendix A). Hence, judging by its quite small -1% rBias and fairly narrow LoA [$\pm 36\%$] the Ueno model uses a different and quite efficient strategy to consider the effect of the thermal environment and the participant's physical work capacity. From a practical point of view, the estimation of percent body fat using the Ueno et al. (2014) model as well as measuring dry bulb temperature in some workplaces may be much simpler than estimating the thermal pulses with any of the two methods available for that purpose (Dubé 2019). The Ueno model thus presents a nice option to the ergonomics expert studying relatively dry work environments since the authors developed their model in a controlled chamber at 40% humidity. The authors do not specify what the air velocity was, nor the radiant temperature, therefore, it might be interesting to test the robustness of their model and maybe improve it with additional combinations of relative humidity, radiant heat and air velocity.

The main advantage in determining the thermal pulses is that it integrates the effect of all four thermal environment parameters as well as that of clothing insulation without the need to measure any of them, as measuring them may prove to be difficult in some work environments. For instance, when the workers have extended workplaces where they constantly move between different locations with varying thermal environments (e.g., construction industry) or work with large tools in changing postures, locating the measuring instruments so as to protect them from worker movement while collecting representative exposure data may be difficult. In many cases, mounting the measuring instruments on the worker can quickly lead to their destruction. In such cases, determining the thermal pulses appear as a good option. Among the models tested in this study with HRcorr, the very best estimations were obtained with models that used the participant's WM-HR relationship established through a submaximal step-test from Meyer and Flenghi (1995) together with the equation improved by Dubé et al. (2015) (Dube, IsoForm, Malch). These

combinations produced very small rBias ($<5\%$), the lowest rRMSE ($\leq 13\%$) and the narrowest LoA ($\leq \pm 4.6 \text{ ml.kg}^{-1}.\text{min}^{-1}$ or $\pm 25\%$). This result shows that individual calibration with a submaximal step-test can yield accurate WM estimations.

Besides the Ueno model with HRraw and the Dube model with HRcorr, the IsoTable performed surprisingly well among models not using MWC as an input, slightly underestimating with HRcorr. It thus seems that the slope of the WM-HR relationships in IsoTable would need to be slightly steeper to better reflect the higher than average MWC of our forest workers when HRcorr is used. The Keytel2 and Rennie models underperformed compared to the others (Figure 4.3). The results for the Rennie model suggest that the HR-Flex model may underestimate WM in daily work (Table 4.5) as supported by Johansson et al.'s findings (2006).

The 95% LoA draws a picture of the prediction accuracy that an ergonomics expert could expect when evaluating WM for a single participant. RMSE and bias, on the other hand, show how accurate a method can be when WM is obtained and averaged for a number of instances or a group of participants, that is, a group of 39 participants in this study. In the context of most ergonomics experts, the number of workers who usually can be practically monitored is much smaller, and hence with a smaller sample, the estimation errors can be expected to be much larger than those reported here. According to ISO 8996:2004 WM prediction from work HR measurements offers a $\pm 10\%$ error, but Malchaire et al. (2017) reported that the error is likely closer to $\pm 14.5\%$ for the work rate measured in this study ($18.5 \text{ ml.kg}^{-1}.\text{min}^{-1}$ = close to 480 Watts). If rRMSE best describes these errors, then only the three model combinations using step-test data and HRcorr meet these levels (IsoForm_HRcorr_Steptest with rRMSE=12.2%, Malch_HRcorr_Steptest with rRMSE=12.4%, and Dube_HRcorr with rRMSE=12.8%), while two other combinations come fairly close (IsoForm_HRcorr_Jackson with rRMSE=16.0% and IsoForm_HRcorr_MwcIso with rRMSE=17.1%). On the other hand, if the error in ISO 8996:2004 and in Malchaire et al. (2017) is

best described by rBias, then with HRraw, 7 models produced an rBias smaller than $\pm 14.5\%$, while 5 produced an rBias smaller than $\pm 10\%$ (Figure 4.5). Using the equation proposed by Bland and Altman (1986), and solving for N, one finds that among the models using HRraw, the Ueno is the best performing by far, and to achieve a $\pm 14.5\%$ accuracy on a mean prediction bias using this model, a group of 7 participants would be required (Figure 4.5), which is practical in many field interventions. To achieve $\pm 10\%$ with the Ueno model, 16 participants would be required, which represents a somewhat large sample in many field studies. On the other hand, with HRcorr 15 models produced a rBias lower than $\pm 14.5\%$ of the mean measured value, while 11 models produced a mean bias lower than $\pm 10\%$. Among these models, six of them offer the possibility to achieve a $\pm 14.5\%$ accuracy on a group mean prediction bias with 10 participants or fewer (Figure 4.5). The other models require 17 or more participants. If the physical activity level can be correctly estimated and the thermal pulses determined, then the most practical model combinations are either the Malch_Jackson or the IsoForm_Jackson since they do not require a step-test and only 7 participants to obtain a WM prediction from HRcorr with $\pm 14.5\%$ accuracy on the group mean prediction bias 95% of the time. If the thermal pulses cannot be determined, then the Ueno model is the only option requiring 7 participants to achieve $\pm 14.5\%$ accuracy.

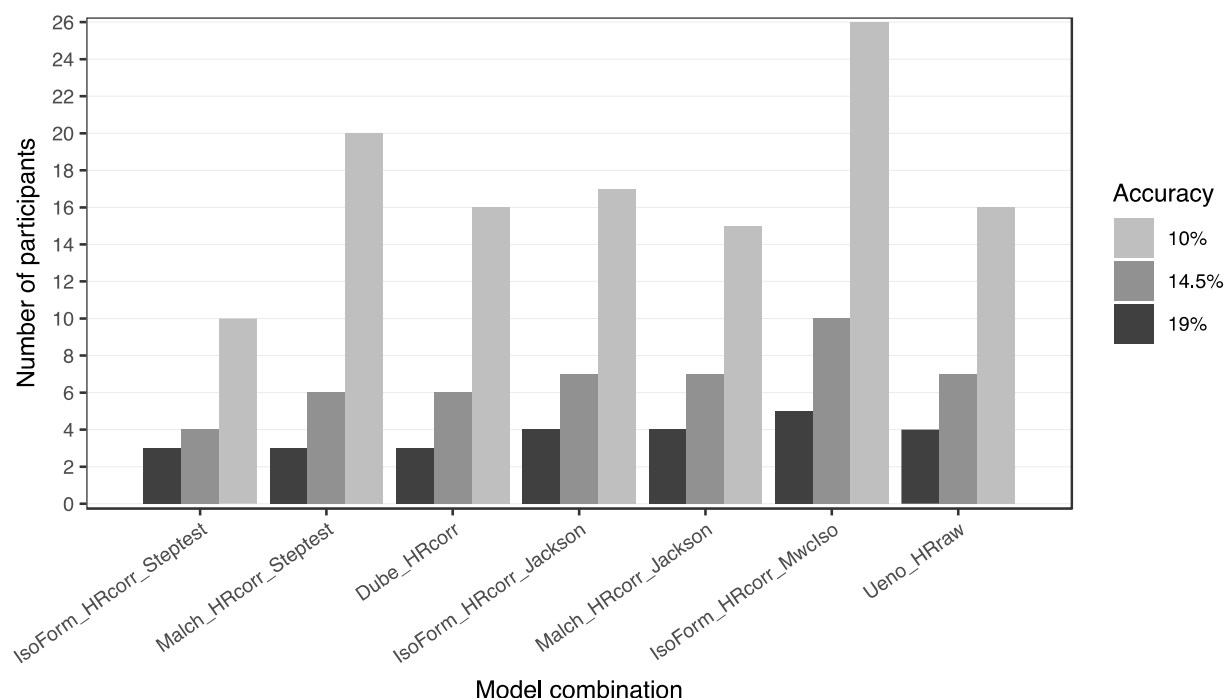


Figure 4.5 Sample sizes required with the seven best performing model combinations for different accuracy levels.

One of the frequent uses of HR-based models to estimate WM is in the assessment of heat stress through indices such as the WBGT (ACGIH 2018). For instance, according to ACGIH (2018) a 27 °C WBGT limit is associated with a 480 Watts metabolic rate ($18.5 \text{ ml.kg}^{-1}.\text{min}^{-1}$) as measured in this study when that work level is performed by acclimatized workers during up to 45 minutes per hour with the remaining 15 minutes resting (115 Watts) in the same environment (i.e., 45/15 work/rest cycle in a 27 °C WBGT environment). For work to be performed continuously (i.e., without rest) by acclimatized workers during 60 minutes at 27 °C WBGT, the work rate must not exceed 390 Watts according to ACGIH (2018), that is, about 19% lower than 480 Watts. Hence, in an environment where the measured WBGT is 27 °C underestimating the true WM by 19% would likely entail a risk of heat stress since it could lead to a wrong decision, that is, that the worker can work continuously during the hour rather than with a 45/15 work/rest cycle. Using the same logic as in the preceding paragraph, seven models could be used to achieve $\pm 19\%$ accuracy

on the group mean with 5 or fewer participants (Figure 4.5). If the thermal pulses will not be determined, then the Ueno model with HRraw is the most practical since with 4 participants only and no step-test it can achieve $\pm 19\%$ mean bias. It must be noted that at lower work rates, a 19% bias on WM will likely lead to a larger WBGT difference since the relationship between WBGT and WM is logarithmic. Therefore, to keep the WBGT difference within 1 °C, for instance, the WM estimation error needs to be smaller, and hence one should expect to use a larger number of participants with the best performing models tested in this study.

4.4.1 Study limitations

This study is based on a group of experienced male forest workers performing their regular work in the usual conditions. Caution is thus warranted when applying this study's results to a female worker population. Since the workers in this study had a higher MWC than their reference population (Canadian male workers from Statistics Canada, 2013), it would be interesting to test the same models on a group of workers whose characteristics, including MWC are closer to the average of the general worker population. Also, the MWC methods tested in this study are based on worker populations from Western countries, such that they may not be transferable to other populations. For instance, according to Westerterp et al. (2019), the WM predicted values of Asian subjects by the Western subjects-based equations using height, weight, age, and gender were significantly higher than actual WM values. Regarding models' implementation, it should be noted that only a limited range of PAL (Physical Activity Level) values was observed in our dataset for the application of Jackson's MWC formula; all workers classified as level 7 for PAL. Despite this limited range of PAL values in our dataset, results show that Jackson's formula performed well, but one should exercise care when applying the results to other groups with varying level of physical activity. Finally, care should be exercised when applying the results of this study to types

of work that are different from forest work (i.e., mostly dynamic muscular work involving large muscle groups with little or no static work and little psychological stress).

4.5 Conclusion

This study compared a sample of HR-based WM estimation models on a dataset collected from a group of experienced male forest workers performing their actual work in usual thermal conditions. Each model's group mean WM estimate was compared to the mean measured WM. Results indicated that the use of individual calibration (i.e., determination of the WM-HR relationship from a submaximal step-test) produced the most accurate WM estimates, however, a few models not using calibration also produced very good accuracy. The presence of a thermal component degraded prediction significantly and thus needs to be considered if accurate WM prediction is to be achieved with most HR-based models. Results also show that models including MWC do provide better WM estimates. On the other hand, among the models not using MWC as an input, the single model that includes a thermal environment parameter (dry bulb temperature) performed very well, thus offering a quick and easy alternative to the ergonomics expert who does not require the utmost accuracy in WM estimation. From the results of this study, professionals who need the most accurate WM estimations with the smallest number of participants in their intervention are highly encouraged to use individual calibration to estimate MWC of the participants, and to determine the thermal pulses if the presence of heat strain is suspected. If calibration cannot be used, then the model from ISO 8996:2004 used with its accompanying MWC method or the method proposed by Jackson et al. (1990) will offer very good accuracy if the thermal pulses are determined. The model from Malchaire et al. (2017) together with the Jackson MWC method will also provide very good accuracy. When neither thermal pulse determination nor calibration are considered, then the model from Ueno et al. (2014) offers a very good alternative. This study further

shows that the best performing model combinations provide accurate enough estimates (i.e., small rBias) of heavy work rates to allow the assessment of thermal stress with the WBGT index.

4.6 Statement of authors' contributions

- Sahar Arab: statistical analysis, implementation of algorithms, running the algorithms to get results, creation of tables, drawing figures, partial data cleaning, writing the paper. 40%
- Philippe-Antoine Dube: data collection and cleaning, proof reading, comment, proposing the structure of tables. 20%
- Denise Dubeau: proof reading, comments, checking the results. 10%
- Isabelle Augur: commenting on the statistical aspects, drawing LoA figures. 10%
- Daniel Imbeau: proofreading, partial writing, interpretation of results, comments. 20%

CHAPTER 5 RESEARCH 2: REGRESSION DECISION TREE WITH K-FOLD CROSS-VALIDATION TO PREDICT WORK METABOLISM BASED ON HEART RATE IN FOREST WORKERS

5.1 Overview

In Chapter 4, we used statistical analysis as a prescriptive data analytics tool to evaluate the accuracy and robustness of various work metabolism (WM) prediction models in the literature. Our results indicated that those existing models in the literature that are fairly accurate and reliable require individual calibration or the computation of thermal pulse, which is quite unfavorable and complicated for practitioners. Inspired from Chapter 4, in this chapter, we aim at proposing novel prediction models which do not necessitate the use of either individual calibration or thermal pulse.

In this chapter, we present new regression decision tree (RDT) models that use k-fold validation to predict work metabolism (WM). A total of 41 forest workers participated in the data collection including a combination of brushcutters and tree planters from various areas of the Province of Québec (Canada), and their heart rate (HR) and oxygen consumption ($\dot{V}O_2$) were measured. All RDT models (RMSE = < 3.08 ml/kg/min) including the averaged model (RDT_AV) (RMSE = 2.67 ml/kg/min) outperformed the model proposed by Ueno et al. (2014) (RMSE = 4.41 ml/kg/min) and the model from ISO 8996:2004 that uses maximum work capacity method proposed by Statistics Canada (2013) (RMSE = 4.65 ml/kg/min). The RDT models hence offer practitioners a practical, cost- and time-efficient method for WM estimation without the need for the determination of the thermal component.

5.2 Introduction

Ergonomics practitioners measure work metabolism (WM) to evaluate the physical demands of work considering the thermal stress indices such as Thermal Work Limit (TWL), Predicted Heat Strain (PHS), and Wet-Bulb Globe Temperature (WBGT) (ISO 7933 2004; ISO 11079 2008; ISO 7730 2006). Measuring WM is crucial as it can cause undue fatigue that can endanger worker health and safety and also result in the reduction of work quality and productivity (Chengalur, Rodgers, and Bernard, 2004). WM assessment is also helpful in determining work-rest regimens for physical work. According to Chapter 4, WM can be estimated by measuring oxygen consumption ($\dot{V}O_2$) during the work activity. All existing models analyzed in Chapter 4 were simple regression models. However, currently there are more complicated machine learning (ML) algorithms that can potentially provide more accurate predictions.

Decision tree (DT) is one of the most widely used ML techniques that is applied particularly for the approximation of nonlinear functions. The main advantage of a decision tree is that it finds the best linear/nonlinear combination of predictive features. The combination of predictive features generated by a decision tree can be represented as interpretable rules or logic statements. An extension of DT is referred to as regression decision tree (RDT), which is a DT algorithm applied for regression problems. An RDT discovers the linear and non-linear relationships between predictor and output variables. This method fits a regression model at each node and predicts based on the combination of the models at terminal nodes (Youngjae Chang and Hyeonsoo Kim, 2011). The results from Loh (2002) show that the RDT can be used as a good fitting method for nonlinear regression problems. An RDT determines a piecewise function by solving a nonlinear programming model (Toms and Lesperance, 2003; Strikholm, 2006; Greene et al, 2015).

In Chapter 4, we demonstrated that the most reliable and accurate prediction models in the literature necessitate either individual calibration or the determination of the thermal pulse. However, the computation of individually calibrated data and also thermal pulses for each worker for each data record is quite costly and timely. Therefore, these models from the literature are not easily applicable and practical in the real world. The other shortcomings of the models analyzed in Chapter 4 is that they are all simple regression-based models which ignore the nonlinear relationship between input variables.

Motivated by the above shortcomings, in this study, we develop a series of regression decision tree models for predicting worker's metabolic rate (WM) by utilizing variables that can be readily measured in a workplace setting, such as the raw heart rate (HR), without the calculation of the thermal pulse. By doing so, our proposed models can be easily utilized by practitioners. Our proposed regression decision tree models are developed based on a mixed-integer programming formulation, which take into account HR, physical characteristics, and ambient conditions. These models also account for the nonlinear relationship between these variables. To develop and test our proposed models, we utilize the raw HR and $\dot{V}O_2$ values collected in the field. Our computational analysis indicates that our proposed models are exceptionally precise and surpass conventional methods, such as the Ueno et al. (2014) and ISO 8996 models that were vastly analyzed in Chapter 4.

5.3 Methods

The data collected in this study were measured in the months of July to October between 2008 and 2013. This data collection was performed during four research projects on physical workload and productivity of forest workers in the province of Québec, Canada. The participants' selection criteria included two aspects: 1) they needed to have at least three years of work experience and 2)

voluntarily participated in the study. All data of this study were approved by Polytechnique Montréal's Research Ethics Committee (CÉR-07/08-17, CÉR-08/09-14, and CÉR-11/ 24-04). The data for this study come from the dataset assembled and used by Dubé et al. (2015, 2016, 2019) and the author of this dissertation did not have any role in the data collection procedure.

In Section 4.2.2, we described how the HR and VO₂ values were measured. Apart from these two types of measurements, the following measurements were taken as we needed all these measurements in our studies: 1) body temperature, which was measured by the temperature intra-abdominal using the Jonah® thermal capsule (Philips Respironics, Murrysville, PA). 2) Thermal environment measurements, which consisted of the air temperature (T_a ; °C), the temperature psychrometric humidity (T_h ; °C), black globe temperature (T_g ; °C), relative humidity (RH; %), atmospheric pressure (P_a ; kPa) and air velocity (V_a ; m/s). These measures were taken at each data collection using a weather station mounted on a tripod near the site where the forestry worker carried out his work. Measurements were taken at intervals of 10 seconds, the smallest interval possible to record values over a full day of work depending on the memory of the device used. 3) Clothing isolation which was estimated summing the individual values of the pieces of clothing worn from the tables in the standard ISO 9920:2007. 4) Characteristics of workers such as age, weight and height. The subject was weighed in the morning before lunch when possible (at the forest camp) or at the workplace (forest path) using a portable scale.

We note that although the aforementioned data set dates back to 2008, it is still reliable and worthy of research for two reasons: 1) the nature of forestry jobs for physical workers has not changed in the past 15 years, and 2) the devices used for measuring heart rate and oxygen consumption have not been upgraded with new technology that shows any significant differences between the previously collected data and the newly collected data. Therefore, the aforementioned

data set still provides a reliable basis for conducting significant research in the field of physical ergonomics for forestry workers.

5.3.1 Participants

The participants of this study are 41 healthy forest workers including seven tree planters and 34 brushcutters with a minimum three-year experience from various areas of the province of Québec. They all signed an informed consent form before participating in the study, and then completed a Physical Activity Readiness Questionnaire, (PAR-Q; Thomas et al., 1992). Table 5.1 shows the participants' characteristics.

Table 5.1 Description of participants' characteristics and ambient conditions during data collection.

Variables	Learning set (n=34) Mean $\pm$ SD (range)	Test set (n=7)
Participants:		
Age (years)	44.4 $\pm$ (20.0 – 67.0)	54.8 $\pm$ 6.3 (44.0 – 64.0)
Weight (kg)	76.8 $\pm$ (53.5 – 100.0)	74.71 $\pm$ 8.0 (63.5 - 86.2)
Height (m)	1.7 $\pm$ (1.6 - 1.9)	1.7 $\pm$ 0.1 (1.6 - 1.8)
BMI ^a (kg.m ⁻²)	25.0 $\pm$ (19.0 - 30.1)	25.0 $\pm$ 2.3 (22.8 - 29.8)
HR _{rest} ^b (bpm)	64.0 $\pm$ (42.0 – 80.0)	58.9 $\pm$ 4.8 (53.0 - 68.0)
Ambient conditions:		
Ta (°C)	17.9 $\pm$ 9.9 (7.2 - 26.4)	15.1 $\pm$ 6.7 (9.4 - 23.3)
Tg (°C)	22.52 $\pm$ 7.8 (8.9 - 35.7)	21.05 $\pm$ 11.2 (10.5 - 33.7)
RH (%)	71.7 $\pm$ 22.4 (30.1 - 99.1)	77.3 $\pm$ 14.5 (53.88 - 88.23)
Va (m.s ⁻¹)	0.9 $\pm$ 0.8 (0.1 - 4.1)	0.2 $\pm$ 0.2 (0.0 - 0.6)
WBGT (°C)	20.3 $\pm$ 3.5 (8.9 - 35.6)	15.6 $\pm$ 6.4 (10.1 - 22.9)

^a BMI: body mass index.

^b HR_{rest}: seated resting heart rate (beats per min - bpm).

Ta = dry-bulb temperature; Tg = globe temperature; RH = relative humidity;

Va = air velocity; WBGT = Wet-bulb globe temperature.

The data used in this chapter is based on the same dataset as Chapter 4, with the exception of two additional forest workers who were not included in the previous chapter. These two workers'

data were made available after the publication of Chapter 4 as an article. Thus, the research in the current chapter includes a total of 41 forest workers, consisting of the original 39 workers from Chapter 4 and the newly added two workers.

5.3.2 Data collection procedure

We have previously explained the data collection procedure in Chapter 4. Here, we will provide a brief review of the same procedure. The forest workers did not smoke, drink coffee, or engage in a demanding activity during the morning of the day that the data were collected. One of the researchers explained the experimental procedures to the forest workers either outside the forest camp where they lodged or on the side of the road near their worksite one the day before the data collection.

