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Objective quantification of in-hospital patient mobilisation after cardiac surgery

Author:
Jeroen van Haaren BSc

Supervisors:
Prof. J.G. Grandjean MD PhD
Prof. P.H. Veltink PhD
M. Groenier PhD
F.R. Halfwerk MD MSc
R. Klaassen PhD
R. van Delden PhD

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Thorax Centrum Twente

MST

UNIVERSITY OF TWENTE.

Preface

The past 12 months can be described a as valuable and educational experience. I have been able to conduct interesting and relevant research within my areas of interest. During my research I had to build bridges between different disciplines and had the opportunity to come in contact with different inspiring professionals. These experiences have contributed to my personal development. My supervisors created an atmosphere in such way that I was motivated to make my own mark and to show what I am worth as a technical physician. I am grateful for their input and tried to utilise all the tools that were offered to me. I have experienced the relationship between my supervisors and I as pleasant, which certainly contributed to the positive thoughts that I have retained from my graduation process. Therefore, I would like thank my supervisors. I would also like to thank Thoraxcentrum Twente for providing many opportunities and supporting my clinical ambitions. I have experienced Thoraxcentrum Twente as a sincere and welcoming organisation and I am open to cooperation in the future.

September 29, 2020
Jeroen van Haaren

Abstract

Introduction Early patient mobilisation is important to ensure fast recovery after cardiac surgery. Mobilisation can be improved using patient-specific information and exercises that match their current functional level. To achieve this, first patient mobilisation should be quantified objectively.

Purpose To determine a method to quantify in-hospital mobility objectively in patients after cardiac surgery.

Methods A list of device requirements was made, used to select a tri-axial accelerometer suitable for clinical research. A neural network algorithm was developed to classify accelerometer data into classes of physical activities of interest. In experimental setting, optimal dual sensor placement configuration was determined. A clinical pilot study was conducted aimed at classifying postoperative physical activity of inpatients after cardiac surgery, using one sensor attached the right upper leg and one attached to the right upper arm. To make reliable classifications, preoperative physical activity data from patients was used to train the neural network.

Results The device regarded best for use in this research was the AX3 accelerometer (Axivity Ltd.). Preoperative data from 31 patients resulted in a trained algorithm with overall activity classification accuracy of 96%. Postoperative physical activity was classified in 29 patients. Patients spent most of their time lying or sitting. The amount of other forms of physical activity was low, mostly demonstrated between 8 a.m. and 11:59 a.m. No significant differences were found between male and female patients.

Conclusion The method used was successful at obtaining objective quantification of inpatient mobilisation after cardiac surgery. Results suggest sufficient scope to motivate inpatients to be more (frequently) active on a daily basis.

Keywords: cardiac surgery, inpatient mobilisation, objective quantification, accelerometry, Machine Learning, neural network

Acronyms

ACSM American College of Sport Medicine. 33

AD anterodistal. 16, 17, 19, 64

ANN Artificial Neural Networks. 13, 14

AP anteroproximal. 16

BMI Body Mass Index. 7, 17, 21

CABG Coronary Artery Bypass Grafting. 17, 22

CE Conformité Européenne. 10, 59–61

COPD Chronic Obstructive Pulmonary Disease. 21

CVA Cerebro Vasculair Accident. 17

DL Deep Learning. 13

EuroSCORE I The European System for Cardiac Operative Risk Evaluation I. 21

EuroSCORE II The European System for Cardiac Operative Risk Evaluation II. 17, 21

GDPR General Data Protection Regulation. 10

HAR Human Activity Recognition. 14, 36

ICU Intensive Care Unit. 7, 8, 17, 20, 22

IQR interquartile range. 17, 21, 22, 26–30, 73

KATZ-ADL Katz Index of Independence in Activities of Daily Living functioning. 17, 35

LD laterodistal. 16

LOSO Leave-One-Subject-Out. 14, 16, 19, 20, 22–24, 36, 67, 68, 70–72

LP lateroproximal. 16, 17, 19, 64

MET Metabolic Equivalent of Task. 33

METC Twente Medical Ethics Committee Twente. 17

ML Machine Learning. 2, 8, 9, 13, 14, 32, 38, 39

MOVeMeNTT Mobilisatie Objectiveren op de Verpleegafdeling middels Metingen Na Thoraxchirurgie in Thoraxcentrum Twente. 17