HR values were recorded until the end of the workday by RS800, Polar Electro Oy, Kempele, Finland. $\dot{V}O_2$ measurements were also observed using a Fitmate Pro from Cosmed, Rome, Italy, or a K4b² from Cosmed, Rome, Italy. These measurements were performed during a work period (average: 31.5 min, range: 11-74 min) and an ensuing 10-min seated rest pause (average: 9.9 min, range: 8-12 min). According to manufacturers' requirements, the $\dot{V}O_2$ measurement instruments were calibrated one day before the data collection. $\dot{V}O_2$ was recorded at 1-min intervals. HR data was averaged to 1-min intervals during the work period to match the $\dot{V}O_2$ measurement rate. The Fitmate Pro and K4b² apparatuses are recognized to overestimate $\dot{V}O_2$, and therefore the measured values were altered as in Dubé et al. (2015) and Duffield et al. (2004).

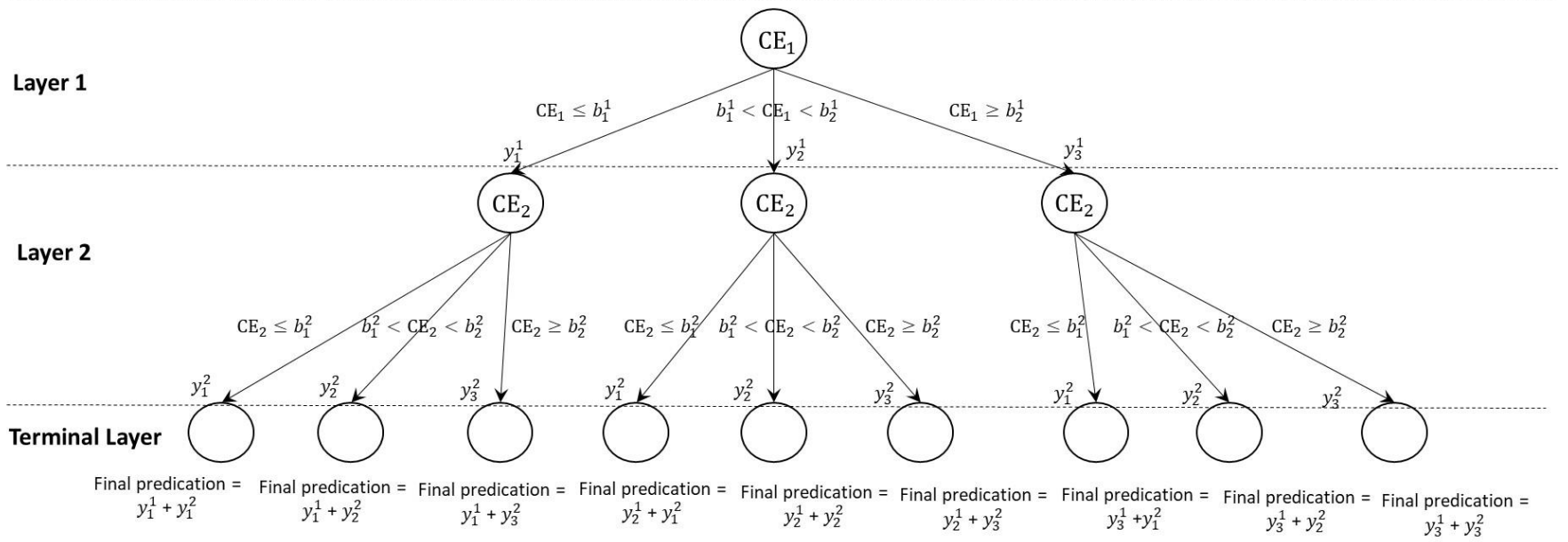
The dataset included $\dot{V}O_2$, HR measurements, individual participants' physical characteristics (age, weight, height, and BMI), and ambient conditions (ta). The data of 34 participants were

considered as learning data (1048 data samples) and the data of 7 participants were considered as test data (174 data samples).

5.3.3 Model development

In this study, we propose RDT models based on a novel mixed-integer programming formulation. The proposed approach finds a linear combination of input variables, referred to as conditional expressions, to be evaluated in different levels of the decision tree. Each developed RDT model partitions the possible values of conditional expressions into several segments, where, for each segment, a separate prediction based on the input variables is provided. Each data sample falls in exactly one of the segments in each layer of the tree. The prediction for each data sample is the sum of conditional predictions for its corresponding segments in all layers of the tree. Finding the conditional expressions, the partitions, and predictions in all layers are performed simultaneously by the mixed-integer programming model.

Figure 5.1 shows an example regression decision tree with two layers proposed by our approach. In this figure, we have conditional expressions CE_1 and CE_2 in layers 1 and 2 of the decision tree. In layer 1, the conditional expression CE_1 has been partitioned into three segments of $(-\infty, b_1^1]$, (b_1^1, b_2^1) , and $[b_2^1, \infty)$. In layer 2, the conditional expression CE_2 has been partitioned into three segments of $(-\infty, b_1^2]$, (b_1^1, b_2^2) , and $[b_2^2, \infty)$. In this tree, y_k^l denotes the prediction for the partition k in layer l . Each sample falls in one of the terminal layers where the prediction is equal to the sum of prediction in the two previous layers.



CE_l : The conditional expression in layer l .

b_k^l : The breaking point k for the conditional expression CE_l .

y_k^l : The prediction for the k -th node/interval of the conditional expression CE_l .

Figure 5.1 An example regression decision tree with two layers.

In Appendix B, we have proposed a mixed-integer programming model that generates our RDT models. A solution of this integer programming model offers a decision tree for the prediction of samples. To use the proposed model, we performed a k-fold validation ($k=5$) analysis. To do so, the learning dataset was randomly shuffled and was split into 5 groups. We obtained five RDT models by solving the proposed mixed-integer programming model for each fold. To obtain each RDT, one of the data folds was considered as a validation dataset and the four remaining groups were considered as a training dataset. Then, an RDT model was fitted using the proposed mixed-integer programming model on the training set and was evaluated on the validation set. Then we computed the evaluation score (i.e., RMSE) and discarded the model. The set of input variables associated with the best performance (lowest RMSE) was selected in each round.

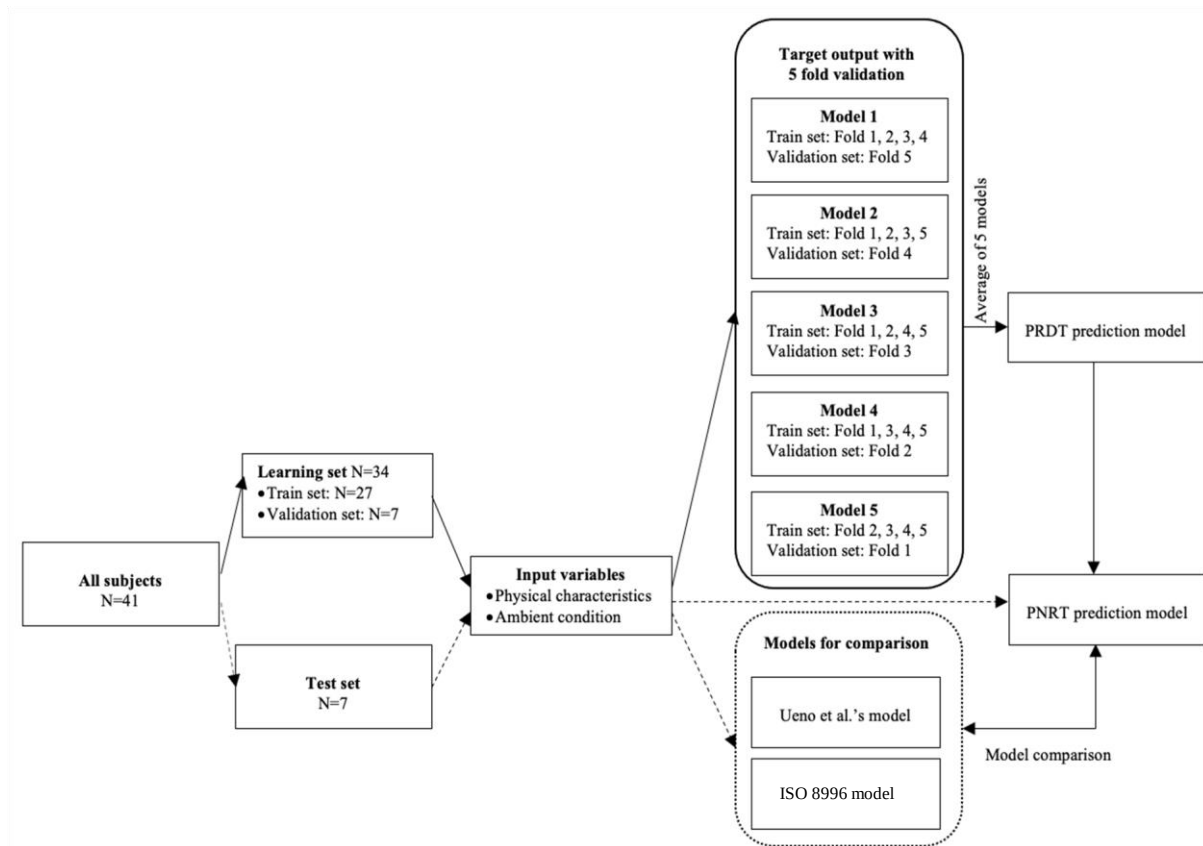


Figure 5.2 An overview of the study.

After producing five RDT models, the outputs of the averaged RDT model were computed using the whole learning set by computing the average results of these five RDT models. It is noteworthy that each participant in the learning dataset is assigned to an individual group and stays in that group in the k-fold analysis. This means that each participant is given the opportunity to be used in the validation set once and was used to train the model 4 times. Figure 5.2 presents an overview of this study.

5.3.4 Model comparison

In this chapter, we evaluate our proposed models in comparison with the model proposed by Ueno et al. (2014), and the model from ISO 8996:2004 that uses the maximum work capacity method proposed by Statistics Canada (2013). This is because, Chapter 4 demonstrated that these two WM prediction models exhibited the highest level of performance among the models which do not entail the determination of the thermal pulse or individual calibration.

Ueno et al. (2014) presented two linear oxygen consumption models using HR, weight, body fat percentage, and thermal environment parameters. One of the models was derived from seven young male university students (age: 22.9 ± 0.7 years) and the other model was derived from seven old male workers (age: 61.7 ± 2.2) as follows:

$$\begin{aligned} WM_Ueno \text{ for young men (Watts.m}^{-2}) \\ = -0.32 \times Temperature(C) + 2.43 \times Weight - 1.49 \end{aligned} \quad (1)$$

$$\begin{aligned} &\times Body \text{ fat percentage} + 403 \times HR_{res} - 44.9, \\ WM_Ueno \text{ for old men (Watts.m}^{-2}) \\ = 1.76 \times Temperature + 0.54 \times Weight - 0.99 \end{aligned} \quad (2)$$

$$\times Body \text{ fat percentage} + 330 \times HR_{res} - 10.2,$$

where

$$Body \text{ fat (\%)} = 1.2 \times BMI + 0.23 \times Age - 16.2, \quad (3)$$

$$HR_{res} (\%) = 100 \times (HR_{WM} - HR_{rest}) / (HR_{max} - HR_{rest}). \quad (4)$$

Ueno et al. (2014) do not indicate how HR_{max} nor HR_{rest} were determined. Therefore, the common HR_{max} = 220 - Age was used for the former, and resting HR while seated was used for the latter. In Ueno et al. (2014), for the participants whose age was 22.9 or lower, the $\dot{V}O_2$ value was obtained from equation (1) that is for young males. Also, for the participants whose age was 61.7 or higher, the $\dot{V}O_2$ value was obtained from equation (2) which is for old males. Ultimately, for the participants aged between 22.9 and 61.7, the $\dot{V}O_2$ values obtained by equations (15)-(16) were interpolated with respect to the age of the participant.

Section 6.2 of ISO 8996 :2004 proposed equations (5)-(8) to estimate $\dot{V}O_2$ based on HR, MWC, age, weight, and metabolism at rest (M_{rest}). In this model, HR_{rest} is measured while the participant is taking a seated rest pause (e.g., before the morning step-test).

$$WM_IsoForm (Watts.m^{-2}) = \frac{MwcIso - M_{rest}}{HR_{max} - HR_{rest}} \times (HR_{WM} - HR_{rest}) + M_{rest} \quad (5)$$

where:

$$MwcIso (Watts.m^{-2}) = (41.7 - 0.22 \times Age) \times Weight^{0.666} \quad (6)$$

$$HR_{max}(bpm) = 205 - 0.62 \times Age \quad (7)$$

$$M_{rest} (Watts.m^{-2}) = 55 \quad (8)$$

Also, as we discussed in Chapter 4, ISO 8996:2004 prediction model results in a higher level of accuracy when used with the maximum work capacity proposed by Statistics Canada (2013), rather than the original maximum work capacity proposed by ISO 8996:2004. Therefore, in this chapter, we considered ISO 8996:2004 with the maximum work capacity of Statistics Canada (2013).

Table 15 from Statistics Canada (2013) shows maximum work capacity values for different age groups of males and females. For example, for the 50th percentile of age group 20 to 39, 50 to 59, and 60 to 69, the maximum work capacity values were 44, 34.4, and 26.8 ml.kg⁻¹.min⁻¹, respectively. All these data were collected between 2009 to 2011 for the Canadian Health Measures Survey.

5.3.5 Statistical analyses

The Bias, relative bias (rBias), root mean square error (RMSE), relative root mean square error (rRMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were computed to assess and compare the performance of the different models in estimating $\dot{V}O_2$ from HR, against $\dot{V}O_2$ measured:

$$\text{Bias} = \frac{1}{n} \times \sum_1^n (WM_{\text{predicted}} - WM_{\text{measured}}), \quad (9)$$

$$\text{rBias} = \frac{\text{Bias}}{\text{mean } WM_{\text{measured}}} \times 100, \quad (10)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_1^n (WM_{\text{predicted}} - WM_{\text{measured}})^2}, \quad (11)$$

$$\text{rRMSE} = \frac{\text{RMSE}}{\text{mean } WM_{\text{measured}}} \times 100, \quad (12)$$

$$\text{MAE} = \frac{1}{n} \sum_1^n |WM_{\text{predicted}} - WM_{\text{measured}}|, \quad (13)$$

$$\text{MAPE} = \left(\frac{1}{n} \sum_1^n \frac{|WM_{\text{predicted}} - WM_{\text{measured}}|}{WM_{\text{measured}}} \right) \times 100. \quad (14)$$

The agreement between measured and estimated WM was assessed using LoA analysis as described by Bland and Altman (1986). Prediction bias was calculated as the mean difference between estimated and measured WM and 95% LoA as bias $\pm 2 \times$ standard deviation of the differences (SD_{diff}). A 95% LoA were computed on differences (in $\text{ml.kg}^{-1}.\text{min}^{-1}$). A Shapiro Wilks test showed no departure from normality in biases ($p > 0.05$). Data were tabulated in Microsoft Excel. Statistical analyses were conducted with Microsoft Excel, R version 3.6.0, and C++ programming language.

5.4 Results

Table 5.2 shows RDT 1, RDT 2, RDT 3, RDT 4, and RDT 5 which are the five models obtained from k-fold ($k=5$) validation. Also, RDT_AV model represents the average of these five models.

All five models and the RDT_AV model yielded significantly better performance than Ueno et al.'s and ISO models in terms of Bias, RMSE, MAE.

Table 5.3 presents the results obtained for each WM estimation method based on the test data of seven forest workers during actual work activities. It shows that the average of WM estimations for all participants per model and the corresponding mean Bias, MAE, MAPE, RMSE, and rRMSE. In addition, it includes a ranking of different WM estimation models based on RMSE. In Figure 5.3, the black (zero-mean bias) line represents the perfect estimation of WM measured. In this figure, a low spread in the data points indicates a better precision in the estimates.

Results show that the Ueno et al.'s model underestimated measured WM with an overall mean difference of 1.91, whereas ISO model overestimated measured WM with an overall mean difference of 1.06 ml/ kg. min. The bias for our proposed RDT models varied between -0.21 and 0.39. In addition, the WM relative difference was the smallest with RDT 5 followed by other RDT models (0.34% and 0.36 % respectively) and the largest with Ueno et al.'s model (10.9%).

Table 5.2 RDT models' formulations.

	Layers	Coefficient of Input Variables in Conditional Expressions				Partitions for Conditional Expressions	Coefficient of Input Variables in Predictions y_{it}				
		Age	BMI	HR	Ta	Threshold	Age	BMI	HR	Ta	Intercept
RDT 1	$l = 1$	0.741218	0.971946	0.149743	0.583384	< 70.72	2.38247	-2.64955	-2.40232	-3.15364	-9.84451
						70.72 - 83.16	-0.77301	0.60070	-2.52867	-2.30127	-8.06730
						83.16 - 90.24	-0.70355	0.03239	-2.51028	-2.46979	6.56871
						90.24 - 97.62	-0.41113	0.25673	-2.59756	-2.18711	-10.35970
	$l = 2$	0.0264535	-0.119885	0.439661	0.541296	< 41.29	0.32717	-1.63277	3.11669	2.63197	19.97820
						41.29 - 81.55	0.43728	-0.40828	2.67002	2.26363	20.86830
						> 81.55	0.41784	-1.89190	2.62657	3.06176	48.37310
						> 97.62	-0.36569	0.22813	-2.60274	-2.10043	-13.91130
RDT 2	$l = 1$	0.16736	0.195536	0.869097	0.701724	< 110.75	2.33591	-2.05552	2.42948	1.29313	-11.25650
						110.75 - 123.93	2.22825	-1.71138	2.14942	1.41942	10.44360
						123.93 - 141.04	2.25035	-2.07405	2.25813	1.53191	6.12144
						141.04 - 156.72	2.12483	-1.20061	2.19449	0.89990	11.85300
	$l = 2$	0.911495	0.835615	0.176064	0.229068	< 61.50	0.40989	-2.47218	-1.85740	-2.53855	26.90907
						61.50 - 107.62	-2.45461	1.60052	-2.20272	-1.47763	28.16190
						> 107.62	-2.10078	0.83858	-2.01432	-1.61738	11.56805
						< 86.03	-2.54735	1.65862	-2.3793	1.24398	-12.3667
RDT 3	$l = 1$	0.647	-0.631662	0.70838	0.213355	86.03 - 97.49	-2.57793	1.13117	-2.60865	2.22389	6.30227
						97.49 - 107.14	-2.76964	2.20339	-2.69383	1.65508	6.13848
						107.14 - 120.83	-2.6665	2.15754	-2.53752	1.27052	-9.41024
						> 120.83	-2.70939	2.07151	-2.67976	1.72748	4.72108
	$l = 2$	0.468864	0.776209	-0.0033725	-0.794513	< 11.26	-3.08437	2.86232	2.96660	-0.88996	-3.15940
						11.26 - 42.22	2.54302	-2.32508	2.75964	-1.56353	17.70000
						> 42.22	2.02209	1.30823	1.76382	4.23910	20.59610
						< 71.64	2.45939	-1.60969	2.70259	-3.30673	-5.22652
RDT 4	$l = 1$	0.337413	-0.889209	0.853461	0.0645608	71.64 - 87.91	2.29397	-1.38282	2.61676	-3.01757	-0.925971
						87.91 - 105.01	2.18152	-1.06202	2.50758	-3.00892	4.60019
						105.01 - 123.52	2.19340	-1.13735	2.49121	-3.19425	12.60080
						> 123.52	1.86251	-1.53321	2.45474	-1.86184	9.83099
	$l = 2$	0.450773	0.013178	0.0341979	0.71867	< 23.82	-0.25765	-2.33664	-2.20315	2.97965	16.72816
						23.82 - 48.83	-2.44029	0.90749	-2.35399	2.95687	13.43796
						> 48.83	-2.34165	1.68229	-2.30155	2.28095	-2.06607
						< 67.42	-1.93771	-3.11182	3.19584	1.73367	-11.7045
RDT 5	$l = 1$	0.462565	-0.774013	0.71122	-0.0909698	67.42 - 80.74	-2.05147	-2.94607	3.09017	1.99176	-6.63879
						80.74 - 92.13	-2.14665	-2.10555	2.86096	2.24629	-5.87353
						92.13 - 107.59	-2.13452	-2.81305	3.02112	1.68244	1.95525
						> 107.59	-2.10079	-3.45325	2.9315	2.32746	14.4498
	$l = 2$	0.928595	0.468915	0.0116693	-0.718645	< 17.63	5.51339	-5.97553	-2.1483	-2.68058	43.3137
						17.63 - 62.65	1.91467	2.34901	-2.79627	-2.03019	18.4412
						< 62.65	2.24126	0.760934	-2.61303	-1.70795	17.8341

Table 5.3 WM ($\text{ml.kg}^{-1}.\text{min}^{-1}$) results for models against measured WM (mean $\pm$ SD: 17.59 ± 2.66 $\text{ml.kg}^{-1}.\text{min}^{-1}$).

Statistic	RDT 1	RDT 2	RDT 3	RDT 4	RDT 5	RDT_AV	Ueno	ISO
WM $\pm$ SD	17.93 ± 1.47	17.98 ± 1.40	17.38 ± 1.70	17.44 ± 1.69	17.53 ± 1.73	17.65 ± 1.23	15.67 ± 3.04	18.65 ± 3.53
Bias $\pm$ SD _{diffs}	0.35 ± 2.41	0.39 ± 2.65	-0.21 ± 3.07	0.14 ± 2.79	-0.06 ± 2.90	0.06 ± 2.67	$-1.92 \pm 3.97^*$	$1.06 \pm 4.53^*$
[95% LoA]	[-4.37, 5.07]	[-4.81, 5.59]	[-6.15, 5.92]	[-5.62, 5.33]	[-5.74, 5.62]	[-5.17, 5.3]	[-9.70, 5.86]	[-7.81, 9.93]
rBias (%)	1.97	2.22	1.21	0.82	0.34	0.36	10.90	6.03
RMSE	2.83	2.90	2.99	2.86	3.08	2.67	4.41	4.65
rRMSE (%)	16.09 {2}	16.47 {4}	17.01 {5}	16.27 {3}	17.51 {6}	15.19 {1}	25.06 {7}	26.43 {8}
MAE	2.05	2.33	2.26	2.16	2.31	2.06	2.96	3.75
MAPE	12.54	13.98	12.97	12.54	13.59	12.25	16.08	22.10

* Indicates a significant scale effect, that is, regression of differences against the mean of predicted and measured WM is statistically significant ($p < 0.05$)

{ }: Performance ranking within the row based on RMSE; 1 is the best performance. The bold numbers indicate the best-performing model based on RMSE or rRMSE.

The smallest MAE was obtained with RDT 1 (2.05), followed by RDT_AV (2.06), whereas the highest MAE was obtained with ISO model (3.75). In terms of RMSE, RDT_AV model (RMSE = 2.67, rRMSE = 15.19) yielded the most accurate WM estimates, followed by RDT 1 (RMSE = 2.83, rRMSE = 16.09), RDT 4 (RMSE = 2.86, rRMSE = 16.27), RDT 2 (RMSE = 2.90, rRMSE = 16.47), RDT 3 (RMSE = 2.99, rRMSE = 17.01), and RDT 5 (RMSE = 3.08, rRMSE = 17.51). The paired t-test ($p < 0.05$) showed no significant difference between the measured WM values and those estimated by the RDT_AV model and RDT models 1-5. On the other hand, the Ueno et al.'s model significantly underestimated the measured. The ISO model significantly overestimated the measured WM.

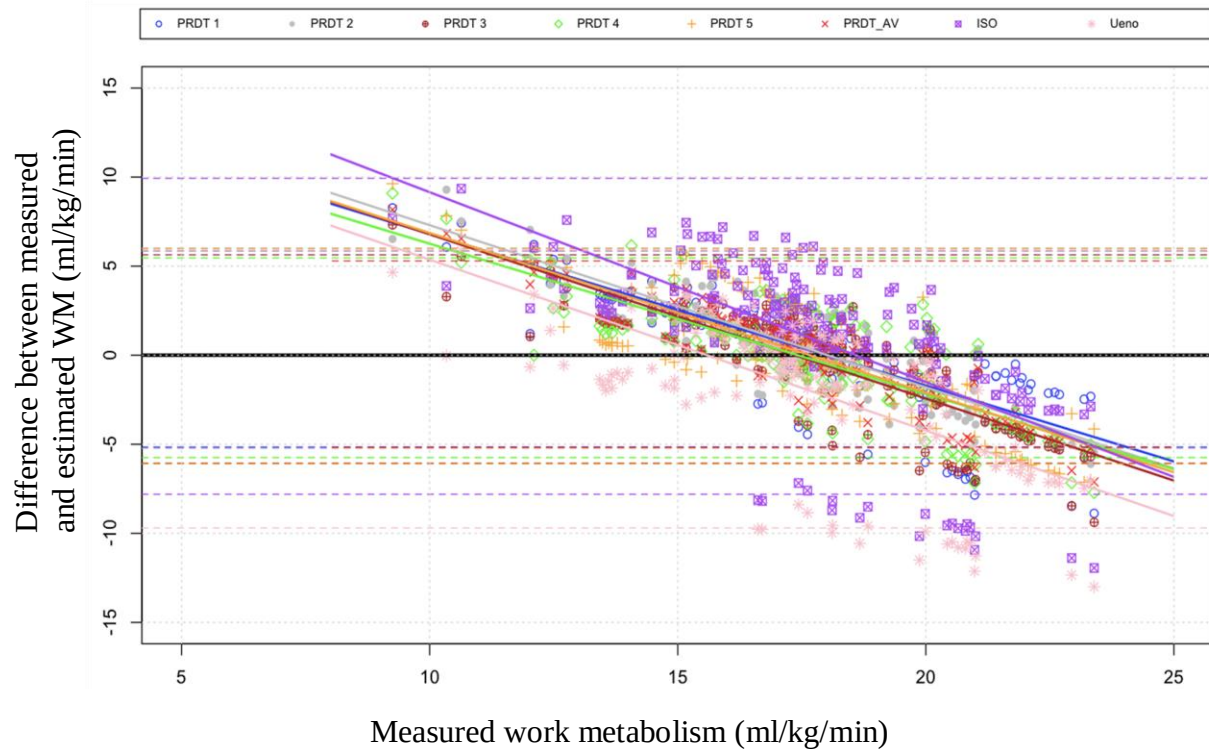


Figure 5.3 Bland-Altman (or difference) plots of measured vs. estimated WM. Mean bias is indicated by a colored solid line and LoA are indicated by dashed lines.

The Bland-Altman plot in Figure 5.3 depicts the LoA between measured and estimated WM values. The difference between the measured and estimated WM was smallest with RDT_AV model and RDT 5. On the other hand, the largest bias was with Ueno et al.'s model. Moreover, the LoA associated with RDT 1, RDT 2, and RDT_AV get narrower. However, Ueno et al.' and ISO models, the LoA are widest. Figure 5.3 shows the trend lines of these models. Trend lines that are closer to the horizontal black line have tighter LoA boundaries.

5.5 Discussion

This study aimed to present a model which can predict WM of workers during medium to high-intensity work using heart rate monitoring and prediction parameters and without the need for the determination of the thermal pulse. This study represents a significant improvement over existing

WM prediction methods. The proposed model uses the heart rate, age, BMI, and ambient temperature of 41 forest workers.

In Chapter 4, we found that the existing WM prediction methods that showed good agreement between measured and estimated WM, relied on heart rate measurements with the determination of the thermal component. However, according to Ueno et al. (2014), the individual calibration is impractical for outdoor workers due to the associated time and cost requirements. On the contrary, our analysis in Chapter 4 demonstrated that WM prediction models that are solely based on heart rate measurements and do not consider the thermal component, result in poor agreement between estimated and measured WM. There exist two exceptions to this observation, namely, the models proposed by Ueno et al. (2014) and ISO 8996:2004 with the maximum work capacity method recommended by Statistics Canada (2013).

The current study represents an improvement over existing studies (Ueno 2014; ISO 8996:2004) that used heart rate monitoring to estimate work metabolism, without the determination of the thermal component. Moreover, in the current study, we proposed regression decision tree models based on mixed-integer programming methodology. These models yielded predictions that correlate significantly with test samples as well as the independent validation samples.

The RDT_AV prediction model resulted in more accurate WM estimates compared to Ueno et al.'s and ISO models. Moreover, all proposed RDT models yielded better WM estimates in comparison with Ueno et al.'s and ISO models as indicated in Table 5.3. The results show that the proposed RDT models including the RDT_AV produced percentage differences less than 2.2% which are significantly better than those in WM estimation values of Ueno et al.'s and ISO model's.

The paired t-test indicated a significant difference between the measured and estimated WM by Ueno et al. and ISO models, which was not the case for the RDT prediction models. The fact that

the RDT prediction models provided better prediction indicates its ability to deal with the nonlinearity between WM and input variables. This finding is also supported by the comparable LoA associated with the RDT models. The agreement between the measured WM values and those estimated by the RDT models suggests the potential of the developed model to be a very efficient replacement for the models using HR without the determination of the thermal component. The developed model can be used directly to assess WM from HR measured during work provided that age, BMI, and ambient temperature of the participant are known.

RMSE and bias show the prediction accuracy that an ergonomics expert could expect when WM is obtained and averaged for some instances or a group of participants. The 95% LoA, on the other hand, draws a picture of the prediction accuracy when assessing WM for a single participant.

Generally, the number of workers monitored by ergonomics experts is small, and hence the estimation errors are expected to be the same as those reported here. According to Malchaire et al. (2017), WM prediction from work HR measurements reported an error of $\pm 14.5\%$, but ISO 8996: 2004 offered that the error is likely closer to $\pm 10\%$ for the work rate measured. If rBias best describes these errors, then all RDT and ISO models meet this level, while Ueno et al.'s model comes fairly close with rBias = 10.9% (Figure 5.3). On the other hand, if the error in ISO 8996: 2004 and in Malchaire et al. (2017) is best described by rRMSE, then only RDT_AV model produced an rRMSE fairly close to $\pm 14.5\%$, while no model produced an rRMSE smaller than $\pm 10\%$. Finally, if an MAPE best describes these errors, then all RDT models produced an MAPE less than to $\pm 14.5\%$, while no model produced an MAPE smaller than $\pm 10\%$. Bland and Altman (1986) presented an equation to determine the sample size required to achieve $\pm a\%$ mean bias with a 95% confidence interval. Based on that equation, all RDT models are the best performing by far. As Figure 5.3 shows, to achieve a $\pm 14.5\%$ accuracy on a mean prediction bias, a group of 5

participants are required for RDT 1, RDT 4, RDT 5, and RDT_AV. Also, 6 and 7 participants are required for RDT 2, and RDT 3 would be required, respectively. These numbers of participants are practical in many field interventions. To achieve $\pm 10\%$ with the RDT_AV, 10 participants would be required, which represents still a logical number in field studies.

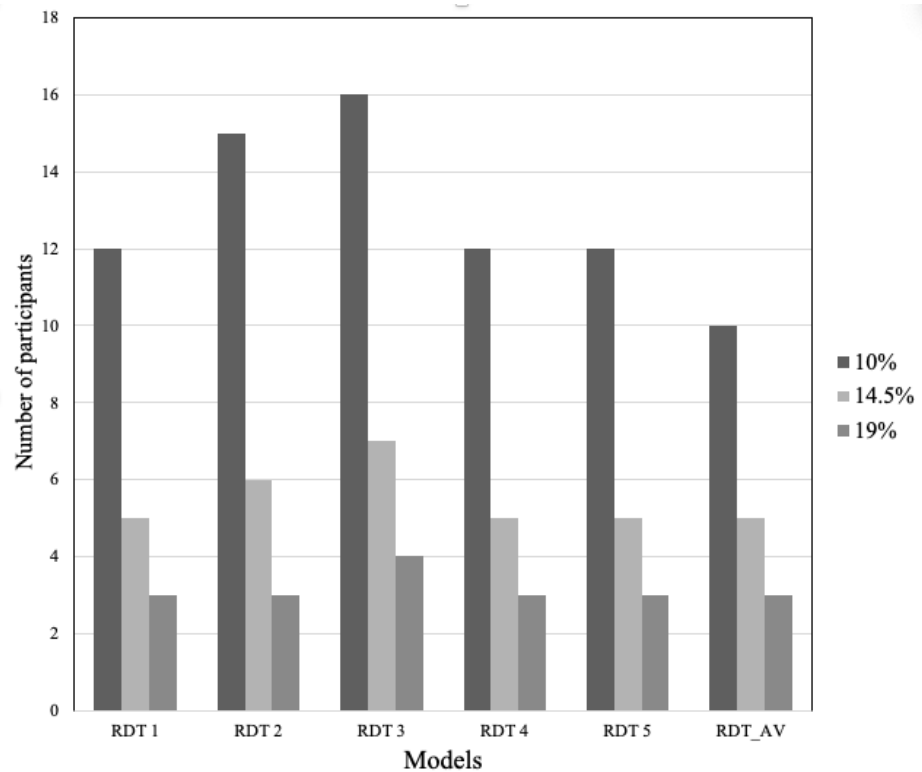


Figure 5.4 Sample sizes required for different accuracy levels.

The heat stress assessment such as WBT can be determined by HR-based WM model estimations. According to ACGIH (2018), when WBGT is 27°C, it is likely to underestimate the true WM by 19% which entails a risk of heat stress since it could lead to a wrong decision. This means that the worker can work continuously during the hour rather than with a 45/15 work/rest cycle. Figure 5.3 also shows that all RDT models could be used to achieve $\pm 19\%$ accuracy on the group mean with 4 or 3 participants. These RDT models are practical since they can achieve $\pm 19\%$ mean bias with only 3 or 4 participants and without the determination of the thermal pulse.

5.6 Conclusion

The statistical analysis that we performed in Chapter 4 demonstrated the lack of accuracy and reliability of those simple prediction models in the literature that do not use individual calibration or thermal pulse. Motivated by the findings of Chapter 4, in this chapter, we investigated the possibility of developing more precise WM prediction models without any need for individually calibrated data and the calculation of the thermal component. We proposed novel RDT prediction models based on an integer programming formulation. The developed models use appropriate formulas of input variables in different partitions to estimate WM. As explained in Chapter 4, most existing models in the literature consider a linear relation among input variables. However, the proposed RTP models allow for considering non-linearity between variables through considering partitions and therefore can better exploit the relation between variables and provide more accurate estimates.

The proposed machine learning-based model is an easy-to-use with a high prediction performance in comparison with some popular regression models. Our proposed model presented a set of rules that are interpretable and understandable by practitioners. Further studies could include a larger number and variety of participants and as well a variety of actual work activities with different intensities for RDT models.

5.7 Statement of authors' contributions

- Sahar Arab: statistical analysis, designing the algorithm, implementation of algorithms, running the algorithms to get results, creation of tables, drawing figures, partial data cleaning, writing the paper. 80%
- Dube et al. (2015, 2016, 2019): data collection and cleaning. 20%

CHAPTER 6 RESEARCH 3: QUALITATIVE DATA ANALYSIS ON THE USERS OF VIRTUAL ERGONOMICS AND THEIR PERSONAS

6.1 Overview

In this chapter, we discuss a case study about the use of qualitative data analytics in the area of cognitive ergonomics. This topic contributes to the overall goal of this dissertation, that is to demonstrate the benefit of using various data analytic tools in different areas of ergonomics. More specifically, in this chapter, we investigate the application of qualitative data analytics for the cognitive evaluation of DHMS, a well-known virtual ergonomics tool. We aim to discover what barriers these employees confront while using DHMS and what should be modified in DHMS tools to help improve their efficiencies and designs. In this research, we carry out qualitative semi-structured interviews with 33 current and potential users of DHMS including ergonomists, designers, managers, manufacturing, and maintenance engineers. First, we provide some descriptive statistical analysis about the background of the participants. Then, we perform qualitative data analyses including constant comparison analysis and content analysis to analyze the interviews of the users. Then, based on the data obtained from our qualitative analysis, we perform a persona analysis which results in categorizing the users into three persona groups. For the clustering step of the persona analysis, we have proposed a new nonlinear integer programming model. Finally, we discuss these results and identify the users' needs, limitations, and capabilities.

6.2 Introduction

Cognitive ergonomics is one of the main areas of human factor engineering and still has a significant potential to improve work conditions of employees, especially in the technology industry. BIMA (2019) reports that the rate of depression and work-related stress among the employees of the technology industry is five times higher compared to the general population. According to this report, 52% of individuals have encountered anxiety or depression, and 45% feel that there is an insufficient level of mental health support. This chapter is a complement of Chapters 4 and 5 and aligns with the overall goal of the dissertation, which is to explore data analytics in various areas of ergonomics. Here, we focus on a case study in the field of cognitive ergonomics, that revolves around the topics of virtual ergonomics and digital human modeling.

Advances in simulation and virtual reality have led to a new application field referred to as virtual ergonomics (Wilson and D'Cruz, 2006; Jayaram 2006). Virtual ergonomics helps designers identify and correct various ergonomics-related issues that may happen in the future for operators/users. Using virtual ergonomics results in the design of products that are more comfortable, safe, and productive. The main users of virtual ergonomics include ergonomists, engineers, and industrial designers (Chryssolouris 2000; Pappas 2007; Robert and Lesage, 2010). Virtual ergonomics is becoming more significant than before since people spend more time in digital environments, especially after COVID-19 pandemic.

DHM is one of the virtual ergonomics tools which links ergonomics and computer-aided engineering design. A digital human model is defined as a computerized three-dimensional manikin representation that helps designers to visualize a human and analyze different aspects of the body before actually being placed in a work environment. There are several ways to model a human in DHM. In the following, we explain some of the most common DHM approaches:

1. **Kinematic modeling:** In this approach, the movement and motion ranges of the human body are analyzed through a 2D or 3D dynamic model that evolves over time (Howard et al. 2010; Gragg et al. 2012). This digital model simulates the body movements either by the motion capture technology or the mathematical modeling of the body's parts and joints. Kinematic models are often used in analyzing human movements in physical tasks and sport activities. They are also useful in ergonomics evaluation of the products and workstations design considering the dynamic movements of the worker.
2. **Biomechanical modeling:** The focus of biomechanical approach is to model the physical forces on the human body during different activities using the laws of mechanics (Tripathi et al. 2015; Zaman et al. 2022). This method is usually used to evaluate and re-design the manual tasks of workers including lifting, carrying, reaching, and walking. It is beneficial in avoiding injuries by identifying the potential ergonomic issues.
3. **Anthropometric modeling:** Anthropometric approach concentrates on the various measurements of the human body such as height, weight, body mass index, the lengths of different body parts, and the motion ranges of joints (Bertilsson et al. 2010; Bonin et al. 2020). The main application of this approach is in the analysis and design of products and workstations that are suitable for humans with different body sizes. Automobile, furniture, and clothing sectors are some instances of the industries that benefit from anthropometric modeling.
4. **Physiological modeling** focuses on various internal systems of the human body including the circulatory, respiratory, musculoskeletal, muscular, and nervous systems (Wang and Lau 2013; Shehab et al. 2022). The main application of this method is usually in medical

simulations where the effects of different treatments and medications on the body are studied.

5. Cognitive modeling approach aims at studying the psychological operations of the human brain such as perception and decision-making (Thorvald et al. 2009). This method is mainly used to simulate and analyze how people interact with their environments, make decisions, and perform tasks. Cognitive modeling is applicable in the area of artificial intelligence and robotics for training them to act like humans.

DHMS enables designers to simulate human body and its interaction with the product or workplace in a virtual environment by inserting a digital human model in the Computer Aided Design (CAD) environment. DHMS supports the designers to assess a product's ergonomic features during the early design phase. This early assessment reduces or removes the need for physical mock-ups and real human subject testing (Badler et al., 1993; Morrissey, 1998; Zhang and Chaffin, 2000; Perez and Neumann 2015; Karmakar, 2016). Therefore, it lessens development cost, reduces design time, enhances quality, and improves productivity (Aqlan 2017; Chaffin 2005; Hanson 2006). DHMS also assists manufacturers and designers in predicting potential risks in the design process during productivity optimization (Demirel and Duffy, 2007).

Various commercial DHMS tools are available in the market, each with a unique focus on different human aspects. In Table 6.1, we have summarized these tools, along with their modeling approaches, features, and primary applications. Some of these software tools analyze body postures, while others concentrate on the design of workstations and parts considering the physical limitations of the human body. In Appendix C.1, we have provided more explanations of the digital tools listed in Table 6.1.

Current DHMS users include people with varied training and needs from different industries such as manufacturing, automotive, aviation, and aerospace. According to Charland (2016), DHMS users are often trained engineers with little to no training in ergonomics. Their needs range from designing a part, designing a complete workstation, or an assembly line. Non-engineer users of DHMS such as industrial designers are often interested in designing a product (e.g., a new treadmill or a new hand tool). Ergonomists with varied backgrounds are also among the DHMS users (Charland, 2016). In a study, a group of 46 ergonomists (74%) and engineers (26%) were interviewed to understand their perception of the DHMS utility in ergonomics (Perez and Neumann, 2015). This study showed that DHMS is time consuming, challenging to use, and requires a significant training effort to achieve efficient use. It seems that all DHMS pose the same difficulties (Vogt 2005). Also, another study showed that the use of DHMS necessarily requires excellent skills in various fields such as ergonomics, CAD, and product design (Lockett 2005).

Table 6.1. A summary of commercial DHMS tools with their modeling approaches, features, and primary applications.

Software	Modeling approaches					Features				Primary applications
	Biomechanical modeling	Kinematic modeling	Physiological modeling	Anthropometric modeling	Cognitive modeling	Motion Capture ¹	Ergonomics module	Environment Simulation ²	Clothing and Accessories	
ADAMS	✓	✓		✓		✓			✓	Mechanical evaluation in part design.
ANSYS Human Body Model	✓	✓	✓	✓		✓	✓	✓	✓	Simulation of the human body under various physical forces such as impact, vibration, and thermal stress.
AnyBody Technology	✓	✓	✓	✓		✓	✓		✓	Musculoskeletal modeling and analysis of human movement in sports, product design, medical research, rehabilitation, etc.
CogTool					✓					Simulation of human-computer interaction for user interfaces.
DELMIA		✓		✓		✓	✓	✓	✓	Simulation and analysis of manufacturing processes in a 3D virtual environment.
ESI Group Virtual Human Builder	✓	✓		✓		✓	✓	✓	✓	creation of digital human models for simulations, analysis, and design in various industries.
Human Solution RAMSIS	✓	✓		✓		✓	✓	✓	✓	Design and analysis of vehicle interiors (including the human body) to maximize driver comfort and safety.
LifeMOD	✓	✓		✓		✓	✓			virtual human modeling with application in sports science and sports science rehabilitation.
NEUROBS Presentation					✓					Design and implementation of cognitive psychology and neuroscience through complex visual and auditory stimuli.
OpenSim	✓	✓		✓		✓			✓	Simulation of the movement of the human musculoskeletal system. Applications in sports science and medical research.
PTC Creo Human Factors Design		✓		✓			✓		✓	Design of products and workstations that are optimized for human use.
SAMMIE	✓	✓		✓		✓	✓	✓		Creation and analysis of digital human models in workplace environments to improve ergonomics and safety of work.

Table 6.1 (continued) A summary of commercial DHMS tools with their modeling approaches, features, and primary applications.

Software	Modeling approaches					Features				Primary applications
	Biomechanical modeling	Kinematic modeling	Physiological modeling	Anthropometric modeling	Cognitive modeling	Motion Capture ¹	Ergonomics module	Environment Simulation ²	Clothing and Accessories	
SANTOS	✓	✓	✓	✓			✓	✓		Design and test of digital human bodies in using systems and equipment with applications in various industries.
Siemens Jack	✓	✓		✓		✓		✓	✓	Simulation and analysis of ergonomics and human factors in product and workstation design.
The Virtual Brain			✓							Simulation and analysis of the dynamics of brain activity.
3DSSPP	✓			✓			✓	✓		Simulation of the physical demands in materials handling tasks such as lifting, lowering, pushing, pulling, and carrying.
Dassault Systèmes CATIA Human Builder	✓	✓	✓	✓		✓	✓		✓	Design and analysis of human body models in a virtual environment.
Dassault Systèmes SIMULIA Living Heart			✓			✓				Simulation of the human heart and the cardiovascular system.
Dassault Systèmes SIMULIA AnyBody	✓	✓		✓		✓			✓	Simulation of human body motion and dynamics. It is used to analyze biomechanical performance of various products such as medical devices, sports equipment, automotive and aerospace designs, and workstation design.