MST Medisch Spectrum Twente. 6, 10, 17, 53, 55, 57

NCA Neighbourhood Component Analysis. 14, 15

NYHA New York Health Association. 21

SD standard deviation. 17

STROBE Strengthening the Reporting of Observational Studies in Epidemiology. 16

TCT Thoraxcentrum Twente. 6–8, 17, 33, 37, 52

UT University of Twente. 10

VSNU De Vereniging van Universiteiten. 10

Contents

1 Introduction

In the Netherlands, 16.000 open heart surgeries are performed annually [1], 1100 are performed at Thoraxcentrum Twente (TCT) of Medisch Spectrum Twente (MST) (Enschede, The Netherlands). After undergoing cardiac surgery, the average hospital stay is five to seven days [2]. Early patient mobilisation is important to ensure fast recovery after cardiac surgery [3], [4]. Mobilisation improves postoperative physiological functional capacity, accelerates functional recovery, and shortens hospital stay [5]–[11]. In addition, it reduces postoperative complications, pain and depression, and is associated with lower mortality, morbidity and costs [5], [12].

Physical therapists and nurses play an important role in stimulating patient mobilisation in order to optimise recovery. Under supervision of a physiotherapist, patients should make physical efforts such as walking (stairs), cycling on a hometrainer and practising breathing techniques. Besides that, recovery benefits from additional unsupervised physical activity of the patient. Despite the importance of mobilisation after surgery, patients frequently display inactive behaviour and are bed-bound. Patients are often unaware of the importance of mobilisation, they are afraid to damage the wound area or fear chest pain. Next, patients overestimate intensity of mobilisation and can be hindered by pain and fatigue [13], [14]. Inactivity results in loss of muscle strength, decreases physical function, lengthens hospital stay and increases cardiovascular mortality and morbidity [15]–[18].

1.1 Improving postoperative mobilisation

In TCT, interventions (project called 'Moving is improving!') have been carried out to improve mobilisation [19]. In order to improve mobilisation, posters have been developed which hang in every room in TCT (Figure 1).

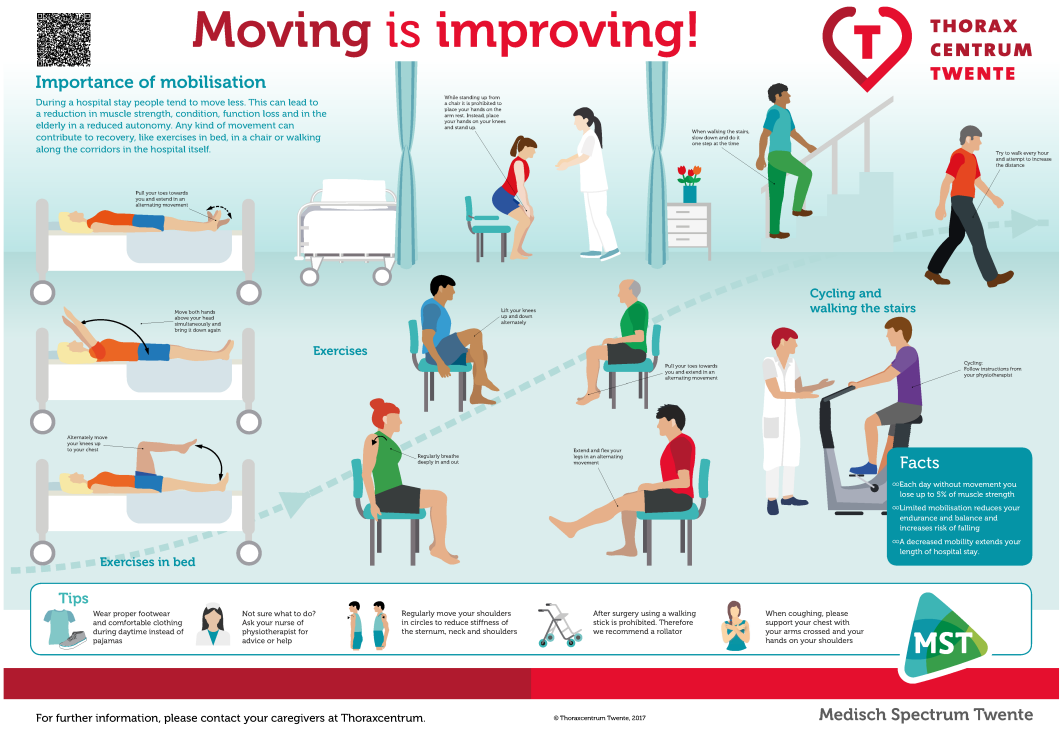


Figure 1: *The mobilisation poster developed in TCT [19]. The poster shows the patient journey from lying in bed to sitting in a chair and walking (out of the hospital).*