¹ Motion Capture: This feature that enables the user to capture the movements of a real person and apply it to a virtual character. In this technique, the motions of the individual are recorded and tracked using the sensors of a special suit worn by the subject.

² Environment Simulation: Software with this feature can simulate different environmental factors, such as lighting, temperature, and noise levels on human performance and behavior.

The current and potential users of DHMS are diverse, and there is very little information about them in the literature (Perez & Neumann, 2015). Hence, the literature barely provides enough information to guide the design of DHMS. Nobody seems to be interested in documenting who the users of DHMS are, what their context of use is, and what their expectations for these tools are. Therefore, it seems useful and necessary to carry out this characterization. Moreover, the consideration of users' needs, limitations, and capabilities is one of the critical aspects of product development and design (Cooper and Ross 1984, Mukhopadhyay 2012). In the context of virtual ergonomics, this means that it is essential to better document: I) who the current and potential users are and better define their characteristics and needs with respect to DHMS; II) the reasons for using or not using DHMS, and III) whether or not DHMS is useful to those who currently do not use it.

There are different approaches in the literature for characterizing typical users of systems and products. Among them, persona analysis is a proven and increasingly popular approach, especially for the development of software tools (Goodwin 2009). A persona is a fictional character representing very different users with common characteristics concerning a product (e.g., DHMS). Thus, a persona is a specialized composite model obtained from a cross-sectional analysis of a user population (Goodwin 2009). This approach aims to define typical profiles of users and to document the goals and behaviors of each one for the product to be designed. We have provided more explanation about the structure of this approach in Section 2.2.12 of Chapter 2.

In this chapter, we study the current and potential users of various DHMS tools to better understand their needs and the obstacles that they confront with when using DHMS tools during the design process. This work will help DHMS developers better address these cognitive challenges of the users in the future. We also explore the strengths of these digital tools. To this end, in this chapter, we have accomplished the following tasks:

- **Interviews:** We interviewed a group of engineers, ergonomists, and industrial designers and performed various qualitative data analyses on the collected interviews.
- **Descriptive statistical analysis:** Based on the interview data, we first provide some descriptive statistical analysis of the data. This analysis provides some insights about the background of the participants.
- **Qualitative analysis:** Then, we perform some qualitative analyses on the descriptive part of the interviews and extracts the users' goals and need, and also the obstacles they face in using DHMS tools. These qualitative analyses also highlight the main advantages and disadvantages of DHMS tools.
- **Persona analysis:** Based on our qualitative data analyses, we performed a persona analysis that resulted in three personas representing different categories of DHMS users, their characteristics, and their viewpoints and needs in using DHMS. In this step, we have proposed a novel integer programming model that performs the categorization of participants more effectively.
- **Discussion:** In addition to presenting the results of our various analysis, we have provided a discussion of these results.

The remainder of this chapter is organized as follows: In Section 6.3, we have provided some details about the data including the structure of the interviews, the participants, and the data preparation. In Section 6.4, we have provided the results of the descriptive statistical analysis. In Section 6.5, we have explained our qualitative analysis and its results. In Section 6.6, we have developed a novel integer programming model for persona analysis and then have discussed the results of the persona analysis. In Section 6.6, we have provided a discussion of the results. Finally, we have concluded this chapter in Section 6.7.

6.3. Details of data

The data of this research were collected through interviews between July and October 2015 at Dassault Systèmes company in Québec, Canada. The present study was part of a larger project and approved by the Research Ethics Board at Polytechnique Montreal and the University of Montreal (No. CÉR-14/15-15). The author of this dissertation did not have any role in interviewing the participants, but partially contributed in translating the interviews from French to English and also in transcribing them. In the following, we have provided all details about the questions of the interviews, the participants, and the data preparation and analysis.

6.3.1 Questionnaire

A base questionnaire was assembled and used to guide the interviews. The questionnaire was created based on Goodwin (2009), and the interviews comprised a mix of open-ended and closed questions. The interviews were conducted by three members of the research team among whom two had extensive experience in DHMS and virtual ergonomics. Interviewers did not hesitate to ask more specific questions for clarification purposes. At the beginning of each meeting, the lead interviewer read the introduction about the goal and rules of the discussion and then obtained informed consent from the participant and received permission for recording the conversation. The questionnaire included the following 24 questions in three sections.

Section 1 (Questions 1 to 7): The first section of the above interview was to learn about the interviewees and break the ice with them.

Question 1: What is your age group? 20-29, 30-39, 40-49, 50-59, 60 and over?

Question 2: What is your role/position in the company?

Question 3: What tasks do you often do in the company?

Question 4: How many years of work experience do you have?

Question 5: What is your education?

Question 6: What is your field of expertise (design, manufacturing, etc)?

Question 7: Do you do any 3D modeling? If yes, how much time do you spend on it daily or weekly?

Section 2 (Questions 8 to 14): The second section contained questions related to their work context.

Question 8: Can you describe your work environment and the context in which you evolve?

Question 9: In your current position, do you make decisions about projects or do you do the jobs assigned to you about the projects?

Question 10: How many employees does your company have?

Question 11: How many employees in your company use CAD/DHM software?

Question 12: Do you or anyone else in your company perform ergonomics analysis? If yes, do you have a separate department or team of ergonomists?

Question 13: If you work with other departments, do you work with them in parallel or cascade?

Question 14: Do you need the approval of a human factors specialist or an ergonomist?

Section 3 (Questions 15 to 24): The third section covered questions about the use of DHM.

Question 15: Do you do DHM? If yes, how often? If no, is there someone within the process that does DHM?

Question 16: If you or someone else perform DHM, which software do you use? and how often?

Question 17: If you do not perform DHM, how important do you think it is?

Question 18: If you do not perform DHM, in your work, do you develop products that will have interactions with humans? If so, why you don't use it?

Question 19: If you perform DHM, for how long you have been doing it?

Question 20: If you perform DHM, what is your level of expertise in doing it?

Question 21: If you perform DHM, can you describe a typical use of DHM in your work?

Question 22: If you perform DHM, what are your main goals of using DHM in 3 or 4 words?

Question 23: If you perform DHM, in your opinion, what are the strengths and weaknesses of DHM tools?

Question 24: In your opinion, what is the usability of DHM in a scale of 1 to 10?

The purpose of the third section of questionnaire was to document what the use of the DHMS was, the level of the user's expertise, the frequency of use, the goals for using it, typical application examples, and finally the participant's opinion about current DHMS and their usability. If the participant did not do DHM, but he/she knew DHM, the questions were limited to reasons for not using DHM and potential applications and benefits of DHM in the future.

All interviews were recorded, and after each interview, the team had a discussion to summarize the results and develop a common understanding. Among all interviews, 16 were held in French, and the others were conducted in English. Each meeting lasted 25 to 72 minutes. All interviews were conducted by telephone except one of them which was in person. Two interviews were not considered since one participant had to leave for an emergency in the middle of the conversation, and the other participant discussed ergonomics issues that were not related to the interview.

6.3.2 Participants

In this study, participants were chosen based on four criteria; I) the roles of the participants, including engineers, technicians, designers, and ergonomists, II) their expertise, including

industrial design, mechanical design, assembly, maintenance, and operations, III) the size of the company where the participants worked. This include small companies with 1 to 99 employees, medium companies with 100 to 499 companies, and large companies with more 500 or more employees. IV) the type of business, which was from eight industry sectors. Covering people with a wide range of interests in virtual ergonomics and DHMS was desired. Therefore, some participants with no DHMS experience were selected in this study. To ask people to participate in the study, they were contacted by emails, two Facebook pages (Dassault Systèmes and DELMIA), six LinkedIn pages (Virtual Ergonomics, Dassault Systèmes, Digital Manufacturing, Immersive technology, Simulation-Driven Engineering, and DELMIA), seven CEO forums (V4, V5, V6, DELMIA, General Discussion, MFG, and Manufacturing), and two Twitter pages (Dassault Systèmes and DELMIA). As a result, 86 people accepted our invitation. People from academia (students and professors), as well as those from product development teams without experience in human-centered design, were excluded, such that 31 men and two women were invited to participate in the interviews.

6.3.3 Data Preparation and overview of the analysis

For data preparation, we first transcribed the interview recordings and translated them to English. We read all the transcriptions and re-listened to all interviews to confirm the accuracy of the transcription. Then, based on the numerical data of the interviews, we perform some descriptive statistical analysis to provide a general perspective about the background of the users. In Section 6.4, we have provided the results of descriptive statistical analysis.

In the next step, we performed qualitative data analyses of the text interviews using constant comparison analysis and content analysis. To perform these analyses, we partially took help from NVivo that is a qualitative data software used for non-numerical and unstructured data (Jones and

Diment 2010, Sotiriadou 2014, Countouris 2014, Zamawe 2015, Gaber and Gaber 2018). We performed the main part of the qualitative analysis manually by reading the interview transcripts over and over again, where NVivo just helped to keep track of different categories in a more organized way. In Section 6.5, we have provided the results of the qualitative analysis.

After performing the qualitative analyses, we performed a persona analysis to identify the main categories of users with various characteristics. For the clustering step of persona analysis, we have proposed a new integer programming model. In Section 6.6, we will provide more details on our proposed approach for persona analysis and its results.

6.4 Descriptive statistical analysis of interviews

Here, we provide some descriptive statistical analyses to provide insights into the participants' background. In Table 6.2, we have summarized the information on participants' age and their expertise area.

Table 6.2. Participants' characteristics.

Age	Ergonomist			Non-ergonomist		
	Design	Manufacturing	Maintenance	Design	Manufacturing	Maintenance
20-29	0	0	1	3	1	0
30-39	0	2	0	4	1	0
40-49	2	3	1	5	3	2
50-59	1	0	1	2	0	1
60 or more	0	1	1	1	0	0

According to this table, most participants were between 40-49 years old. They mainly worked in three expertise fields including 18 in design (e.g., products and parts), 11 in manufacturing (e.g., operations/plant management, plant/workplace development), and 7 in maintenance and repairs management. It should be noted that some participants possessed expertise in two of those mentioned areas which is why the sum of these numbers is not equal to the number of participants. In addition, ten participants introduced themselves as ergonomists.

Moreover, in Table 6.3, we have provided some statistical analyses to describe the work experience of participants with different expertise areas and also their backgrounds in using CAD and DHM.

Table 6.3. Participants' work experience.

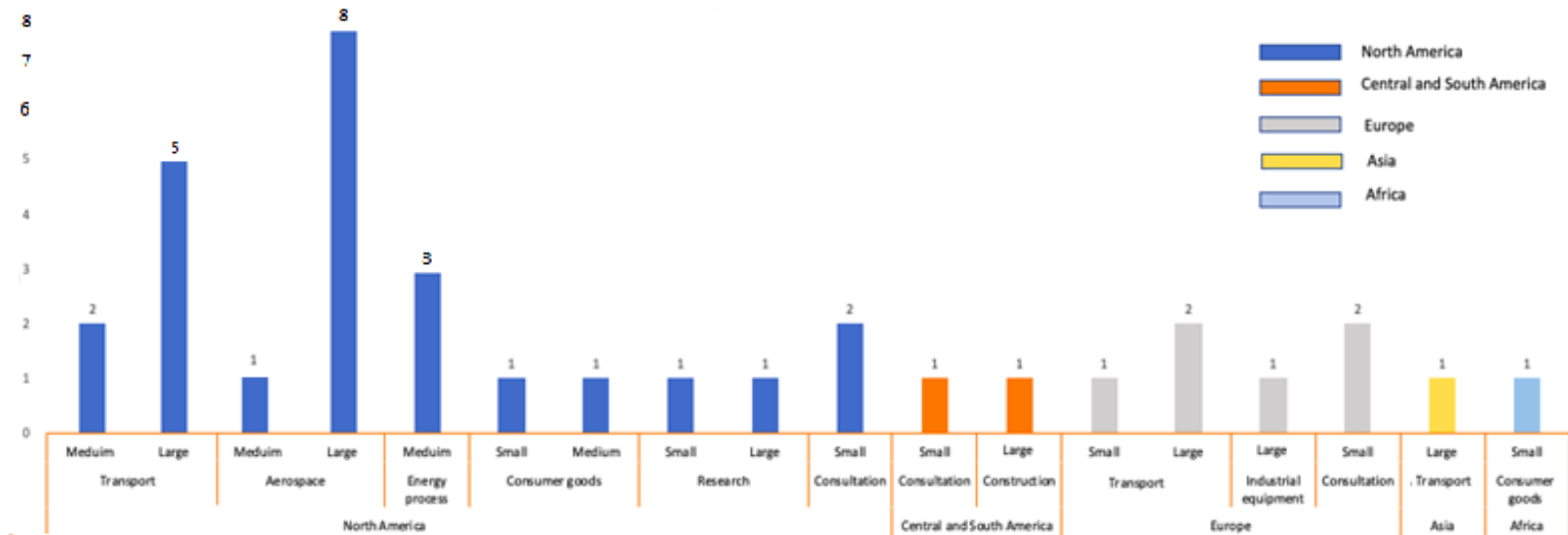
Area	Participant's experiences in years				Number of participants
	AVG(STD)	Range	Median	Mode	
Work	15.56(9.18)	2-36	15	21	31
Design	15.90(9.76)	2-40	16	10	21
Manufacturing	10.64(6.72)	2-23	14	15	11
Maintenance	10.90(11.83)	2.5-34	4	4	5
CAD	12.24(8.81)	2-40	10	10	25
DHM	9.08(6.29)	2-23	7	15	13

Table 6.3 shows that the median of participants' work experience was 15 [2-36] years (median [range]). Around one-third of the participants had 20 to 25 years of work experience and 79% of participants had 10 [2, 40] years (median [range]) experience in CAD. Eight participants (27%) never worked with CAD, while three (9%) worked with CAD 100% of their time. The other participants worked with CAD software between 10% and 95% of their work time.

Moreover, according to Table 6.3, among 33 participants, 63% worked with DHMS, and 39% of them had 7 [2, 23] years (median [range]) of experience with DHMS. The latter group allocated 15% to 80% of their daily work time to DHMS. Six of them had DHMS experience of more than ten years, while eight participants used DHMS only once or twice. One participant worked with DHMS once a month to create mannequins and check dimensions. Also, one participant did not work with DHMS, since he was a manager. However, in his company, four people worked with DHMS 100% of their time.

In Figure 6.1, we have categorized the participants based on the location, the sector, and the size of their companies. Figure 6.1 shows that 61% of companies were in transportation, mobility,

aerospace, and defense industries. It also indicates that 70% of all companies were located in North America. The number of employees in these companies varied from 1 to 224,000. In this study, one-third of the participants worked in extremely large companies with more than 10,000 employees. From this perspective, the participants were mainly categorized into three groups: I) 3D users in companies with less than 1,000 employees: they consisted of 27% of the participants who never or once in life worked with DHMS; II) ergonomists who never or rarely worked with 3D software: they made up 30% of participants; 60% of ergonomists worked in the companies with more than 1000 employees; and III) 3D users working with DHMS in the companies with more than 1,000 employees: they comprised one-third of participants.



Small: The number of employees in the industry is between 1-99.

Medium: The number of employees in the industry is between 100-499.

Large: The number of employees in the industry is 500 or more.

Figure 6.1 The number of participants per continent and per industry.

6.5 Qualitative analysis of interviews

As the main part of our analysis, in this section, we have provided the results of our qualitative analyses that are categorized into three themes; I) working context of the participants including the characteristics of their companies, II) DHMS characteristics, needs, and goals, III) DHMS advantages and disadvantages.

Tables 6.4 to 6.10 present the outcomes of our qualitative analysis. We have proposed all these tables based on constant comparison analysis and content analysis. We refer the readers to Sections 2.2.2 and 2.2.5 for reviewing these qualitative analysis approaches. In each of these tables, there is a column of “Variables” that represent the most important criteria based on participants’ opinions that we extracted in our analysis. In all tables, there is also a column of “Subcategories” that provides different possible values/settings for the given variables. These variables and subcategories were obtained using constant comparison analysis and content analysis. Using the content analysis, we have analyzed the interview of participants separately and have proposed an appropriate title for the new variables or subcategories. Then, according to the constant comparison analysis, we allocated the participants one by one to different groups. Whenever a new participant’s opinion could not be placed in one of the existing variables/subcategories formed using the previous participants’ opinions, we added a new group for variables or subcategories.

In the following sections 6.5.1 to 6.5.3, we present the summary of our qualitative analysis. In Appendix C.2, we have provided 13 large tables which represent the comprehensive results of our qualitative analysis. We encourage the readers to take a look at these tables while reading sections 6.5.1 to 6.5.3 to get a better idea of the size of analyzed data and obtained results.

6.5.1 Working context of the participants including the characteristics of their companies

In Table 6.4, we have analyzed the interviews based on the participants' authority in the design process.

Table 6.4. Decision-making power for design changes.

Variables	Subcategories	Description of variables and subcategories	The number of participants
Make recommendations		The participants made recommendations, but They are not allowed to made decisions on the design	24
	→ Decision-making by customers	The customers made decisions on the design	5
	→ Decision-making by ergonomists	Ergonomists made decisions on the design	2
Make decisions		The participants made decisions	7
	→ Power of the design change	The participants with the power of decision-making and changed the design	3
	→ No power of the design change	The participants with the power of decision-making but not allowed to change the design	3
	→ The team made decisions	The team made decisions and changed the design	1

Table 6.4 shows that the DHMS users have various levels of authority in the design process. For example, 73% of participants were not allowed to make design decisions, and were only allowed to make recommendations and suggestions for the design; in some companies, ergonomists made the final design decisions, while in others, the customers who bought the products made the decisions. Among the participants who made recommendations, 71.4% worked in companies with less than 10000 employees. Around 42% of these participants had DHMS experience. Furthermore, seven participants had the decision-making responsibility. Among these seven participants, four of them worked with DHMS working in extremely large companies with more than 10,000 employees.

In Table 6.5, we have analyzed the existence of ergonomics departments in different companies and their authorities. In the case that there is no ergonomics department in the company, we have analyzed how the designs are checked and approved in the company.

Table 6.5. Ergonomics department in companies.

Variables	Subcategories	Description of variables and subcategories	Number of participants
Ergonomics department			
	→ Sign-off and ergonomic checks	Sign-off and ergonomics checks were done in Ergonomics departments	11
	→ No sign-off and ergonomic check	Ergonomics checks were done in Ergonomics departments, but there is no sign-off	1
No Ergonomics department		There was not any ergonomics department in the company.	
	→ Experience based	No specific knowledge in ergonomics, they checked ergonomics issues based on their experience	9
	→ Health and safety department	Ergonomics is important for the company, but they just have health and safety department	3
	→ Ergonomist	Ergonomists had to sign for being able to continue the process	2
	→ Research center	Ergonomists worked in research centers	2
	→ Inspection	There were no ergonomics checks, but they did inspection process.	2
	→ Ergonomics check	They did ergonomics checks, but did not have an ergonomist	1
	→ Validation by DHMS or physical mock-up	No sign-off and no ergonomics checks were done, Validation performed by DHMS physical mock-up	1
	→ Ergonomists from consulting firm	No ergonomists worked in the company. When they needed an ergonomist, they asked from consulting firm	1

In Table 6.5, we can observe that 36% of the participants worked in companies with an ergonomics department. All of these participants had DHMS experience and their companies had more than 10,000 employees. Also, they all were responsible for approving a recommendation and signing off before it could move forward; Sign off implies that the design is final, and no further revisions are possible. However, 64% of participants worked in companies without an ergonomics

department. In nine companies with no such department, participants indicated that they checked ergonomics aspects based on their ergonomics experience, but none of them had DHMS experience, and their companies had less than 10,000 employees. In addition, in some firms without ergonomics departments, the participant asked ergonomists from consulting companies to check their design work. The checking was most often performed via checklists which were internal checklists or published in the literature. Moreover, regarding the work structure, 12 participants reported that they work in departments that collaborate with other departments of the company in parallel, while 21 participants stated that they work as a team (cascade setting) with other parties in their companies.

6.5.2 DHMS Characteristics, needs and goals

Appendix C1 is an extensive listing of different software packages used in DHMS, with a description of each one. Appendix C2 shows the DHMS tools used by all those who participated in answering the questionnaire and interviews. As indicated at Table C2.7, CATIA is the most frequently used software (14 participants), and the other software packages listed there (JACK, RAMSIS, CAVA, Compact Rio, 3DSSPP, Rhino, ANFOR) have 2 or 1 participants. Table 6.6 shows the opinions of DHMS users with varying levels of work experience and frequency of use regarding the level of difficulty they encountered when using the tool.

Table 6.6. Difficulty level of using DHMS.

Difficulty level of DHMS	DHMS Experience		Time allocated to DHMS in percentage	
	< 10 years	>=10 years	<50%	>=50%
<5	24%	1%	20%	14%
>=5	48%	19%	52%	14%

According to Table 6.6, most of the users that labeled DHMS tools with a difficulty level of 5 or higher are those that have less work experience in this area and also less frequently use DHMS tools. More specifically, about 14% of the participants who worked with DHMS more than 50% of their time stated that the difficulty level of DHMS was less than 5. In contrast, 52% of participants who worked with DHMS less than 50% of their time scored the difficulty level of using DHMS more than 5. Moreover, 52% of participants who did not work with DHMS regularly scored the maximum level of difficulty. Besides, 48% of participants with less than ten years of DHM experience scored more than 5 for the difficulty level. Moreover, 1% of participants who worked with DHMS for more than ten years rated less than 5 to the difficulty level of the software. Finally, ergonomists who comprised 24% of participants considered the difficulty level of the DHMS software more than 5, while 60% of them scored 10.