The poster provides information and exercises to patients after cardiac surgery. With this intervention, patients gain insight into the importance of mobilisation, how the process of mobilisation is organised, and how to contribute to it. Therefore, patients regain control of recovery. Also visitors can motivate patients to exercise. As a result, patients show a rapid increase in functional mobility after discharge from the intensive care unit (ICU) (Table 1).

Table 1: *Patients achieving mobilisation milestones after cardiac surgery [19].*

	Day(s) after ICU-discharge		
	1 (n = 188)	**3** (n = 157)	**5** (n = 60)
Milestone			
Always lying in bed	55%	5%	3%
Walking in the corridor	30%	85%	95%
Bicycling on a hometrainer	0%	45%	62%

An unexpected finding is that males appear to mobilise faster than females. For example, 20% of males can cycle and walk stairs again after four days, while only 6% of females can. It has not been investigated whether the cause lies by a significant gender difference in baseline characteristics (e.g. age and/or Body Mass Index). Doppelbauer et al. [20] and Mungovan et al. [5] also observed gender differences in mobilisation. These respective studies demonstrate that male patients after orthopaedic and cardiac surgery showed a higher level and/or greater increase in mobilisation compared to female patients. These observed differences consolidate the desire to improve upon the interventions performed in TCT to stimulate mobilisation. Interventions should advance towards a patient-specific mobilisation strategy as functional mobility of patients recovering from cardiac surgery is thought to increase faster with patient-specific information and exercises that match their current functional level [19]. This might also be the solution to minimise gender differences. Adequate patient-specific mobilisation can be achieved when in-hospital patient mobilisation is quantified objectively. Objective quantitative insight in patient mobilisation is also valuable for investigation of differences between male and female patients in TCT.

Regardless of the importance of adequate postoperative mobilisation, this is not monitored systematically and objectively as part of clinical care [21]. Mobilisation is often determined based on patient's self-reports and direct observations of medical personnel. The literature shows a wide range of possibilities to assess patient mobilisation. In general these can be divided into three categories. Monitoring by patient-reports, professional scoring and wearable devices. An overview of these methods is presented in Appendix A in tables 12 and 13. When determining a method to measure mobilisation several things must be considered [22]. Quality of physical activity measured (e.g. activity type, duration, frequency, and intensity) and objectivity of the data are important [22]. Also patient burden, costs, and patient characteristics (e.g. age, gender, body weight, and co-morbid conditions) are decisive [22]. Unfortunately we can conclude that patient mobilisation is challenging to quantify objectively.
The growing emergence and availability of low cost, reliable wearable activity monitors (e.g. "Fitbits") offers possibilities towards objective quantification of mobilisation. These devices often permit simple, objective, and continuous quantification and remote real-time monitoring of physical activity [21]. Devices commonly used to monitor physical activity are pedometers, accelerometers, heart-rate monitors and armbands [22]. Pedometers often work by accelerometry and estimate the number of steps taken through detecting motion of a person's hands or hips. Accelerometers measure acceleration in one, two or three directions (uni-, bi- or tri-axial accelerometers), allowing determination of movement quantity and intensity. Integrated multisensor systems (armbands) often combine accelerometry with other sensors (e.g. heart rate or skin temperature) to optimise physical activity assessment [23]. Pedometers provide a limited measure of physical activity, due to insufficient ability to detect certain activity patterns. Multisensor devices are sensitive to assessing the energy expenditure associated with complex and non-ambulatory activities, but often expen-

sive and offer limited battery capacity. Multi-axial accelerometers are able to detect movement in different orientations, providing information about the type, intensity and duration of physical activity [22]. In addition, accelerometers are often small, allow versatile use, are relatively inexpensive and have sufficient battery capacity.