In Table 6.7, we have used qualitative analysis to examine the participants' viewpoints regarding the usefulness of DHMS. According to Table 6.7, among 25 participants who discussed the utility of DHMS, one-third of them stated DHMS was useful in their work. In contrast, 42% of participants declared that DHMS is not useful since positioning a mannequin is time consuming ($n=4$), costly ($n=2$) and the results are inconsistent ($n=7$), and in most cases, they had to erase the mannequin and start over since it was complicated for them to learn how to position it. They stated that the analysis was easier and faster in reality with physical mockups. Besides, 79% of the participants with more than 2 years of DHMS experience stated that it was very useful for them. Finally, 67% of the CATIA V5 users and also all users of CATIA V6 and Jack indicated that DHMS was considerably helpful.

Table 6.7. Utility of the DHMS.

Variables	Subcategories	Description of variables and subcategories	The number of participants
Useful			11
	→ Positioning the mannequin	Positioning the mannequin	1
	→ Design	Assembly line design and workplaces	1
	→ Analysis	Force and collision analysis	1
	→ Time-saving		1
	→ Quick result	The software provides results quickly.	1
Not useful			
	→ Time-consuming	Working with the software is time consuming.	4
	→ Costly	The software is expensive.	2
	→ Inconsistent	The software provide inconsistent results.	7
	→ Inaccurate	The software answer is not accurate	1

In Table 6.8, we have performed qualitative analysis on the needs and expectations of the participants. Based on the results of Table 6.8, we can categorize the participants' needs into three groups:

- I) Accuracy: The accuracy of the software result was an important issue for all participants to trust results. Here, by accuracy, they mainly referred to the accuracy in an ergonomics analysis and the positioning of mannequins. Nine participants mentioned they needed that the software describes their results with complete details, e.g., if their designs had problems, they were required to access analysis results. They also needed lists of suggestions by the software to correct their design.

Table 6.8. The needs of participants.

Variables	Subcategories	Description of variables and subcategories	The number of participants
Accuracy		The DHMS be accurate	33
Ergonomic evaluation		The DHMS must have ergonomic evaluation module	28
	→ Training in ergonomics	The trained participants in ergonomics	10
	→ Experience based	The participants checked ergonomics issues with their experience, without ergonomic knowledge	10
	→ Biomechanics	The participants interested in biomechanics	2
	→ By chart	The participants checked ergonomics issues by charts	1
	→ Confirmation of ergonomics department	The participants needed the confirmation of ergonomics department in his/her design	1
	→ No specific knowledge in ergonomics just need feasibility	The participants who needed just feasibility	1
	→ Ergonomic knowledge	The participants with ergonomics knowledge	1
Aesthetics			13
	→ Detailed	The results must be in detail	9
	→ Soft tissue	The DHMS must have soft tissues	3
	→ Real look	The design must look real	1

II) Ergonomics evaluation: 85% of the participants (non-ergonomists: n=18, ergonomists: n=10) demanded an advanced ergonomics evaluation module in DHMS, especially for accessibility (clearances and body interference with objects) and comfort zones. In total, 11 participants (non-ergonomists: n=1, ergonomists: n=10) were trained in ergonomics and performed ergonomics analyses. Moreover, 10 non-ergonomist participants carried out analyses based on their experiences without any training or certification in ergonomics. One of the ergonomists interviewed felt comfortable in performing simple analysis, but not for complex assessments such as fatigue or strength. In contrast, a participant with no specific knowledge in ergonomics just needed to know if a simulated task was feasible. At the analysis level of the design, one participant knew what he/she needed to do, and the ergonomics department approved their results quickly. In the company of this participant,

the ergonomics department was reliable, and their analyses were respected. One participant had anthropometric charts to validate his/her design. The charts were given to him/her by him/her supervisor to check some ergonomics aspects of the design. Around 64% of non-ergonomists asked for an appropriate user manual and integration of ergonomics standards in DHMS, especially for reach zones. One participant stated that he/she needed to have all the biomechanical details such as shock absorption, how the joints fold, etc.

III) Aesthetics: 40% of participants asked for better graphics (aesthetic) of the software, which included 83% of DELMIA V5 users. For example, three participants asked for adding the human soft tissue behavior in DHMS to design hands.

Next, in Table 6.9, we have analyzed the participants' goals for using DHMS that has resulted in five main variables and an overall of ten subcategories.

Table 6.9. Goals of using DHMS.

Variables	Subcategories	Description of variables and subcategories	The number of participants
Typical scenario	Interactions	Several interactions (pelvis, feet, hands) and handlebar movements, moving on a seat.	7
	Mannequin	To show just one object	3
			23
Display of results	Pass or fail	To show that the final design pass all the ergonomic	13
	Detailed results	To show details in the final design	10
			23
Illustration or communication	Work in a specific amount of time	To show how the software work in limited time	1
	Information transmission	To transmit information to designers	1
	Communication	To show good looking for the design	1
			21
Validation	Feasibility of task	Worth case scenario and extreme cases	1
	Solution	Validate solutions that will meet the needs of users	2
	Proof of happening	To show whether it will work with detailed reasons	1
			19
Understanding of scenarios		To create and analyze different situations or scenarios	6

According to Table 6.9, we can consider five main goals for participants that use DHMS:

- I) To evaluate typical scenarios: 70% of participants mentioned that they usually deal with repetitive or slightly different digital modeling situations for which they use DHMS tools. Some participants designed a mannequin interacting with one object. Some other participants designed a mannequin interacting with several objects such as a handlebar and a seat causing several environmental constraints.
- II) To illustrate, and communicate scenarios: 63% of participants used DHMS tools for illustrating scenarios and communicating with others. For example, some participants used DHMS to illustrate to customers how they were able to create a 3D view of a mannequin in a specific amount of time. They also could identify problems and solutions to communicate with other designers and engineers.
- III) To display the results: 39% of participants stated that they used DHMS to see if the design is a fail or a pass. 30% of participants aimed to have a report with complete details. One participant stated he/she needed to access the biomechanical details such as shock absorption, how the joints fold.
- IV) Validation: 58% of participants validated the feasibility of tasks, extreme scenarios, and extreme cases during the design. They also validated solutions that will meet the needs of the designers' team who will use the DHMS result.
- V) Understanding of scenarios: 18% of participants mentioned that their goal of using DHMS is to understand scenarios.

In addition, participants considered the following criteria in their design; Reaching area analysis (64% of participants), vision analysis (45% of participants), report of analysis design (36% of participants), force analysis (18% of participants), different anthropometries (15% of participants), and ergonomics standards (6% of participants). 42% of participants considered at least five criteria.

All in all, the participants working most of their time with DHMS stated that using DHMS was not difficult. On the other hand, the participants performing DHMS less than half of their time stated that using DHMS was difficult. Accuracy of the results, ergonomics evaluation module, and aesthetic of the software were the criteria that they needed during the design by DHMS. Finally, the goals of the participants for using DHMS were understanding, illustration, and communication of scenarios.

6.5.3 Advantages and Disadvantages of DHMS

We have also performed qualitative analysis on participants' viewpoints about the advantages and the disadvantages of using DHMS. We have provided the results of this analysis in Table 6.10.

According to Table 6.10, the main benefit of DHMS mentioned by 12 participants (ergonomist: n=8, non-ergonomists: n=4) was the power of communication provided by the display of mannequins in the design. The second advantage that seven participants (ergonomists: n=5, non-ergonomists: n=2) stated was the capability of DHMS to visualize and anticipate possible ergonomic problems in the design. They believed that DHMS allowed them to have control in the entire process of designing and analyzing a product before it was ever launched. Moreover, the design modification at early stages in the absence of a physical mockup was another advantage of DHMS that seven participants (ergonomists: n=3, non-ergonomists: n=4, designers: n=5) pointed out.

Table 6.10. Advantages and disadvantages of using DHMS.

Variables	Subcategories	Description of variables and subcategories	Number of participants
Advantages of DHMS			
	→ Communication	Show the mannequins in the design	12
	→ Visualization/anticipation	Visualization and anticipation of possible ergonomic problems	8
	→ Early design changes	Making changes to early design	7
	→ Time- saving	Save time	6
	→ Cost- reduction	Reduce the cost of design	4
	→ Model-reduction	Reduce the number of models to be made	1
	→ Analysis	Perform analysis in hazardous or inaccessible locations or poor positioning	1
	→ Conceptualization	Conceptualization is easier	1
	→ Presentation of ideas	Present the ideas that never existed	1
	→ Quick result	Achieving to result quickly	1
Disadvantages of DHMS			
	→ Difficulty	Difficulties in positioning	12
	→ Tim-consuming	Positioning takes too long	10
	→ Unreal look	Mannequins do not look natural	9
	→ Inconsistency	Lack of consistency in the results	7
	→ Analysis	Analysis depends on user knowledge	6
	→ Practice required	The need of practice to learn	4
	→ Counterintuitive	Not Intuitive, no feeling, not dynamic	3
	→ Buttons	Buttons distributed everywhere	2
	→ No feedback	Tell users if the posture is in acceptable range of motion	1
	→ Costly	Expensive	1

Also, time saving and cost reduction were two other significant reasons that 10 participants identified as the benefit of using DHMS. They stated that they could achieve the results quickly and it resulted in real cost savings to the industry. This cross-departmental integration increased the quality and the speed of information flow.

On the other hand, Table 6.10 shows that more than one-third of the participants stated that they had problems in positioning a mannequin (ergonomists: n=9, non-ergonomists: n=3). 10

participants (ergonomists: $n=5$, non-ergonomists: $n=5$) mentioned that they had to spend lots of time to position a mannequin. In some cases, setting up the mannequin's posture required more than one day. They also stated the analysis of the design could also be time consuming. Moreover, nine users complained about unnatural-looking mannequins. Finally, six ergonomists criticized the analysis phase; they stated that this part of the design was dependent on the user's knowledge. Therefore, the participants with no ergonomics knowledge had some troubles with the analysis phase. Besides, some participants were not satisfied with the interface design of DHMS. For example, they stated that the buttons in the software were not well ordered. Therefore, they needed more time to learn and design. One non-ergonomist participant with 15-years of experience in CAD but without experience in DHMS complained about the cost of the software and stated that if using DHMS is faster and cheaper than rapid prototyping, then he was interested in using it. Finally, one participant complained about not having feedback in the software, especially for the mannequin's postures. He stated the software had to tell users if the posture is in an acceptable range of motions.

Overall, the participants stated that the most important benefits of DHMS were the power of communication provided by the display of mannequins, the ability of the anticipation and visualization of possible ergonomic problems in the design, the design modification at early stages without the need for a physical mockup resulting in time saving and cost reduction. In contrast, the most undesirable factors in using DHMS were difficulty in positioning a mannequin, spending lots of time to position a mannequin and analysis of the design, unnatural-looking mannequins, and the inconsistency of the DHMS results in the analysis phase.

6.6 Persona analysis: methodology and results

The next step in our study is to perform the persona analysis to identify the different groups of DHM users sharing similar behaviors, expectations, and goals. To do so, we need to use the data of the users that were extracted as variables in our qualitative analysis in the previous section. We realized that the data of users for some of these variables are not dispersed and therefore they are not appropriate to be used for categorization of users in persona analysis. Hence, we split the variables into two groups of dominant and non-dominant variables and considered the former group for conducting our persona analysis. In Appendix C.3, we have provided the list of dominant and non-dominant variables.

As mentioned in our literature review in Section 2.2.12 of Chapter 2, categorization is the main step of persona analysis. In the next subsection 6.6.1, we will explain the novel integer programming model that we have proposed for the categorization step of persona analysis. Then, in subsection 6.6.2, we will discuss the results of our persona analysis.

6.6.1 Methodology of persona analysis

In this subsection, we propose a novel mixed integer programming model for the categorization step of our persona analysis. Our proposed model takes the data of users for the dominant variables as input and returns the optimal categorization of users such that the most similar ones fall in the same group. In the following, we have explained the sets, parameters, and variables used in this model.

Sets:

- I : The set of users/subjects that we want to cluster.
- K : The index set of potential clusters defined by $K = \{1, \dots, |K|\}$. Here, $|K|$ is the maximum number of acceptable clusters that is set by the decision maker in advance.

Parameters:

d_{ij} : The distance between subjects $i, j \in I: i \neq j$, which is defined with respect to the values of their dominant variables extracted from their interviews. Small values of d_{ij} shows that the two subject have more similar profiles with respect to their dominant variables, while larger values of this parameter indicate a significant difference between the profiles of the two subjects. The details of computing d_{ij} using the dominant variables are given in Appendix C.4.

Decision variables:

x_{ik} : 1 if subject i is allocated to cluster k ; 0 otherwise.
 y_k : 1 if cluster k is formed; 0 otherwise.
 z_{ijk} : 1 if both subjects i and j are allocated to cluster k ; 0 otherwise.
 w_k : The number of subjects allocated to cluster k .
 p_k : The number of pairs of subjects in cluster k .

Using the above notation, we propose the following integer programming model:

$$\min \sum_{k \in K} w_k \left(\frac{\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijk}}{p_k} \right) \quad (1)$$

$$\sum_{k \in K} x_{ik} = 1 \quad i \in I \quad (2)$$

$$w_k = \sum_{i \in I} x_{ik} \quad k \in K \quad (3)$$

$$p_k = \frac{w_k(w_k - 1)}{2} \quad k \in K \quad (4)$$

$$\sum_{i \in I} \sum_{j \in I: i \neq j} z_{ijk} = p_k \quad k \in K \quad (5)$$

$$z_{ijk} \leq x_{ik} \quad k \in K, \quad i, j \in I: i \neq j \quad (6)$$

$$z_{ijk} \leq x_{jk} \quad k \in K, \quad i, j \in I: i \neq j \quad (7)$$

$$x_{ik} \leq y_k \quad k \in K, i \in I \quad (8)$$

$$w_k \geq 3y_k \quad k \in K \quad (9)$$

$$y_k \geq y_{k+1} \quad k \in K \setminus \{|K|\} \quad (10)$$

$$x_{ik}, z_{ijk}, y_k \in \{0,1\} \quad k \in K, \quad (11)$$

$$i, j \in I: i \neq j$$

$$w_k, p_k \geq 0, \text{ integer} \quad k \in K \quad (12)$$

Objective function (1) minimizes the total weighted average distance between the members of each cluster. In (1), $\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijk}$ computes the total distance between all subjects allocated to cluster k . This term is divided by p_k , the total number of pairs of subjects in cluster k . Therefore, $\frac{\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijk}}{p_k}$ represents the total average distance between the subjects allocated to cluster k . Finally, $\frac{\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijk}}{p_k}$ is multiplied w_k , the number of members in cluster k , to consider larger weights in the objective function for larger clusters.

Constraint (2) indicates that each subject i is allocated to exactly one cluster. Constraint (3) computes w_k based on x_{ik} variables. Similarly, constraint (4) calculates p_k using w_k variables. Constraint (5) links p_k variables to z_{ijk} variables by forcing some of them to take positive values. Constraints (6) and (7) state that z_{ijk} variables can take 1 only if the corresponding x_{ik} and x_{jk} variables are set to 1. Constraint (8) indicates that x_{ik} can be equal to 1 only if y_k takes 1. Constraint (9) implies that any cluster formed by the model must have at least 3 members. Constraint (10) is a symmetry breaking constraint that makes the model start with forming clusters with smaller indices first. Constraints (11) and (12) also declare the binary and integer nature of variables.

After the running the proposed integer programming model, the clusters are formed. Then, within each cluster, the member that has the smallest total distance from all other members is selected the persona of that group. The main advantage of the proposed model compared to existing models in the literature is that it minimizes the total weighted average distance between all members of the same cluster, instead of minimizing the total distance from a single member as in

the K-medoid clustering method (Dasgupta 2008 and Zatti et al. 2019). Therefore, all members in the same cluster will be more coherent compared to K-medoid method. However, this advantage comes at a significant cost: The proposed model is nonlinear due to objective function (1) and constraint (4). In Appendix C.5, we have shown how to linearize the above model by defining new variables in an extended space.

6.6.2 Results of persona analysis

In this study, most ergonomists worked in large companies, while non-ergonomist participants worked in both large and small companies. Still, to have representative personas, it was necessary to have at least one participant in small businesses. The participants worked in three roles in companies: I) ergonomists, II) 3D users working in extremely large companies with more than 10,000 employees, and III) 3D users working in companies with less than 1000 employees. It was now a matter of quantifying these participants to see if they could represent personas. As mentioned earlier, out of the 30 variables that were found during the data analytics process (reported in Appendix C.3), 14 variables were considered dominant and thus were used directly to create the personas. In Appendix C.6, we have provided a table that shows which variables are in common for the members of each persona group.

The first group of persona included ten ergonomists. One ergonomist did not perform 3D and virtual ergonomics. He/she was not relevant as a persona for the development of virtual ergonomics software. Three ergonomists who worked with DHMS shared 78% of the same dominant variables (11 out of 14). The second group included 12 3D users working in extremely large companies with more than 10,000 employees. They shared 14% of the same dominant variables (2 out of 14), which could not be considered as the characteristics of a persona. Among them, seven participants had 42% of the same variables (6 out of 14), which were considered as

the characteristics of a persona. Moreover, three 3D users working in extremely large companies with 10,000 employees were associated with 64% of the same dominant variables (9 out of 14). Hence, they were considered a persona. Finally, the third group included nine 3D users working in companies with up to 1000 employees. This group has 35% of the same dominant variables (5 out of 14), and therefore could be considered as a persona. Among them, seven participants shared the same subset of 50% dominant variables (7 out of 14).

The first persona represented users who were ergonomists. She worked in a very large company with more than 10,000 employees. She believed in the importance of ergonomics in creating a safer and more efficient design. She was a member of the human factors team in a small but important department. She supported other departments, by doing suggestions and recommendations. Her opinion was valuable and taken very seriously. To do ergonomics verifications, she used DHM and mockups. She was convinced of the added value of DHM, but she was not comfortable with working in 3D. If it was easier, she would definitely use it more. She also would like to be 100 % confident in the analysis generated by such a tool.

The second persona was an industrial engineer. He represented 3D users in extremely large companies with more than 10,000 employees. Product line optimization was the core of his work, which was mainly involved in process definition, line balancing, and workplace design. Even if ergonomics was not his main focus, his designs had to meet some requirements to ensure the tasks were feasible, and workers were safe. To perform verifications on his designs, he used DHMS together with checklists provided by the ergonomics department. When an analysis was too tricky for him, he validated his results with the ergonomists.

The third persona was a mechanical engineer. He represented 3D users in businesses with up to 1000 employees. His company did not have the time and budget nor the awareness of the

importance of ergonomics. He had to do various activities related to design and manufacturing, due to the size of his business. He was in charge of multiple projects from beginning to end. He would have liked to check if his product was usable and if assembly tasks were feasible and arrive more quickly at a design that would meet the demands of his customers. Accordingly, to perform verification on his design, he would use his common sense. For example, he validated with people available in the company. He was interested in using DHMS if it resulted in a quicker and better design.

6.7 Discussion

In this section, we discuss our findings in this case study in Dassault Systèmes to better highlight the significant contributions of this chapter in the area of qualitative data analytics in cognitive ergonomics, which is one of the key objectives of this dissertation. In the following, we elaborate our findings about the users' goals and expectations, their satisfaction with the available DHMS tools, the usability and utility of these tools, and their limitations.

Recognizing DHMS users' goals plays a significant role in the design of a solution. Our findings show that all participants have similar views on DHMS regardless of the industry, role, area of expertise, or the size of the business. Users create a virtual environment that helps them in visualizing mannequins with different objects in a 3D virtual space. Most participants pointed out the same goals for using DHMS that are validation, illustration, communication, and understanding of the design scenarios. Apart from illustration and validation, most ergonomists had two other primary goals for using DHMS, which were to access detailed results and the interaction between mannequins and objects.

Our results also indicated that the participants that used the DHMS all the time were almost satisfied with it. On the other hand, some participants encountered resistance to work with the

software due to the deficiency in DHMS ease of use and learning. Moreover, the usability of the software does not depend on the participants' experience or expertise in using DHMS. This is because, among six participants working with DHMS for more than ten years, only two of them gave less than five to the difficulty level of the software. Hence, to increase the usability of DHMS, learnability, efficiency, and satisfaction should be taken into account. To this end, DHMS developers have to consider how easy it is for users to accomplish the design on the first try and how quickly they can design mannequins. (Williams and Wellbourne-Wood, 2006). Provide a user manual is one of the ways to help DHMS users in learning how to use the software. It will also save them time and money.

Users with more experience in working with DHMS stated the software is more useful for their designs. However, the participants with less experience in using DHMS expressed that DHMS does not meet their needs, which is the main factor of the utility of the software. Some examples are how to position a mannequin, how to analyze faster and easier, and how to reach a result representing reality.

The lack of human appearance, realism, animation, and dynamic of mannequins are some other obstacles mentioned by users. For example, a goal of 70% of participants was to create a mannequin with movements and interactions to better show how the human model would perform. To do this, the work task animation is needed since this feature allows users to set up the mannequin posture and to create movements. Hence, DHMS developers have to design more realistic virtual mannequins to see the realistic movements, human physical constraints, the accuracy of joint chain, physical limits, skin representation, muscle representation, gender, and facial expression. In addition, a study conducted by Lämkuil et al. (2007) reports that the appearance of mannequins influences users when judging a work posture.

The results also showed that all non-ergonomist DHMS users asked for an automatic ergonomic assessment module since positioning mannequins and identifying risk factors such as bad working postures are complex and time-consuming resulting in cost increase. They also require large-scale subject testing with physical mockups. Moreover, 64% of non-ergonomists asked for an appropriate user manual and the integration of ergonomics standards in DHMS. Hence, it can be concluded that the current and potential DHMS users are still looking for a DHMS solution to help them make decisions to produce desirable products and design safe workstations resulting in time and cost saving. Hence, it is required to develop new ergonomics analysis tools and provide appropriate user manuals with the integration of ergonomics standards. For example, the software has to check a set of numerical criteria such as maximum weight to be lifted or a maximum part insertion force or to perform more sophisticated analysis, such as an awkward posture or a difficult reach. Overall, anthropometry, kinematic model, and posture manipulation are the basic human function features that have to be checked during the design. As an example, a manual and visual access evaluation for properly installing and inspecting components of a product can save many unnecessary steps and thousands of labor hours later on during the production and maintenance of the product over its lifetime. Reach, space, and vision analysis are the main features that the participant of this study checked during the design. In addition, for ergonomics evaluations, creating scalable activity scenarios and providing an ergonomic score are necessary to compare the current design with the optimal one. Therefore, DHMS suppliers must support non-ergonomist users frequently which would increase their loyalty to the software.