Relevant mobilisation parameters must be determined if wearable activity monitors are deployed to quantify postoperative mobilisation in patients after cardiac surgery. Relevant inpatient mobilisation parameters differ from day to day in TCT. In the first one to two days after ICU-discharge, patients are mostly bed-bound and are instructed to perform upper-body exercises. During the following days until hospital discharge, physical activity should increase in the following order: patients get out of bed, sit in a chair, increasingly walk (in the corridor), bicycle on a hometrainer, and eventually walk stairs. Accordingly, relevant mobilisation parameters are the different forms of physical activity, which can be divided in static activity and dynamic activity. Static activities include lying, sitting and standing and dynamic activities include walking, cycling and walking stairs. Both the static and dynamic activities need to be measured in order to obtain an objective picture of mobilisation.

1.2 Objective

Patients recovering from cardiac surgery benefit from an adequate, patient-specific, amount of mobilisation. To achieve this, it is important to quantify patient mobilisation objectively. The aim of this research, therefore, is to determine a method to quantify in-hospital mobilisation objectively in patients after cardiac surgery. This method should be capable to measure both the static activities (i.e. lying, sitting, and standing) and dynamic activities (i.e. walking, cycling, and walking stairs) in order to provide information throughout the entire postoperative in-hospital phase at the surgical ward.

The following questions are central in this research:

- How can the static activities and dynamic activities be measured objectively?
- What (commercially available) device is suited best to quantify both the static activities and dynamic activities?
- How can this device be deployed in a clinical pilot study to quantify mobilisation of patients after cardiac surgery objectively?
- Based on results of the clinical pilot study, what are differences in mobilisation between men and women after cardiac surgery?

The remainder of this thesis is organised as follows. Composition of device requirements is presented in the methodology section. These requirements are used to select a device appropriate for use in this research. Subsequently, there is elaborated on the working principle of the device chosen, which is accelerometry, possible sensor placements, and how Machine Learning is applied for automatic activity classification. Experimental methods and a clinical pilot study are then described. Experimental methods are performed to determine optimal sensor placement, which is used in the clinical pilot to classify physical activity of patients after cardiac surgery. The results section describes the conclusion from device selection and demonstrates optimal sensor placement. Ultimately, results of the clinical pilot study are presented. The discussion focuses on the (clinical) implication of the results, limitations of this research and recommendations for research in the future. This thesis is finalised with a conclusion.
This thesis contributes to science in several ways. First, it offers an overview of devices that can be used for research and/or direct application in (non-)clinical setting. Second, insight is provided into the application of Machine Learning for classifying human accelerometer data from wearable devices. Third, clinical research has been performed in which postoperative physical activity of patients has been measured objectively at a highly specific level. The results obtained can serve as foundation for improvements on postoperative mobilisation.

2 Methodology

This section presents methods used to arrive at the selection of an accelerometer device and sensor placement suitable for this research. Besides that, there is elaborated on the application of ML to classify physical activity from accelerometer data. The conduction of a clinical pilot study is also demonstrated. This study was designed in such manner that a neural network algorithm was trained on preoperative patient data, and subsequently applied to classify postoperative physical activity of patients after cardiac surgery.

2.1 Device requirements

Numerous devices are available to monitor physical activity, and the amount increases with advancements of technology. Discussions with experts in different fields (physiotherapy, rehabilitation, telemonitoring, eHealth, and activity monitoring) served as foundation for the device requirements depicted in Tables 2 and 3. An overview of these conversations is presented in Appendix B Table 14. A list of potential devices was established through literature research. The specifications and properties of devices were examined (Appendix B Tables 15 - 17). The devices were subjected to the device requirements, and scored accordingly, in order to include in this research. Scoring was performed by the author.

Table 2: *Technical requirements for developing a method to classify inpatient physical activity after cardiac surgery. Requirements are ranked from highest to lowest importance.*