The personas in our study contribute to the development of improved DHMS since it helps the members of the virtual ergonomics team have the same understanding of the users' needs, and know if the design of the product is adequate, and finally and have a consensus. It is also important

to note that personas may change as products develop. Once the Product Opportunity Assessment is complete, it will be important to check that the personas are still adequate and add some information to make them more specific to the chosen product, if necessary. It will also be essential to choose who is the main persona so that DHMS developers address 100% of his/her needs.

Overall, the results and findings mentioned above demonstrate that this chapter complements Chapters 4 and 5. It proves the significance of quantitative data analytic approaches in reducing the cognitive load of Tech employees, similar to how we demonstrate the significance of quantitative data analytics in alleviating physical pressure on workers in Chapters 4 and 5.

6.8 Conclusion

This chapter aligns with the overall objective of this dissertation by addressing the application of data analytics in a case study in the area of cognitive ergonomics. We investigated the users of DHMS tools with the aim of identifying their characteristics, needs, obstacles, and goals in using DHMS. Moreover, the participants were asked to share their opinions about the advantages and disadvantages of DHMS. In this study, we also considered the size and other characteristics of their companies, such as whether an ergonomics department or any ergonomist existed in those companies to sign off the design. The findings of this chapter is expected to help DHMS developer in producing more user-oriented DHMS tools resulting in lower cognitive loads.

For data collection, 33 participants were interviewed and the transcribed and translated data were analyzed using qualitative data analytics and descriptive statistical methods. Then we proposed a novel integer programming model for the categorization of participants in different group based on the data obtained from our qualitative analysis. Using this model, personas were created based on participants' characteristics to help DHMS developers to better know the current

and potential users of DHMS more precisely. Finally, we identified the following user's priorities in improving and developing existing/new DHMS tools:

- Integration of ergonomics standards into the software to better analyze the design for users with no ergonomics knowledge.
- Presentation of the results of their designs with more details and feedbacks.
- Enhancement of the ergonomics module to reduce the complexity of using software and reduce costs.
- Design of a user manual to save time for people with no or little knowledge in ergonomics.
- Enhancement of the aesthetic features of the software.

All in all, the most important factors that prevent participants from using the DHMS were the difficulty level of DHMS, consuming time, mannequin's unreal look, lack of consistency in the results. On the other hand, the power of visualization, communication, analysis, and early design changes, reduction of cost, and time are the motivational factors for the use of the DHMS.

6.9 Statement of authors' contributions

- Sahar Arab: validating the transcripts of interviews, descriptive statistical analysis of data, qualitative analysis of data, integer programming model for persona analysis, creation of tables, creation of figures, writing the paper. 50%
- Julie Charland, Hélène Drouin, and David Brouillette: organization and conduction of interviews, analysis of results to create personas. 30%
- Daniel Imbeau: proofreading, proposing the modification of figures, proposing the way to shrink the presentation of data in tables. 20%

CHAPTER 7 GENERAL DISCUSSION

This chapter provides a general discussion on the three research studies conducted in this dissertation. The main goal of this dissertation was to investigate the application of advanced data analytics approaches in the area of physical and cognitive ergonomics, based on real-world case studies. We focused on three human-centered ergonomics problems and used quantitative and qualitative data analytics approaches for them. In the following sections 7.1, 7.2, and 7.3, we discuss the knowledge gaps and contributions of these three works, respectively.

7.1 Research 1: Knowledge gap and contributions

In Research 1, we studied the application of quantitative data analytics in the area of physical ergonomics for forestry workers in Quebec. There are many existing models for the prediction of work metabolism in physical works which can be used in different settings with various input parameters. The knowledge gap in the literature was that no one had ever studied these existing prediction models and concluded which one is more accurate and reliable than others. No one knew what the effects of individual adjustment or considering the thermal component in these prediction models are. There was no guideline for practitioners and ergonomists to know under which environmental conditions they can use which prediction model with the most reasonable inputs in terms of time and cost.

Research 1 fills the aforementioned knowledge gap. More specifically, the contribution of this work is that we implemented 50 existing methods for the prediction of work metabolism of forestry workers and performed extensive statistical-oriented data analysis to evaluate these methods. These 50 models originated from 9 HR-based models with different possible combinations of input parameters such as two types of HR data (raw HR and corrected HR without thermal component) and five different estimates of maximum work capacity (MWC). We compared these models based

on various estimation errors (e.g., RMSE, rRMSE, Bias, and rBias), Student's two-tailed t-test for paired observations ($p < 0.05$), Bland-Altman plot, and LoA. Our statistical analysis resulted in very useful and handy guidelines for practitioners and ergonomists as discussed in the following.

In Research 1, we discovered the following findings: Our results showed WM estimates obtained by individual calibration (i.e., determination of the WM-HR relationship from a submaximal step-test) produced the most accurate estimation. On the other hand, a few WM estimation models not using calibration also produced very good accuracy such as the IsoForm, and Malch models with either the Jackson or MwcIso methods using HRcorr. Moreover, we discovered that the presence of the thermal pulses results in a significant underestimation of WM values with most HR-based models. Hence, including the thermal component in the model was required to obtain accurate WM prediction. In fact, by determining the thermal pulse, we consider the effect of all four thermal environment parameters as well as that of clothing insulation without the need to measure any of them. That is why determining the thermal pulses highly contributes toward accurate predictions.

Besides, our results indicated that models using MWC provide better WM estimates. However, among the models not including MWC as an input, a single model (Ueno_HRraw) that includes a thermal environment parameter (dry bulb temperature) performed very well. Therefore, this model is a quick and easy alternative to practitioners and decision makers who do not require the highest accuracy of WM estimation. Also, our results indicated that using individual calibration is highly recommended to estimate MWC of the participants when the most accurate WM estimations with the smallest number of participants are needed. If calibration cannot be used, then the model from ISO 8996:2004 used with its accompanying MWC method or the method proposed by Jackson et al. (1990) will offer very good accuracy when the thermal pulses are determined. The model from

Malchaire, Ambrosio Alfano, and Palella (2017) together with the Jackson MWC method will also provide very good accuracy. When neither thermal pulse determination nor calibration are considered, then the model from Ueno, Ikeda, and Tai (2014) are good alternatives. This study also indicated that the best performing model combinations provide accurate enough estimates (i.e., small $rBias$) of heavy work rates to allow the assessment of thermal stress with the WBGT index.

7.2 Research 2: Knowledge gap and contributions

According to the results of Research 1, we realized that individual calibration, thermal pulse determination, and measuring the ambient conditions significantly contribute to the accuracy of the best existing WM prediction models in the literature. However, all of them are undesirable for practitioners since they are timely and costly. The knowledge gap in the literature was that no one had proposed a highly accurate WM prediction model without using individual calibration, thermal pulse determination, and the measurement of the ambient conditions. This gap originated from the fact that the existing models in the literature were mainly based on simple regression models, without benefiting from advanced machine learning techniques.

Research 2 fills the aforementioned knowledge gap. More specifically, the contribution of this work is that we proposed six highly accurate regression decision tree models to predict WM which do not rely on individual calibration, thermal pulse determination, and measurement of the ambient conditions. We developed these models based on a new integer programming formulation which sets of the coefficients of input variables in the conditional and prediction expressions of the regression decision tree model. In order to validate the proposed approach, we used the K-fold validation method which together with integer programming model resulted in six regression decision tree models. We compared our proposed models with the best existing models in the

literature on a data set of forestry workers in Quebec. In this comparison, we used different estimation errors (e.g., RMSE, rRMSE, Bias, and rBias), Student's two-tailed t-test for paired observations ($p < 0.05$), Bland-Altman plot, and LoA.

In Research 2, we discovered the following findings: Our results indicated that the proposed RDT models significantly outperform the model by Ueno et al. (2014) and the model from ISO 8996:2004 with the maximum work capacity method estimated by Statistics Canada (2013). More specifically, the proposed RDT models resulted in rBias (%) of less than 2.2% that are significantly better than those of Ueno et al.'s (10.90%) and ISO model's (6.03%). We also observed that among our proposed RDT models, the average model (RDT_AV) is the most accurate one with respect to RMSE criterion. The average model resulted in an RMSE of 2.67, while proposed models 1 to 5 respectively resulted in RMSEs of 2.83%, 2.90%, 2.99%, 2.86%, and 3.08%. It is also worth mentioning that RMSE of Ueno and ISO were 4.41% and 4.65%.

In addition, the paired t-test showed that Ueno et al. and ISO models from the literature result in a significant difference between the measured and estimated WM, while it was negligible for the proposed RDT prediction models. This superiority of our models originates from their ability in modeling the nonlinearity between WM and input variables, that is also supported by the comparable LoA analysis. Moreover, we performed further analysis to determine the minimum required number of participants to achieve different accuracy level as it is critical factor in assessing the applicability of any prediction method in practice. Our results indicated that the average RDT model only needs 3, 5 and 10 participants to respect an accuracy level of 19%, 14.5%, and 10%, respectively.

All of our results demonstrated that our proposed RDT models are more applicable WM prediction methods for practitioners in real world cases since they are cost- and time-efficient

without any need for individual calibration, the determination of the thermal component, or measurement of ambient conditions.

7.3 Research 3: Knowledge gap and contributions

In line with the overall objective of this dissertation, it was yet to answer how qualitative data analytics can be beneficial in the area of ergonomics. Qualitative data are usually found in studies with interview data from users. Therefore, in Research 3, we focused on an interview-based case study on the users of DHMS, which is a very critical area for ergonomic practitioners making designs of industrial parts and work stations. The knowledge gap in the literature was that no one had seriously studied the characteristics of DHMS users, their needs, goals, expectations, and the barriers and limitations that they face in using DHMS in the design and product development process.

Research 3 fills the aforementioned knowledge gap. More specifically, the contribution of this work is that we analyzed the interview data of DHMS users by descriptive statistical analysis and also qualitative data analysis methods including content analysis and constant comparison analysis. Using these analyses, we extracted 30 variables, out of which we detected 14 dominant variables. Then, using the extracted variables, we performed a persona analysis to categorize different groups of users with various profiles and selected the persona for each group. For the categorization step of persona analysis, we first transformed the variables extracted from our qualitative analysis into a distance parameter for each pair of users/subjects. Then, we proposed a novel nonlinear integer programming model that takes the distance parameters as input and returns the obtained groups. The proposed model minimizes the total weighted average distance within the pairs of users in clusters. To be able to use this model efficiently, we developed a linearized version of it through defining new decision variables in an extended space.

In Research 3, we discovered the following findings: Our qualitative analysis showed that all users regardless of their backgrounds mainly use various DHMS tools for visualizing mannequins with different objects in a 3D virtual space. Most users mentioned that their main goals are validation, illustration, communication, and understanding of the design scenarios. Moreover, most ergonomists mentioned two additional goals for using DHMS that included having access to detailed results and the interaction between mannequins and objects. Also, our results indicated that the difficulty in learning various features of DHMS tools is the main reason that some users are reluctant to work with them. Surprisingly, we found out that this dissatisfaction with the usability of DHMS tools is independent from the users' experience or expertise, which indicates that DHMS developers must provide more helpful user manuals to facilitate the learning for users.

From a utility perspective, we realized that DHMS tools satisfy the expectations and needs of experienced users. However, less experienced users mostly expressed their dissatisfaction with DHMS in meeting their needs in various cases such as how to position a mannequin, how to analyze faster and easier, and how to reach a result representing reality. Other users' obstacles discovered by our qualitative analysis included the lack of human appearance, realism, animation, and dynamic of mannequins. Additionally, our analysis showed that all non-ergonomist DHMS users need to access an automatic ergonomic assessment module since positioning mannequins and identifying risk factors are complex and time consuming for them. As an instance, these users asked for an accessibility and comfort zone analysis module with more detail and recommendations. We also discovered that reach, space, and vision analysis are the main features that the users check during the design and therefore DHMS developers must focus more on the improvement of these features. In addition, aesthetics or graphic of the software was the other concern of the users. The users indicated that they need to see a realistic look of a mannequin and

have a better sense of reach, space, and force analysis. The participants also identified the benefits of DHMS as follows: I) the power of communication provided by the display of mannequins in the design, II) the capability of DHMS to visualize and anticipate possible ergonomic problems in the design, III) the design modification at early stages in the absence of a physical mockup, IV) time saving, and V) cost reduction.

Moreover, our persona analysis discovered that the DHMS users can be categorized into three main categories. The first category included ten ergonomists which could be well represented by a female human factor engineer as a persona that works in a large company. The second groups of users included 3D users working in large companies which were represented by an industrial engineer as a persona working in the area of product line optimization, process definition, line balancing, and workplace design. The last group consists of 3D users working in small companies. The mechanical engineer, that represents this group as the persona, works on design and manufacturing, is in charge of multiple projects from beginning to end, and mostly use his common sense for ergonomics evaluations.

CHAPTER 8 CONCLUSION AND RECOMMENDATIONS

In this chapter, we summarize the contributions and the limitations of this dissertation and provide recommendations for future research.

8.1 Advancement of knowledge

In this dissertation, we contributed to advancement of knowledge in the area physical and cognitive ergonomics using advanced qualitative and quantitative data analytics approaches.

- In Research 1 and Research 2 of this dissertation, quantitative data analytics were applied in the area of physical ergonomics on the data from the forest industry in Quebec. In Research 1, descriptive and diagnosis analytics were performed on the existing linear models based on the real data collected from forest workers. The aim of this study was to compare these models which calculated human work metabolism based on heart rate and other physiological and environmental variables. Then, parameters that affected the results such as individual calibration and the determination of the effect of thermal pulses were analyzed. This research aimed to help decision makers in making better decisions for maintaining workers' safety, health, and productivity based on the existing models.
- In Research 2, predictive analytics were performed based on the data and analysis from Research 1. The motivation behind this research was that measuring WM was time consuming and costly. We also wanted to consider the nonlinearity of the relations between variables without considering the thermal pulse in our prediction models. Therefore, we proposed novel machine learning models based on decision trees and integer programming to estimate work metabolism based on heart rate. The proposed approach resulted way more accurate predictions than the models analyzed in Research 1.

- Research 3 aligned with the overall objective of this dissertation by applying qualitative data analytics in the area of cognitive ergonomics on the interview data from the users of DHMS in the technology industry. The aim of this research was to better understand the needs, goals, and expectations of the current and potential users of DHMS. Qualitative data analytics including content analysis and constant comparison analysis were applied to understand the participants' characteristics and their opinions about the advantages and disadvantages of DHMS products. Then, a new integer programming model was proposed to perform the persona analysis to help developers better understand the different groups of users with similar characteristics.

8.2 Research limitations and recommendations

In the following, we highlight the limitations of this dissertation and provide some recommendations for future research.

- The quantitative studies of this dissertation were based on a group of experienced male forest workers performing their regular work in the usual conditions. Hence, it is interesting to perform a similar study based on female workers or workers with less energy demand. Moreover, the target group of these studies was western countries workers. Thus, our results may not be transferable to other populations. As an example, the estimated WM values for an Asian worker by the Western subjects-based equations using physical characteristics were significantly higher than actual WM values (Westerterp, 2019). In addition, the physical activity level of the forest workers in this study was seven and the results are based on this level of activity. Therefore, it is appealing to see the result of the formulation used in this study on the workers with less level of activity.

- To improve the robustness and generalizability of the proposed predictive models in this dissertation, it is of interest to users of larger sample size and variety to train and validate the model. Moreover, the psychophysical demands of work activity were not considered as a variable in the proposed predictive model. For example, considering body discomfort rate as an input variable along with physical variables will give us a better perspective of fatigue aspects associated with the activity.
- In the qualitative study of this dissertation, the questionnaire designed by our team was a general questionnaire and was not designed for a specific expertise or industry. It can be, therefore, a good idea to design a more specific questionnaire for different expertise areas and various industries. Moreover, in this study, the results represent the users' ideas about various DHMS tools. Therefore, the usability analysis of software was not performed. Hence, it is encouraging to perform a study for one specific DHM software and perform a usability test and analysis on it.

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APPENDIX A APPENDIX OF RESEARCH 1

SECTION 1: WM and MWC models

Keytel1:

$$\dot{V}O_{2\max} \text{ (kj. min}^{-1}\text{)} = -95.7735 + 0.6344 \times \text{HR}_{\text{WM}} + 0.3942 \times \text{Weight} + 0.4044 \times \text{Age}$$

IsoForm:

$$\text{WM}_{\text{IsoForm}} \text{ (Watts. m}^{-2}\text{)} = \frac{\text{MwcIso} - \text{M}_{\text{rest}}}{\text{HR}_{\text{max}} - \text{HR}_{\text{rest}}} \times (\text{HR}_{\text{WM}} - \text{HR}_{\text{rest}}) + \text{M}_{\text{rest}}$$

where:

$$\text{MwcIso} \text{ (Watts. m}^{-2}\text{)} = (41.7 - 0.22 \times \text{Age}) \times \text{Weight}^{0.666}$$

$$\text{HR}_{\text{max}} \text{ (bpm)} = 205 - 0.62 \times \text{Age}$$

$$\text{M}_{\text{rest}} \text{ (Watts. m}^{-2}\text{)} = 55$$

Malchaire:

$$\text{WM}_{\text{Malch}} \text{ (Watts)} = \frac{\text{MwcMalch} - \text{M}_{\text{rest}}}{\text{HR}_{\text{max}} - \text{HR}_{99}} \times (\text{HR}_{\text{WM}} - \text{HR}_{99}) + \text{M}_{\text{rest}}$$

where:

$$\text{MwcMalch} \text{ (Watts)} = (19.45 - 0.133 \times \text{Age}) \times \text{Weight}_{\text{ideal}}$$

$$\text{Weight}_{\text{ideal}} \text{ (kg)} = 0.9 \times \left(\text{Height} + \frac{\text{Age}}{10} - 100 \right)$$

$$\text{HR}_{\text{max}} \text{ (bpm)} = 208 - 0.7 \times \text{Age}$$

$$\text{M}_{\text{rest}} \text{ (Watts)} = 60 \times A_b$$

$$A_b \text{ (m}^2\text{)} = 0.007184 \times \text{Weight}^{0.425} \times \text{Height}^{0.725}$$

Kamon:

$$\text{Age 25: \%MWC} = (0.74 \times \text{HR}) - 44$$

$$\text{Age 35: \%MWC} = (0.82 \times \text{HR}) - 52$$

$$\text{Age 45: \%MWC} = (0.93 \times \text{HR}) - 63$$

$$\text{Age 55: \%MWC} = (1.08 \times \text{HR}) - 78$$

$$\text{Age 65: \%MWC} = (1.27 \times \text{HR}) - 93$$

Dubé:

$$\text{WM}_{\text{step}} \text{ (ml. kg}^{-1}\text{. min}^{-1}\text{)} = 7.9 + 2.46 \times H_m - 2.3 \times \frac{\text{Height}}{\text{Stage number}}$$

where:

H_m is the cumulative height climbed during the test in m/min at each step height (or stage)

(respectively 0 at rest; 1.725 for step 1; 3.225 for step 2; 4.725 for step 3; and 6.225 for step 4)

Height is the participants' stature (m)

Stage number is between 1 to 5 (Stage 1 is rest, Stage 2 is the lowest step height, Stage 3 is the second step height, Stage 4 is the third step height, Stage 5 is the highest step height).