Requirements	**Consideration**
(1) Classification of various activities. Activities of interest: - Static: standing, sitting, and lying - Dynamic: walking, cycling, and walking stairs Nice-to-have: Step count, distance covered and fall detection.	As mentioned in the introduction, over a period of 5-7 days, patient physical activity changes from lying in bed and sitting towards walking on the ward, bicycling on a home trainer and finally walking stairs (personal communication, see Appendix B Table 14 (1)).
(2) Sampling rate between 60-100Hz is necessary to develop proprietary algorithms for activity classification. Nice-to-have: A (commercially available) device with adequate analysis and classification algorithms allowing lower sampling rates.	Body movements quickly have a bandwidth of 10Hz. For adequate movement analysis, raw signals should be measured with sampling rates of 60-100Hz. Devices using adequate classification algorithms can allow lower sampling rates.
(3) Battery capacity enables measuring up to five to seven consecutive days.	Patients have an average hospital stay of 5-7 days after cardiac surgery. It would be inconvenient if measurements are interrupted by means of charging the device, considering patient comfort, privacy, and preventing loss of information (personal communication, see Appendix B Table 14 (4)).
(4) Minimal five to seven days of local data storage. Nice-to-have: Data streaming (storage in Europe) for direct feedback towards patients.	Patients have an average hospital stay of 5-7 days after cardiac surgery. Measurements cannot be interrupted by means of exporting data from the device, considering patient comfort, privacy, and preventing loss of information (personal communication, see Appendix B Table 14 (6)).
(5) Measured data must be exportable from the device. Nice-to-have: Raw exportable data.	For (statistical) data analysis, measured data must be exportable. Raw data needs to be available to develop proprietary algorithms for activity classification (personal communication, see Appendix B Table 14 (4-6)).

Table 3: *Clinical requirements for deploying a method to classify inpatient physical activity after cardiac surgery. Requirements are ranked from highest to lowest importance.*

Requirements	Consideration
Patient related	
(1) No burden during hospital stay and no hindrance in mobilisation.	Patient discomfort is undesirable. Hindrance would negatively affect actual mobilisation (personal communication, see Appendix B Table 14 (3-5)).
(2) Minimal soft tissue deformation.	Considering patient comfort, the device is not allowed to cause damage and pain (personal communication, see Appendix B Table 14 (3-5)).
(3) Device placement is outside wound area.	Wound healing and wound care (risk of infection) must not be compromised. Wound areas: sternum, radial artery and greater saphenous vein.
(4) Official regulations regarding patient privacy and integrity can be met.	In order to obtain (patient) permission to execute a clinical trial patient privacy is important and subject to regulation (GDPR, MST, UT and/or VSNU regulations).
Practical	
(5) No impediment in daily nursery care.	Quality of patient care is essential and should not decrease. Besides that, adaptations to perform daily care (such as taking off the device) could cause data manipulation and loss.
(5) Device is CE certified. Nice-to-have: Device is validated in (heart) surgical or general hospital target groups and/or is already in use in MST.	In order to perform a clinical pilot, the device is required to be CE certified.
(7) Total costs to execute a clinical pilot study should not exceed €3000.	A sum of 3000 euros has been made available from Stichting Hartcentrum Twente.
(8) Data analysis is attainable with supplied software and/or with software from the University of Twente. Nice-to-have: Analysis in Matlab.	The need of separate software could be costly and inconvenient, potentially slowing the process of data analysis.

2.2 Device properties

From extensive comparison of eighteen devices (Results Section 3.1), the AX3 accelerometer (Axivity Ltd.) was regarded best suitable for this research (Appendix B Tables 18 and 19). The AX3 is a small, waterproof, and relatively inexpensive tri-axial accelerometer (Figure 2). It is capable of logging acceleration at a sample rate of 100Hz for 14 days. A real time quartz clock and temperature sensor are also incorporated in the device.

Figure 2: *The AX3 accelerometer (Axivity Ltd.). 23x32.5x7.6mm (length x width x height), IPX8 waterproof rating, 512 MB flash memory, and priced €123 [24].*

2.3 Sensor placement

Different parts of the human body can be used for sensor placement. Gemperle et al. [25] described the interaction between wearables and the human body by proposal of the ergonomic guideline of wearability. They designed a "wearability map" to indicate locations for unobtrusive sensor placement (Figure 3). Locations include the collar area, rear of upper arm, forearm, front and rear sides of rib cage, waist, thighs, shin, and top of the foot. These locations are similar for men and women and are characterised by a relatively large continuous surface, and low amounts of movement and flexibility [26]. In patient populations, sensors placed at these locations should not interfere with necessary medical care.

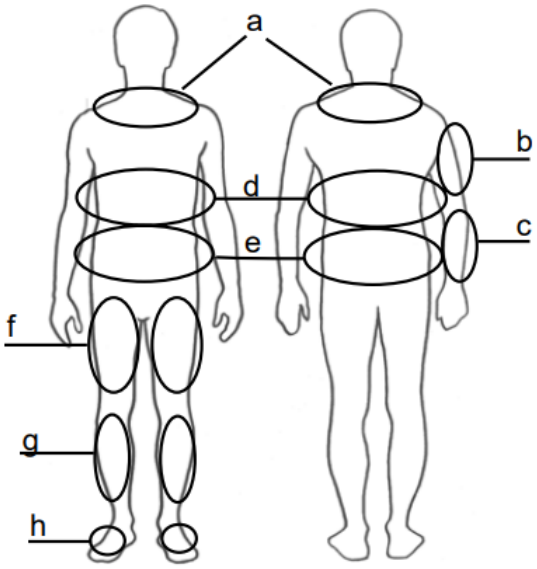


Figure 3: *Areas most unobtrusive for placement of wearable devices: a) collar area, b) rear of the upper arm, c) forearm, d) rear, side, and front rib cage, e) waist and hips, f) thigh, g) shin, and h) top of the foot [25].*

How to attach sensors to the human body is an important aspect of wearability. Attachment can be direct to the skin [27]–[29] and indirect by accessories as straps, belts, wristbands [30]–[32] or integrated into clothing [33]. Sensors should be securely fitted and attached to prevent relative motion between sensors and the human body. Vibration and displacement as a result of loose attachment produces extraneous signal artefacts and degrades sensing accuracy [26].

In general populations, sensors are commonly placed on the waist, sternum and lower back as it enables to measure whole-body movement [26]. These locations are, while ideal for postural classification, not desirable in terms of comfort and practicality considering patients after cardiac surgery. Placement on the lower back interferes with patient comfort as patients often lie on their back in bed, sternum placement is impractical because patients have had a median sternotomy that should not infect, and waist placement is not optimal due to the fact that patients are often limited by objects such as chest drains and external pacemakers around the waist. Sensors can also be attached to the wrist, ankle and thigh. While the ankle and wrist are convenient locations, they are subject to a lot of (irrelevant) movement which can affect classification of both postures and movements negatively. In addition, a sensor on the wrist can interfere with infusions and the wound area of a radial artery that has been removed. As for no medical interference and as less irrelevant bodily movement as possible, the thigh or upper leg is a suitable location for sensor placement. Two sensors are necessary to distinguish postures accurately. Standing, sitting and lying can be distinguished using one accelerometer placed on the thigh and one on the chest [34]. As mentioned before sensor placement on the chest (i.e. sternum) is not desired considering patients after cardiac surgery. Therefore, an alternative second location is necessary, which could be the upper arm, shin or foot. In the case of this research, the upper arm was chosen as an acceptable second sensor placement location. Upper arm placement was chosen as it provides information about orientation of the upper body. Next, the upper arm was assumed to provide information relatively similar to information from a sensor placed on the sternum. An experiment to determine optimal sensor placement configuration, using one sensor on the upper leg and one sensor on the upper arm, is described in Section 2.8. Results of this are presented in results section 3.2.

2.4 Classification of physical activity using accelerometry

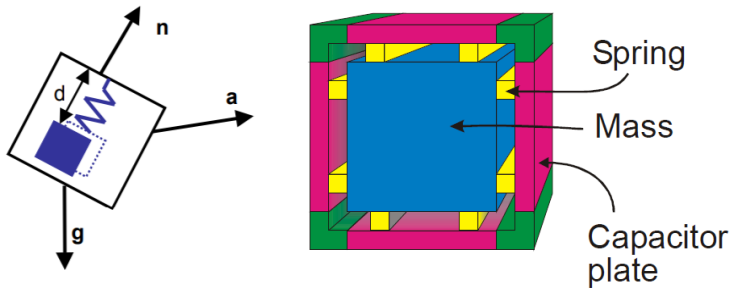
Wearable devices operating according to the principle of accelerometry, such as the AX3, are useful to measure human physical activity, in either clinical/laboratory setting or free-living environment [35]. These devices are often small, low in costs and provide quantitative measurements [35]. A tri-axial accelerometer unit is a transducer that measures acceleration and gravity in three directions. Accelerometers consists of a mass, suspended by a spring in a housing [36]. The mass is allowed to move in so called sensitive directions. The displacement of the mass is a measure of difference of acceleration (a) and gravity (g) along sensitive axis (n) (Figure 4(a)) [36]. This results in an electrical signal $S_{A,n}$ related to these variables according to:

$$S_{A,n} = k_{A,n}(a - g) * n + O_{A,n} \tag{1}$$

with $k_{A,n}$ representing a scaling factor and $O_{A,n}$ an offset. An output vector ${}^{S}Y_A$ can be related to the original acceleration and gravity according to:

$${}^{S}Y_A = {}^{S}a - {}^{S}g \tag{2}$$

The S on the left of the vector is used to indicate that it is expressed in a coordinate system of the sensor housing. Tri-axial accelerometers are assembled by mounting three single axis accelerometers in a box with their sensitive axes in different directions or using a sensor constructed using a single mass, which is the case with the AX3 [37] (Figure 4(b)). In both constructions measured displacement is related to the difference between acceleration and gravity in the same way as stated in equations (1) and (2) [36].