Keytel2:

$$WM_{\text{Keytel2}} (\text{KJ. min}^{-1}) = -55.0969 + 0.6309 \times HR_{WM} + 0.1988 \times \text{Weight} + 0.2017 \times \text{Age}$$

Rennie:

$$\text{Resting energy expenditure (EE)} (\text{KJ. min}^{-1}) = -1.1 + 0.04 \times \text{Weight} + 0.02 \times HR_{\text{rest}}$$

$$\text{Flex point} = 1.7 + 0.23 \times \text{BMI} + 0.93 \times HR_{\text{rest}}$$

$$\text{Slope} (\text{KJ. min}^{-1}. \text{bpm}^{-1}) = -0.12 + 0.002 \times \text{Age} + 0.003 \times \text{Weight}$$

Ueno:

$$WM_{\text{Ueno}} \text{ for younger men } (\text{Watts. m}^{-2})$$

$$= -0.32 \times \text{Temperature} (^{\circ}\text{C}) + 2.43 \times \text{Weight} - 1.49 \times \text{Body fat percentage} + 403 \times HR_{\text{res}} - 44.9$$

$$WM_{\text{Ueno}} \text{ for older men } (\text{Watts. m}^{-2})$$

$$= 1.76 \times \text{Temperature} + 0.54 \times \text{Weight} - 0.99 \times \text{Body fat percentage} + 330 \times HR_{\text{res}} - 10.2$$

where:

$$\text{Body fat } (\%) = 1.2 \times \text{BMI} + 0.23 \times \text{Age} - 16.2$$

$$HR_{\text{res}} (\%) = 100 \times (HR_{WM} - HR_{\text{rest}}) / (HR_{\text{max}} - HR_{\text{rest}})$$

Jackson:

$$\text{MWC Jackson } (\text{ml. kg}^{-1}. \text{min}^{-1}) = 67.350 + 1.921 \times \text{Physical activity level} - 0.381 \times \text{Age} - 0.754 \times \text{BMI}$$

Section 2: Unit conversion equations

Table A.1 Unit conversion equations

Unit conversion equations	Units
$\text{WM (ml. kg}^{-1}\text{. min}^{-1}\text{)} = \frac{\text{WM(Watts)} \times 1000 \text{ ml. liO}_2^{-1}}{\text{Weight(kg)} \times 5.68 \text{ Watts. h. liO}_2^{-1} \times 60 \text{ min. h}^{-1}}$	Watts to ml. kg ⁻¹ . min ⁻¹
The Energy Equivalent of 5.68 Watt.h.liO ₂ ⁻¹ is taken from ISO 8996:2004	
$\text{WM (ml. kg}^{-1}\text{. min}^{-1}\text{)} = \frac{\text{WM(Watts. m}^{-2}\text{)} \times A_b(\text{m}^2) \times 1000 \text{ ml. liO}_2^{-1}}{\text{Weight(kg)} \times 5.68 \text{ Watts. h. liO}_2^{-1} \times 60 \text{ min. h}^{-1}}$	Watts. m ⁻² to ml. kg ⁻¹ . min ⁻¹
where: $A_b(\text{m}^2) = 0.007184 \times \text{Weight}^{0.425} \times \text{Height}^{0.725}$ with Height in cm and Weight in kg	
$\text{WM (ml. kg}^{-1}\text{. min}^{-1}\text{)} = \frac{\text{WM(Kj. min}^{-1}\text{)} \times 1000 \text{ ml. liO}_2^{-1}}{\text{Weight(kg)} \times 20.17 \text{ Kj. liO}_2^{-1}}$	Kj. min ⁻¹ to ml. kg ⁻¹ . min ⁻¹
The Energy Equivalent of 20.17 Kj.liO ₂ ⁻¹ is taken from Scherrer et al. (1981)	

Section 3: TERMS and symbols

Table A.2 Symbols and definitions

Symbols	Definition	Unit
A_b	Body surface area	m^2
Age	Age of the participant	year
BMI	Body mass index	$kg.m^{-2}$
Body fat percentage	Body fat percentage of the participant	%
Dube	Work metabolism model presented by Dubé et al. (2015)	$ml.kg^{-1}.min^{-1}$
Height	Height of the participant	m or cm
Hm	Cumulative height climbed during the test in m/min at each step height (or stage)	m
HR	Heart rate (beats per min)	bpm
HR ₉₉	HR value exceeded during 99% of the duration of the HR recording period	bpm
HR _{corr}	Heart rate without thermal pulses	bpm
HR _{max}	Maximum heart rate	bpm
HR _{raw}	Measured heart rate	bpm
HR _{res}	Heart rate reserve	%
HR _{rest}	Heart rate at rest	bpm
HR _{wm}	The average of 1-min intervals of heart rate during the observed period	bpm
IsoForm	Work metabolism model presented by ISO 8996:2004 with maximum work capacity as input	$ml.kg^{-1}.min^{-1}$
IsoTable	Work metabolism model presented by ISO 8996:2004 without maximum work capacity as input	$ml.kg^{-1}.min^{-1}$
Jackson	Maximum work capacity proposed by Jackson et al. (1990)	$ml.kg^{-1}.min^{-1}$
Kamon	Work metabolism model presented by Kamon (1982) with maximum work capacity as input	$ml.kg^{-1}.min^{-1}$
Keytel1	Work metabolism model presented by Keytel et al. (2005) with maximum work capacity as input	$ml.kg^{-1}.min^{-1}$

Table A.2 Symbols and definitions (cont.)

Symbols	Definition	Unit
Keytel2	Work metabolism model presented by Keytel et al. (2005) without maximum work capacity as input	ml.kg ⁻¹ .min ⁻¹
LoA	Limits of agreement	ml.kg ⁻¹ .min ⁻¹
Malch	Work metabolism model presented by Malchaire et al. (2017) with maximum work capacity as input	ml.kg ⁻¹ .min ⁻¹
Mrest	Resting metabolism	Watts or Watts.m ⁻²
MWC	Maximum work capacity	Watts or Watts.m ⁻²
MwcISO	Maximum work capacity proposed by ISO 8996:2004	Watts.m ⁻²
MwcMalch	Maximum work capacity proposed by Malchaire et al. (2017)	Watts
PD	Percentage difference	%
Physical activity level	The daily physical activity level of the participant	
Rennie	Work metabolism model presented by Rennie et al. (2001)	ml.kg ⁻¹ .min ⁻¹
SD	Standard deviation	
Stage number	Level of effort in the Meyer and Flenghi (1995) step-test	
Statcan	Maximum work capacity estimate from Statistics Canada (2013)	ml.kg ⁻¹ .min ⁻¹
Steptest	Maximum work capacity at HR _{max} = 220 – Age using the WM-HR relationship per Dubé et al. (2015)	ml.kg ⁻¹ .min ⁻¹
Temperature	Ambient temperature	° Celsius
Ueno	Work metabolism model presented by Ueno et al. (2014)	ml.kg ⁻¹ .min ⁻¹
VO ₂	Oxygen consumption	ml.kg ⁻¹ .min ⁻¹
VO _{2 max}	Maximum oxygen consumption	ml.kg ⁻¹ .min ⁻¹
Weight	Body weight	kg
Weight _{ideal}	Lean or fat-free body weight	kg

Table A.2 Symbols and definitions (cont. and end)

Symbols	Definition	Unit
WM	Work metabolism	ml.kg ⁻¹ .min ⁻¹ , Watts, Watts.m ⁻² , Kj.min ⁻¹
WM_ISOForm	Work metabolism model presented by ISO 8996:2004 with maximum work capacity as input	Watts/m ²
WM_Keytel1	Work metabolism model presented by Keytel et al. (2005) with maximum work capacity as input	Kj.min ⁻¹
WM_Keytel2	Work metabolism model presented by Keytel et al. (2005) without maximum work capacity as input	Kj.min ⁻¹
WM_Malch	Work metabolism model presented by Malchaire et al. (2017) with maximum work capacity as input	Watts
WM_Ueno	Work metabolism model presented by Ueno et al. (2014)	Watts.m ⁻²
WMstep	Work metabolism for each stage of the Meyer and Flenghi (1995) step-test, calculated with the equation from Dubé et al. (2015)	ml.kg ⁻¹ .min ⁻¹

APPENDIX B APPENDIX OF RESEARCH 2

In the following, we propose a mixed-integer programming model that generates our RDT models. The indices, parameters, and decision variables associated with the proposed model are listed below.

Indices:

- i : Sample, $i = 1, 2, \dots, |I|$.
- j : Predictor/feature/independent input variable, $j = 1, 2, \dots, |J|$.
- l : Layer in the decision tree, $l = 1, 2, \dots, |L|$.

Parameters:

- K_l : The maximum number of nodes/partitions in layer l .
- X_{ij} : Value of sample i for input variable j .
- $y(measured)_i$: The measured output value of sample i .

Continuous variables:

- $y(estimated)_i$: Predicted output for sample i .
- $Error_i$: Absolute error between predicted output and measured output for sample i .
- CE_l : The conditional expression in layer l whose value determines which path must be followed in the tree (see Figure 5.1).
- y_{il} : Prediction value for the output of sample i in layer l of the decision tree.
- a_{jkl} : The regression coefficient of input variable j for the prediction in partition k of layer l .
- C_{kl} : The intercept of regression function in partition k in layer l .
- b_{kl} : The breaking point k for the conditional expression in layer l .
- d_{jl} : The coefficient of input variable j in the conditional expression CE_l in layer l .

Binary variables:

- V_{ikl} : 1 if the value of the conditional expression CE_l for sample i falls into partition k in layer l ; 0 otherwise.

Using the above notation, we proposed the following mathematical programming model to find a piecewise approximation function. The objective function is to minimize the mean absolute errors:

$$\min \sum_{i \in I} Error_i \quad (1)$$

In Objective function (1), $Error_i$ is computed by $Error_i = |y(estimated)_i - y(measured)_i|$ that is a nonlinear relation. Therefore, to have a linear integer programming model, which can be solved by commercial solvers, we need to linearize $Error_i = |y(estimated)_i - y(measured)_i|$ as follows:

$$Error_i \geq y(estimated)_i - y(measured)_i \quad \forall i \in I \quad (2)$$

$$Error_i \geq y(measured)_i - y(estimated)_i \quad \forall i \in I \quad (3)$$

In constraints (2)-(3), $y(estimated)_i$ is computed using the following constraints.

$$y(estimated)_i = \sum_{l \in L} y_{il} \quad \forall i \in I \quad (4)$$

To compute the values of y_{il} , we have the following constraint in the model.

$$\text{If } V_{ikl} = 1, \text{ then } y_{il} = \sum_{j \in J} (a_{jkl} x_{ij} + C_{kl}) \quad \forall k \in \{1, 2, \dots, K_l\}, \forall i \in I, \forall l \in L \quad (5)$$

Constraint (5) states that if the value of the conditional expression in layer l for sample i falls in partition k (i.e., $V_{ikl} = 1$), then the predictor for this sample in this layer is computed by $y_{il} = \sum_{j \in J} (a_{jkl} x_{ij} + C_{kl})$.

We also know that each sample i in each layer l falls in one of the nodes. Therefore, we have constraint (6) as follows:

$$\sum_{k=1}^{K_l} V_{ikl} = 1 \quad (6)$$

The next constraint links V variables to conditional expressions CE_l .

$$\text{If } CE_l \leq b_{1l} \quad \text{then } V_{i1l} = 1 \quad (7)$$

$$\text{If } b_{(k-1)l} \leq CE_l \leq b_{kl} \quad \text{then } V_{ikl} = 1, \quad \forall k \in \{2, \dots, K_l - 1\} \quad (8)$$

$$\text{If } CE_l \geq b_{(K_l-1)l} \quad \text{then } V_{iK_l l} = 1 \quad (9)$$

In constraints (7)-(9), the conditional expressions CE_l are computed through the following constraint:

$$CE_l = \sum_{j \in J} d_{jl} x_{ij} \quad \forall l \in L \quad (10)$$

Moreover, to make sure that in constraints (7)-(9), we have valid partitions, we need to add the following constraint to the model.

$$b_{(k-1)l} < b_{kl} \quad \forall l \in L, k \in \{2, \dots, K_l - 1\} \quad (11)$$

Since constraints (7)-(9) are if-then constraints, they are nonlinear and we need to linearize them using the following big-M constraint. In these constraints, M is a very large positive constant.

$$CE_l \leq b_{1l} + M(1 - V_{i1l}) \quad (12)$$

$$d_{(k-1)l} - M(1 - V_{ikl}) \leq CE_l \leq d_{kl} + M(1 - V_{ikl}) \quad \forall k \in \{2, 3, \dots, K_l - 1\} \quad (13)$$

$$CE_l \geq d_{(K_l-1)l} - M(1 - V_{iK_l l}) \quad (14)$$

To understand how constraints (12)-(14) are the same as constraints (7)-(9), first we note that, with respect to constraint 6, each sample i falls in one of the nodes in layer l . In the case that this sample belongs to the first node on layer l (i.e., $V_{i1l} = 1$), then constraint (10) will be active and constraints (12) and (13) will be inactive because of the existence of large M values. If the training sample happens in one of the middle nodes of layer l (i.e., $V_{ikl} = 1$, $k \in \{2, 3, \dots, K_l - 1\}$), the

constraint (13) will be active for the corresponding node, and constraints (12) and (14) will be relaxed. The last case is when training sample i falls in the last node of the layer l (i.e., $V_{iK_l} = 1$).

In this case, constraint (14) will be active and the other constraints are deactivated.

We also note that constraint (5) is nonlinear. Therefore, so we linearize it as follows:

$$\begin{aligned} \sum_{j \in J} (a_{jkl}x_{ij} + C_{kl}) - M(1 - V_{ikl}) &\leq y_{il} \\ &\leq \sum_{j \in J} (a_{jkl}x_{ij} + C_{kl}) + M(1 - V_{ikl}) \end{aligned} \quad \begin{array}{l} i \in I, \\ l \in L, \\ k \in \{1, 2, \dots, K_l\} \end{array} \quad (15)$$

The above constraint indicates that if training sample i falls in node k of layer l ($V_{ikl}=1$), then we will have $y_{il} = \sum_{j \in J} (a_{jkl}x_{ij} + C_{kl})$. For other nodes in this layer that the training sample i does not belong to, we have $V_{ikl} = 0$. Therefore, constraint (15) will be relaxed for those nodes. It means that y_{il} will be computed only using the prediction formula for the node that it belongs to and not the other nodes.

APPENDIX C.1 APPENDIX 1 OF RESEARCH 3: EXPLANATION OF DHMS TOOLS LISTED IN TABLE 6.1

In this appendix, we review the digital tools listed in Table 1 of Chapter 6. The following explanations are provided by the authors of this dissertation.

Dassault Systèmes CATIA Human Builder:

Dassault Systèmes CATIA Human Builder is software module used within CATIA, that is a well-known 3D CAD software package. CATIA Human Builder aims at helping designers and engineers in modeling and simulating the interactions of employees with products and workstations. It allows the users to simulate different tasks such as assembly and maintenance that help them identify ergonomic issues in early stages of design. This software also provides posture and reach analysis for evaluating the worker while interacting with the environment. Vision analysis is also one of the features addressed in CATIA Human Builder. This feature is helpful when analyzing the line of sight for the worker is important. This software also offers basic biomechanics and strength analysis.

ADAMS:

Automatic Dynamic Analysis of Mechanical Systems (ADAMS) is powerful digital modeling tool, developed by MSC Software Corporation, that is mainly used for simulating the dynamics of multiple bodies/parts simultaneously. These parts can be connected to each other through joints that constrain their movements. Therefore, this software is useful for analyzing the motions and interactions of different parts with each other and their environments. In the simulation and analysis of the mechanical systems, various parameters such as velocities, forces, and initial conditions can be given as inputs to the software. ADAMS is also capable of modeling complicated dynamic elements such as springs, friction, flexible bodies, and contact between bodies. A limitation of ADAMS is that, compared to specialized human modeling software packages, it does not provide a high level of anatomical accuracy.

ANSYS Human Body Model:

Human Body Model (HBM) is a very strong DHM tool that is developed by ANSYS Incorporation. This software is widely used for the simulation and analysis of human body with physical interactions, such as impacts, vibrations, and thermal changes. It also offers stress and strain analysis to evaluate humans' safety and comfort help in designing workplaces and tools. HBM offers a variety of features for creating detailed human body models, with different anatomy,

postures, and realistic skin and clothing textures. This software provides two type of human bodies including one adult male and one adult female. The male model consists of more than 300 body parts including organs, muscles and bones. It can take various physical characteristics, such as mass, density, and elasticity as inputs for making customized individual models.

AnyBody Technology:

AnyBody Technology is a digital modeling tool, particularly designed for musculoskeletal modeling. It can model the musculoskeletal structure of different creatures, but designer mainly use it for musculoskeletal modeling of human bodies. The human models in this software are designed based on anthropometric data. Designers can use this software for biomechanical and kinematic analysis of the human body in various physical conditions. AnyBody Technology can calculate the stress on muscles, joints, and human tissues, and provide ergonomic analysis. This software can also simulate the relation between the musculoskeletal and the respiratory systems of human bodies. One of the main limitations of this software is that customization of the available models or making completely new digital human models can be complicated and challenging.

CogTool:

CogTool is a software package for user interface prototyping, developed by researchers at Carnegie Mellon University. Using this software, the developer creates an initial version of a user interface and assess its usefulness in real time as he/she modifies it. This software works based on a model that predicts the behavior of the humans in using the interface. CogTool provides different features for building and simulating the user interface , such as tools for defining tasks, goals and the behaviors of the user. The main limitation of CogTool is that it just focuses on predicting user performance in specific tasks and does not provide comprehensive predictions for all aspects of human behavior using the software.

DELMIA:

Digital Enterprise Lean Manufacturing Interactive Application, or shortly (DELMIA) is software developed by Dassault Systèmes for virtual modeling and simulation of the manufacturing and production systems with the goal of identifying the bottlenecks in productivity. This software is also capable of analyzing the dynamic interaction of human labors with the production line and evaluating the safety and ergonomics factors simultaneously. In the modeling process, the software

allows users to make a digital model of the factory layout design and simulate the whole production process. A limitation of DELMIA is that it may require integrating with other software packages to import digital human models which needs additional expertise in this area and could be challenging for users.

ESI Group Virtual Human Builder:

ESI Group Virtual Human Builder is a DHM tool, developed by ESI Group, that helps engineers design parts and work environments with a complete focus on the safety and comfort of the human user. This software enables the engineers to make a digital model of the human based on anthropometrical data and perform a detailed ergonomic analysis through biomechanical and kinematics modeling. This software has various applications in automotive, aerospace, and design of medical devices.

Human Solution RAMSIS:

Human Solution RAMSIS is a DHM tool that is developed by Human Solutions for designing the interiors of vehicles and simulating the interaction of the drivers within the vehicle. The main goal of this software is to help the designer focus on the safety and comfort of the driver. For the digital modeling of the driver, RAMSIS allows the designers to set body dimensions, joint angles and ranges of motion, and consider additional clothing and accessories, if required. This software provides various types of driver-centered analysis such as posture analysis, reach and visibility analysis, and comfort analysis. It also has a data bank of body dimensions for different populations which allow the engineers to optimize their designs for different users. The main limitation of RAMSIS is that, since it is primarily designed for the automotive industry, its features and functionalities cannot be easily used in other industries.

LifeMOD:

LifeMOD is a DHM tool, developed by LifeModeler, which is a biomechanical software company. This software enables the users to create virtual models of different parts of the human body such as the knee and lumbar spine. LifeMOD offers various features such as the creation of customized human models and let the users simulate the dynamics of complicated movements. The main application of this software is in designing orthopedics and medical devices and also designing the training regimens for athletes and fitness enthusiasts.

NEUROBS Presentation:

NEUROBS Presentation is a digital platform developed by Neurobehavioral Systems, Inc., that is mainly used for designing and implementing complicated behavioral and cognitive experiments. This software is used in various areas such as psychology, neuroscience, and human factors engineering and let the researchers perform different experiments such as psychophysics, reaction time studies, Electroencephalography (EEG), fMRI, and eye-tracking studies. This software allows the users to send different stimuli (e.g., text, images, sounds, and videos) to the subject and simultaneously receive neurological responses without any delay from EEG and fMRI systems.

OpenSim:

OpenSim is a free software package for modeling the musculoskeletal structure of the human body and its dynamic movements. It is developed by the National Center for Simulation in Rehabilitation Research at Stanford University and is mainly used in the field of rehabilitation. However, it has also application in other areas such as sports science, and ergonomics. Using this software, the users can model forces on muscles, joint torques, and energy consumption of the body. This software also enables users to analyze forward and reverse dynamic movements. Forward dynamic analysis refers to the case that the user wants to know what the movements of human body would be if specific forces are applied to the body, while the reverse one is applicable when the user is interested in knowing the forces that can results in a specific movement. One of the main limitations of OpenSim is that is, in the reverse dynamic analysis, only the net forces of torques are reported by the software rather than the details these elements acting on joints.

PTC Creo Human Factors Design:

Creo Human Factors Design is a commercial computer-aided design (CAD) software package, developed by PTC, that has a strong ergonomics module for helping engineers in designing products and workstations. This ergonomic module allows the users to analyze the interaction of the human with the environment. It also offers a feature for analyzing the vision and sight analysis of workers in the workstation. This module allows the users to validate the design and get aware of potential risks quickly. This software also has a library of various digital human models representing different genders and ethnic groups. One of the limitations of PTC Creo Human Factors Design is that as strong human-factor-engineering-based software, it does not offer any feature about the physiological simulation.

SAMMIE:

SAMMIE is a DHM tool, developed by Loughborough University in England. This tool helps designers and engineers in evaluating workplace environments to improve ergonomics and safety of work. More specifically, it is used for the assessments of fit, reach and vision of designs in a CAD environment, reflection and mirror evaluations; and generally safety evaluations. Engineers use this software in different industries such as automotive, aerospace, and manufacturing. Some instances of using this software is to design the layout of equipment and furniture in public areas, offices and homes; cockpit, cabin, and interior evaluations of vehicles. One of the drawbacks of this software is the low animation quality of digital human models that prevents the users from completely understanding the natural positions and movements of the mannequins.

SANTOS:

SANTOS is a powerful DHM tool, developed by researchers at University of Iowa. This software is used for the design and test of digital human bodies in their interactions with systems and equipment. This software is used by practitioner in automotive, aerospace, defense, and manufacturing industries. This software offers a very detailed musculoskeletal structure of the human body including bones, joints, and muscles. It also offers the dynamic analysis of human movements based on give forces. Additionally, it simulates the humans' neuromuscular control system that helps users evaluate the way that the nervous system controls movement. SANTOS also offers various physiological analysis such as fatigue prediction. It can also take CAD models as inputs.

Siemens Jack:

Siemens Jack is a DHM tool that is used for simulation and analysis of ergonomics and human factors in product and workstation design. It helps practitioners improve the workers' interaction with products and work environments. Besides providing anthropometric data for various populations, it provides posture and reach analysis and also let the user simulate different tasks such as assembly, maintenance, and operation. It also provides vision and line-of-sight analysis. Moreover, Siemens Jack is capable of performing biomechanical and strength analysis which let the users check joint torques, muscle forces, and strength limits. One of restrictions of using Siemens Jack is that simulating its complicated digital human models can be computationally demanding and requires strong computational resources.

The Virtual Brain:

The Virtual Brain (TVB) is a software package in the area of physiological modeling through which the researchers evaluate humans' brain activity and analyze how it controls and affects our sentiments and

actions. Using TVB, the users model and simulate large-scale brain networks which take input data from various neuro imaging methods such as MRI. These neurological models include various levels of the brain such as neurons, axons and synapses. TVB can be used to evaluate the brain activity during different situations such as resting-state activity and evoked responses. A limitation of TVB is that it may not replicate the real complexity of the brain since it works based on simplified brain models with much fewer nodes and connections compared to the human brain.

3DSSPP:

3DSSPP, that stands for Three-Dimensional Static Strength Prediction Program, is a software tool in the area of DHM that is developed by the Center for Ergonomics at the University of Michigan. This software is mainly designed to model and optimize the interaction of workers with products and workstations. This software lets the users do biomechanics and strength analysis of static postures. It also has a static strength prediction feature which let the users determine how many percentage of a population can exert a required force in a specific posture. Moreover, 3DSSPP can analyze the forces and moments on various body joints while doing different tasks. One of the limitations of 3DSSPP is that it models the lower body such as pelvis parallel with the horizontal and does not let the user modify it.