(a) (b)

Figure 4: (a)*: A single axis accelerometer, containing a mass suspended by a spring. The distance d of the mass with respect to the sensor housing is measured and is a function of acceleration and the direction of gravity with respect to the direction of distance measurement. The unit vector n represents the sensitive axis of the sensor [36].* ***(b)****: Schematic representation of the accelerometer designed by Lötters et. al. [38]. A cubic mass is suspended by springs on all six sides. The displacement of the mass with respect to the housing is measured capacitively, enabling the sensor to be used as a tri-axial accelerometer [36].*

Tri-axial accelerometers measure both inertial and gravitational acceleration. Inertial acceleration is acceleration due to any force except for the gravitational force applied on a rigid body. Gravitational acceleration is due to gravitational force. Acceleration is proportional to external force and hence reflects intensity and frequency of human movement. Velocity and displacement can be derived from accelerometry data. In response to gravity, accelerometry provides tilt sensing with respect to reference planes when accelerometers rotate. The resulting inclination data can be used to classify body posture orientations. Therefore, measured accelerometry data can be used to identify postures and to classify daily movements related to a patient's functional status [26], [35].

In order to classify posture and activity, knowledge of patient's movements is required. Movements need to be identified from the accelerometer signals to recognise movements of individuals in a free-living (in-hospital) setting [35]. In general human, activity can be divided in static activities and dynamic activities (Figure 5). Biomechanically, the human body can be considered to consist of rigid body segments, linked by joints [39], [40]. Positions and orientations of body segments do not vary significantly over time during static activities (e.g. lying, sitting, and standing). Static activities can therefore be identified by body segment orientation with respect to gravitation [40]. During dynamic activity, positions and orientations of body segments do vary over time. During dynamic activities (e.g. walking, cycling, and walking stairs) body segments are naturally moved in cyclical manner. Noncyclical movements are normally present only during short transitions between static and cyclical dynamic activities [40].

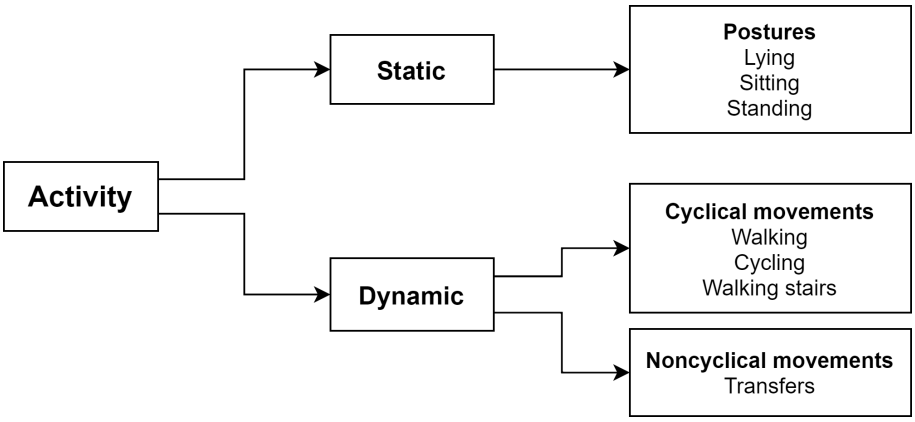


Figure 5: *Human activity classification tree based on division between static and dynamic activities.*

Systems utilising multiple body-worn accelerometers have been used to successfully classify postures and activities [34], [40]–[43]. Postures and activities in these researches include standing, sitting, lying, walking, cycling and walking stairs. This provides support for the viability of classifying movements using accelerometry [35]. Different approaches to classification have been proposed. Research includes fixed-threshold classification [34], [41], [42], reference-pattern-based classification [40], pattern recognition strategies that use statistical algorithms [40], conventional or fuzzy logic [44] or artificial neural networks [45], [46]. More recent research using Machine Learning (ML) and Deep Learning (DL) algorithms to classify human physical activity from triaxial accelerometer data demonstrates high classification accuracy [47]–[49].
Considering the nature of data provided by body-worn sensors, use of an adequate algorithm for classification of physical activity is required. This algorithm should be capable to deal with nonlinear (i.e. linearly inseparable) data, is able to reconfigure, learn, generalise and tolerate noise [50]. ML algorithms known as Artificial Neural Networks (ANN) are suitable in this regard as they can learn and generalise, are flexible, and perform parallel computation [50].