Dassault Systèmes SIMULIA Living Heart:

Dassault Systèmes SIMULIA Living Heart is physiological software module used within SIMULIA, that is a versatile design tool in various engineering applications. SIMULIA Living Heart let the users make a comprehensive 3D model of the heart with structural details such as chambers, valves, and blood vessels. Then, based on this the developed heart model, users can simulate heart actions such as dynamics of cardiac tissues and blood circulation, and also its interaction with other organs. Such simulations allow the users to analyze different heart functions such as contraction, relaxation, and pressure-volume relationships. SIMULIA Living Heart also provide the possibility of electrophysiology simulation, that means users can study the electrical behavior of the heart. One the main limitations of this software is that it does not let the users automatically study the effect of physical pressure that the worker is experiencing on the behaviour of the heart.

Dassault Systèmes SIMULIA AnyBody:

Dassault Systèmes SIMULIA AnyBody is a software in the area of DHM that enables the users to do biomechanics and musculoskeletal simulation of the human body under different forces. This software has a variety of applications such as the design of new products, sport medicine, and rehabilitation. Multibody dynamic simulation is one of the features of this software that allows the users to study the motions of

multiple parts of human body simultaneously, while being under different sources of forces. It also offers a feature on the prediction of postures and movements which lets the user foresee natural motions of the human body to minimize load on muscles and joints. This features help the practitioners design more ergonomics tools and products. This software also provides a feature on muscle force analysis by which users can simulate the muscular contraction and power generation of workers while performing their tasks.

CAVA

Developed by Technia, this software is an add-on to CATIA. The CAVA products consist of design and help tools to enable automotive OEM's and their suppliers around the world to assure compliancy of a car's design to both national and international standards and norms. (<https://www.technia.com/software/cava/>)

HumanCAD human modeling solution

This software creates digital humans in a 3D environment in which a variety of ergonomic and human factor analysis can be performed. HumanCAD aids users with the design of products and workplaces by determining what humans of different sizes can see, reach, or lift. (<http://www.nexgenergo.com/ergonomics/humancad.html>)

**APPENDIX C.2 APPENDIX 2 OF RESEARCH 3:
THE COMPREHENSIVE RESULTS OF QUALITATIVE ANALYSIS**

On the next pages of this appendix, we have provided 13 large tables (Tables C.2.1 to C.2.13) which represents the comprehensive results of our qualitative analysis performed on the descriptive interviews.

Table C.2.1- The age, expertise, role, decision-making power of users, existence of ergonomic departments in their companies, and their work structure.

Users	Age					Field of expertise			Role: Ergonomist or Not? (1:Yes, 0: NO)	Ergonomics department exists or not?	Decision-making power for design change? (1:Yes, 0:No)	Work structure: Cascade (1) or Parallel (0)?
	20-29	30-39	40-49	50-59	60 or more	Design	Manufacturing	Maintenance				
1			1			1				1	1	1
2				1		1		1	1		1	1
3			1					1	1	1		1
4			1					1			1	1
5		1				1				1	1	1
6	1					1				1	1	1
7	1							1	1	1		1
8			1				1	1			1	1
9		1								1	1	1
10					1		1	1	1	1		1
11				1		1		1		1		1
12						1	1				1	
13				1		1					1	
14					1	1						
15			1				1				1	1
16		1				1					1	
17	1					1					1	
18		1									1	1
19		1				1				1	1	1
20	1					1	1				1	1
21			1			1						1
22			1			1						1
23			1			1						
24		1					1					1
25		1				1					1	1
26			1			1			1	1	1	
27			1			1	1		1	1	1	
28			1				1		1	1	1	
29			1			1					1	
30		1					1		1	1		
31			1				1			1	1	1
32		1					1		1	1	1	
33			1				1		1		1	1
Total	4	9	14	3	2	19	12	7	10	15	23	21

Table C.2.2- The region, type, and size of industry

Users	Region					Type of industry								Size of Industry
	North America	South and Central America	Europe	Asia	Africa	Transport and Mobility	Aerospace and defense	Architecture engineering /construction	Energy and utilities	Industrial equipment	Consumer goods & retails	Research	Consultation	
1	1					1								6200
2	1											1		2000
3	1						1							34100
4	1						1							8800
5	1					1								6000
6	1					1								6000
7	1						1							34100
8	1						1							163000
9	1						1							34100
10			1			1								29000
11	1						1							34100
12	1						1							1500
13	1					1								100
14	1						1							200
15			1			1								26000
16			1										1	1
17			1			1								30
18	1								1					3500
19				1		1								66500
20		1											1	30
21		1						1						25000
22	1					1								1000
23					1						1			1
24			1							1				1600
25	1										1			500
26			1										1	2
27	1												1	1
28	1											1		80
29	1												1	10
30	1					1								224000
31	1						1							112000
32	1					1								350
33	1										1			3000
Total	23	2	6	1	1	11	9	1	1	1	3	2	5	-

Table C.2.3- The work experience of users in any area and also in the area of design.

Users	Work experience in any area (years)							Work experience in Design (years)						
	0	1 to 5	5 to 10	10 to 15	15 to 20	20 to 25	>25	0	1 to 5	5 to 10	10 to 15	15 to 20	20 to 25	>25
1						1							1	
2							1							1
3						1							1	
4						1		1						
5				1							1			
6		1							1					
7		1						1						
8					1			1						
9			1							1				
10							1					1		
11						1						1		
12						1							1	
13							1					1		
14					1									1
15					1			1						
16			1							1				
17			1							1				
18				1				1						
19			1							1				
20		1							1					
21				1							1			
22						1								1
23	1							1						
24	1							1						
25				1							1			
26						1							1	
27					1							1		
28				1				1						
29						1							1	
30			1					1						
31						1		1						
32			1					1						
33						1		1						
Total	2	3	6	5	4	10	3	12	2	4	3	4	5	3

Table C.2.4- The work experience of users in the areas of manufacturing and maintenance.

Users	Work experience in Manufacturing						Work experience in Maintenance			
	0	1 to 5	5 to 10	10 to 15	15 to 20	20 to 25	0	1 to 5	10 to 15	>25
1	1						1			
2	1									1
3	1							1		
4	1								1	
5	1						1			
6	1						1			
7	1							1		
8	1							1		
9	1						1			
10		1					1			
11	1						1			
12						1	1			
13	1						1			
14	1									
15					1		1			
16	1						1			
17	1						1			
18	1						1			
19	1						1			
20		1					1			
21	1						1			
22	1						1			
23	1						1			
24			1				1			
25	1						1			
26	1						1			
27					1		1			
28					1		1			
29	1						1			
30			1				1			
31					1		1			
32		1					1			
33					1		1			
Total	22	3	2	0	5	1	27	3	1	1

Table C.2.5- The work experience of users in CAD and DHMS packages.

Users	Work experience in CAD (years)							Work experience in DHM (years)					
	0	1 to 5	5 to 10	10 to 15	15 to 20	20 to 25	>25	0	1 to 5	5 to 10	10 to 15	15 to 20	20 to 25
1						1				1			
2	1										1		
3						1							1
4						1				1			
5				1					1				
6		1							1				
7	1								1				
8			1						1				
9			1					1					
10	1									1			
11					1			1					
12				1				1					
13					1			1					
14							1	1					
15					1			1					
16			1					1					
17			1					1					
18					1			1					
19			1					1					
20		1						1					
21				1				1					
22						1		1					
23		1						1					
24			1					1					
25				1				1					
26		1										1	
27	1							1					
28	1							1					
29						1						1	
30			1									1	
31	1										1		
32	1							1					
33	1							1					
Total	8	4	7	4	4	5	1	20	4	3	2	3	1

Table C.2.6- The frequency of using CAD and DHMS packages by users.

Users	Frequency of using CAD (in percentage)										Frequency of using DHM (in percentage)									
	0-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	90%-100%	0-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	90%-100%
1													1							
2	1																	1		
3		1														1				
4							1								1					
5						1						1								
6		1												1						
7		1																	1	
8			1										1							
9		1										1								
10	1																1			
11		1									1									
12							1				1									
13											1									
14									1		1									
15								1				1								
16			1								1									
17								1			1									
18				1								1								
19							1					1								
20												1								
21											1									
22		1										1								
23											1									
24				1								1								
25								1			1									
26				1								1								
27	1										1									
28	1										1									
29			1											1						
30								1										1		
31	1																			
32	1														1					
33	1										1									
Total	7	6	3	3	0	1	3	1	3	1	12	9	1	3	1	2	1	1	2	0

Table C.2.7- The DHM/virtual ergonomics and design software packages used by users.

Users	Software packages								
	CATIA V5	CATIA V6	JACK	RAMSIS	CAVA	Compact RIO	3DSSPP	RHINO	ANFOR
1	1								
2	1		1						
3	1								
4	1								
5	1			1	1				
6				1	1				
7	1								
8	1								
9	1								
10		1	1						
11									
12									
13									
14									
15	1								
16									
17									
18									
19									
20	1								
21									
22	1								
23									
24						1			
25									
26									1
27							1		
28									
29								1	
30			1						
31	1								
32		1							
33									
Total	12	2	3	2	2	1	1	1	1

Table C.2.8- The difficulty (usability) and usefulness (utility) of DHMS packages by users.

Users	Difficulty/Usability of using DHM (in scale of 1 to 10)										Utility/Usefulness of DHM (in percentage)									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
1							1												1	
2								1											1	
3					1														1	
4	1																		1	
5						1										1				
6						1													1	
7								1											1	
8		1																	1	
9			1										1							
10					1												1			
11																				
12																				
13																				
14																				
15																				
16																				
17					1									1						
18																				
19																				
20		1																	1	
21																				
22							1								1					
23																				
24									1							1				
25																				
26										1					1					
27										1					1					
28										1			1							
29					1													1		
30				1																1
31				1																1
32				1																1
33													1							
Total	1	2	1	3	4	2	2	2	1	3	0	0	3	1	3	2	1	1	8	3

Table C.2.9- The goal of using DHM by users.

	Goals						
Users	Typical scenario		Display of results		Illustrate /communicate	Validation	Understanding of scenarios
	Interactions	Manniquin +1 object	Pass or fail	Detailed results			
1		1			1		
2	1			1	1	1	1
3	1			1	1	1	
4	1				1	1	
5		1		1	1	1	
6		1		1		1	
7	1			1	1	1	
8	1		1		1	1	
9		1	1			1	
10	1			1	1	1	
11							
12			1			1	
13	1		1				
14	1		1		1		
15	1		1			1	
16	1		1		1		
17	1		1		1		
18							
19							
20	1		1		1		
21	1		1		1		
22	1					1	
23							
24					1	1	
25	1			1			1
26					1	1	1
27					1	1	
28					1		1
29	1		1			1	
30	1			1	1	1	
31	1			1	1	1	1
32	1			1	1	1	
33							1
Total	19	4	11	10	20	19	6

Table C.2.10- The criteria for achieving goals considered by users.

Users	Criteria for achieving goals												
	Reaching area analysis	Space analysis	Images	Vision analysis	Report	Clearance	Force analysis	5th, 50th, 95th percentile	Vision line	Results accepted by standards	Doing a task for a certain time safely	3D surface	Video
1	1	1	1	1	1								
2	1	1	1	1	1								
3	1	1	1	1	1								
4	1	1	1	1	1								
5	1	1	1	1	1	1		1	1	1			
6	1	1	1	1	1			1	1			1	
7	1	1	1	1	1			1			1		
8	1	1	1	1	1		1	1		1			
9	1		1	1				1					
10	1	1	1	1	1	1	1						
11													
12	1						1						
13	1												
14	1	1				1							
15	1	1	1				1						
16	1	1	1	1		1			1				
17	1		1			1							
18													
19													
20													
21													
22													
23													
24													
25													
26													
27	1	1		1	1		1						
28													1
29	1	1	1	1		1							
30	1	1	1	1	1	1	1						
31	1	1	1			1							
32	1	1	1	1	1								
33													
Total	21	17	17	15	12	8	6	5	3	2	1	1	1

Table C.2.11- The needs of users.

Users	Ergonomic evaluation							Aesthetics		
	People with ergonomics knowledge	People who needs instruction	Biomechanics	Experience based	By chart	Confirmation of ergonomics department	only feasibility check	Detailed	Soft tissue	Real look
1				1				1		1
2	1							1		
3	1							1		
4				1				1		
5				1				1		
6				1				1		
7	1							1		
8					1			1		
9						1		1		
10	1							1		
11										
12		1								
13		1						1	1	
14		1								
15		1								
16		1								
17		1								
18		1								
19										
20		1								
21										
22										
23										
24		1								
25			1							
26	1									
27	1									
28	1									
29	1									
30	1									
31							1			
32	1									
33	1									
Total	11	9	1	4	1	1	1	11	1	1

Table C.2.12- The advantages of using DHM stated by users.

Users	Advantages								
	Communication	Visualization and anticipation	Early design changes	Time-saving	Cost-reduction	Analysis	Conceptualization	Presentation of ideas	Quick result
1	1								
2		1				1			
3	1		1	1					
4			1						
5			1	1					
6			1	1					
7	1		1	1	1				
8	1	1	1						
9	1								
10	1	1	1						
11									
12									
13									
14									
15									
16							1	1	
17						1			
18									
19									
20									
21									
22									
23									
24									
25									
26	1								
27	1								
28	1								
29	1	1			1				
30	1	1			1				
31									
32	1	1		1					
33		1		1	1				
Total	12	7	7	6	4	2	1	1	0

Table C.2.13- The disadvantages of using DHM stated by users.

Users	disadvantages									
	Difficulty	Time-consuming	Unreal look	Inconsistency	Analysis	Practice required	Counterintuitive	Buttons	No feedback	Costly
1	1	1	1	1						
2	1					1				
3	1		1							
4		1		1					1	
5	1	1	1	1			1	1		
6		1		1		1	1			
7	1	1	1			1				
8			1							
9										
10	1	1	1		1					
11										
12										
13										1
14										
15										
16										
17										
18										
19										
20										
21										
22			1							
23										
24										
25										
26	1	1		1	1					
27	1	1			1					
28	1	1			1					
29										
30	1		1	1	1					
31	1	1	1	1						
32	1						1			
33					1	1		1		
Total	12	10	9	7	6	4	3	2	1	1

APPENDIX C.3 APPENDIX 3 OF RESEARCH 3: THE LIST OF DOMINANT AND NON-DOMINANT VARIABLES

Dominant variables		Non-dominant variables	
Name of variables	Reference Table	Name of variables	Reference Table
Size of the company	Table C.2.2	Age	Table C.2.1
Decision-making power for design change	Table C.2.1	Geography	Table C.2.2
Work structure (parallel or cascade)	Table C.2.1	Industry	Table C.2.2
Ergonomics department in the company	Table C.2.1	Area of expertise	Table C.2.1
Frequency of doing 3D (CAD/CAM)	Table C.2.6	Total number of work experience (years)	Table C.2.3
Frequency of using DHMS	Table C.2.6	Ergonomics department exists or not.	Table C.2.1
Role (Ergonomist ou Non-Ergonomist)	Table C.2.1	Number of years in design	Table C.2.3
Number of years of using 3D (CAD/CAM)	Table C.2.5	Number of years in manufacturing	Table C.2.4
Work experience in using DHM (Number of years)	Table C.2.5	Number of years in maintenance	Table C.2.4
Usability of DHMS	Table C.2.8	Software packages used (3DS, Siemens, Ramsis, etc.)	Table C.2.7
Utility of DHMS	Table C.2.8	Understanding the scenarios	Table C.2.9
Typical scenarios (complex or not)	Table C.2.9	Validation	Table C.2.9
Detailed results	Table C.2.9	Illustration or communication	Table C.2.9
Ergonomic evaluation	Table C.2.11	Criteria for achieving goals	Table C.2.10
		Aesthetic	Table C.2.11
		Advantages of DHMS	Table C.2.12
		Disadvantages of virtual ergonomics	Table C.2.13

APPENDIX C.4 APPENDIX 4 OF RESEARCH 3: THE DETAILS OF COMPUTING PARAMETER d_{ij}

In this Appendix, we explain how to compute the parameter d_{ij} in the proposed integer programming model in Section 6.6.1.

First we need to define the following notation:

Sets:

- V : The set of dominant variables extracted in our qualitative analysis. These variables are listed in Appendix C.3.
- C_v : The set of possible options for variable $v \in V$. Each option refers to one of the columns in the corresponding table of variable v presented in Appendix C.2.

Parameters:

- a_{ivc} : The value of column c of dominant variable v for subject i . These values are binary and presented in tables of Appendix C.2.
- $weight_{vc}$: The importance weight for the column c of variable v . These values are set based on the comments of expertise.

Based on the above notation, the formula that we used to compute d_{ij} is $d_{ij} = \sum_{v \in V} \sum_{c \in C_v} weight_{vc} |a_{ivc} - a_{jvc}|$. In fact, this formula sums up the weighted absolute difference between the values of two subjects. Therefore, low values of d_{ij} indicates that subjects i and j are fairly similar, while large values of this parameter implies less closeness of the subjects.

APPENDIX C.5 APPENDIX 5 OF RESEARCH 3: LINEARIZATION OF THE PROPOSED INTEGER PROGRAMMING MODEL FOR PERSONA ANALYSIS

In this Appendix, we explain how to linearize the nonlinear integer programming model proposed in Section 6.6.1. The main idea of our linearization is to define new variables in an extended space to avoid the nonlinear terms in the proposed model.

First, we note that by substituting $p_k = \frac{w_k(w_k-1)}{2}$ in the proposed objective function, we will obtain this objective function:

$$\min \sum_{k \in K} 2 \left(\frac{\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijk}}{(w_k - 1)} \right)$$

The above objective function is still nonlinear. To deal with it, we define the following new sets and variables:

New set:

N : The set of possible numbers for the members of each cluster. We have $N = \{0, 3, 4, 5, \dots, |I|\}$ where $|I|$ denotes the total number of subjects. Here, we do not have 1 and 2 as members of N since clusters with 1 and 2 members are not allowed in our persona analysis.

New variables:

w'_{kn} : 1 if cluster k include exactly n members; 0 otherwise.
 z_{ijkn} : 1 if both subjects i and j are allocated to cluster k that includes exactly n members; 0 otherwise.

The linearized integer programming model is as follows:

$$\min \sum_{k \in K} \sum_{n \in N} 2 \left(\frac{\sum_{i \in I} \sum_{j \in I: i \neq j} d_{ij} z_{ijkn}}{(n - 1)} \right) \quad (C.5.1)$$

$$\sum_{n \in N \cup \{0\}} w'_{kn} = 1 \quad k \in K \quad (C.5.2)$$

$$w_k = \sum_{n \in N \cup \{0\}} n w'_{kn} \quad k \in K \quad (C.5.3)$$

$$\sum_{i \in I} \sum_{j \in I: i \neq j} z_{ijkn} = \frac{n(n-1)}{2} w'_{kn} \quad k \in K, \quad n \in N \cup \{0\} \quad (C.5.4)$$

$$z_{ijk} = \sum_{n \in N} z_{ijkn} \quad k \in K, \quad i, j \in I: i \neq j \quad (C.5.5)$$

$$z_{ijkn}, w'_{kn} \in \{0,1\} \quad k \in K, \quad n \in N \cup \{0\}, \quad i, j \in I: i \neq j \quad (C.5.6)$$

$$\sum_{k \in K} x_{ik} = 1 \quad i \in I \quad (C.5.7)$$

$$w_k = \sum_{i \in I} x_{ik} \quad k \in K \quad (C.5.8)$$

$$z_{ijk} \leq x_{ik} \quad k \in K, \quad i, j \in I: i \neq j \quad (C.5.9)$$

$$z_{ijk} \leq x_{jk} \quad k \in K, \quad i, j \in I: i \neq j \quad (C.5.10)$$

$$x_{ik} \leq y_k \quad k \in K, i \in I \quad (C.5.11)$$

$$w_k \geq 3y_k \quad k \in K \quad (C.5.12)$$

$$y_k \geq y_{k+1} \quad k \in K \setminus \{|K|\} \quad (C.5.13)$$

$$x_{ik}, z_{ijk}, y_k \in \{0,1\} \quad k \in K, \quad i, j \in I: i \neq j \quad (C.5.14)$$

$$w_k, p_k \geq 0, \text{ integer} \quad k \in K \quad (C.5.15)$$

In the above model, (C.5.1)- (C.5.6) are new relations compared to the original nonlinear model. The other relations (C.5.7)- (C.5.15) existed in the initial model. As you can see, objective function (C.5.1) is linear thanks to the definition of the new variables z_{ijkn} which carry information on the number of members in clusters. Constraint (C.5.2) indicates that each cluster will have exactly one unique number as the number of members in that cluster. Constraint (C.5.3) links w'_{kn} and w_k

variables. Constraint (C.5.4) has substitutes constraints (4) and (5) in the original model. Constraint (C.5.5) links z_{ijk} and z_{ijkn} variables. Constraint (C.5.6) declare z_{ijkn} and w'_{kn} as binary variables.

**APPENDIX C.6 APPENDIX 6 OF RESEARCH 3:
DETAILS OF PERSONAS WITH RESPECT TO DOMINANT VARIABLES.**

Table C.6.1 Common dominant variables for different personas.

Dominant Variables	Persona 1	Persona 2	Persona 3
Size of the company	✓	✓	✓
Decision-making power for design change	✓	✓	✓
Work structure	✓		✓
Ergonomics in the company	✓	✓	✓
Frequency of doing 3D (CAD/CAM)	✓		✓
Frequency of using DHMS		✓	✓
Role (Ergonomist or Non-Ergonomist)	✓	✓	✓
Number of years of using 3D (CAD/CAM)	✓		✓
Work experience in using DHM (Number of years)		✓	✓
Usability of DHMS	✓		
Utility of DHMS	✓		
Typical scenarios (complex or not)			
Detailed results	✓		
Ergonomic evaluation (with or without instruction)	✓	✓	
Parentage of dominant variables in personas	78%	50%	64%