2.5 Development of an Artificial Neural Network algorithm

In general, several steps are required for developing ML algorithms and specifically for the composition of an ANN. First, it is important to find the right topology of a network. An optimum can be achieved through simulations with different topologies, in terms of numbers of neurons per layer and number of hidden layers [50].
A classification algorithm does not make classifications directly from raw sensor data. The next step, therefore, is to perform feature extraction to obtain important data characteristics from which classification is pursued. Choosing highly informative features for classification is important and a problem-dependent task [47]. Janidarmian et al. [51] presented an overview of most

effective time/frequency-domain and heuristic features. Time-domain features are employed most frequently due to high discriminatory ability and low computational cost [51].
An additional process called 'feature selection' can be performed as third step. Feature selection is the technique of selecting a subset from a given set of features by eliminating irrelevant features [52]. Feature selection has become progressively important [53]. It reduces the dimensions of features and hence amount of data used in learning, alleviates the effect of the curse of dimensionality to improve algorithms' generalisation performance and increases execution speed and the models' interpretability [52]. Neighbourhood Component Analysis (NCA) is a non-parametric feature selection method suitable for small data sets [54]. This method computes feature weight vectors (i.e. added value of a given feature for its classification purpose) such that irrelevant feature weights get reduced to zero and can be discarded [52], [54].
In order to evaluate performance of a ML algorithm on limited data sample, K-fold cross-validation is often used. K, which is commonly 10, refers to the number of subsamples that the data sample is split into [55]. K-1 of these subsamples are used for training of the algorithm and the single remaining subsample is used for testing performance. This procedure is repeated K times. A single estimation can then be produced by averaging K results, providing an expectation of the algorithm's classification performance on data not used during training. Leave-One-Subject-Out (LOSO) validation is a good approach for estimation of more realistic algorithmic performance and also avoids possible overfitting [51]. With LOSO-validation, for n = number of subjects in the data sample, the algorithm is trained on all data except for one subject and performance is tested for that single subject. This process is repeated n times and then averaged to make a single estimation on performance. Classification performance of an algorithm can be expressed in different ways. Metrics commonly used are accuracy, precision and recall. Confusion matrices are used to visualise these three metrics. Classification accuracy is the percentage of number of correct predictions to the total number of input samples. Precision (or positive predictive value) is the percentage correctly classified samples of all samples to belong to that class. Recall (or true positive rate) is the percentage correct classifications of the number samples that should have been identified as that class.

In the case of this research an ANN algorithm was developed in Matlab (2019b, the MathWorks Inc, Natick, MA), based on a Matlab script from Bunkheila [56], openly available as part of a Matlab webinar. The script uses a feed forward network comprised of one hidden layer with eighteen hidden nodes. The hidden layer operates by sigmoid activation functions (having a characteristic S-shaped curve) and the output layer by a softmax (normalised exponential) function. A scaled conjugate gradient back propagation function was used to train the network. This function updates weight and bias values according to the scaled conjugate gradient method. Network performance was calculated using a cross-entropy function. The function returns a result that penalises inaccurate outputs, with little penalty for correct classifications. Bunkheila built the algorithm to classify human physical activity from a data set consisting of smartphone accelerometer data [57]. This data set has been used several times in research towards Human Activity Recognition (HAR) [58]–[62]. Bunkheila's code was used as foundation as his aim was to classify similar activities (i.e. lying, sitting, standing, walking, walking upstairs, and walking downstairs) as holds for this research. Bunkheila's Matlab code was adapted to function with data from two AX3 devices. Code adaptations included noise filtering and simultaneous data import from two tri-axial accelerometers with corresponding activity class labels and subject number. Data was categorised in variables from a sensor attached to the arm and a sensor attached to the leg. Additional code was written in order to divide data into segments with a fixed window and remove segments that contained more than one activity class. The activity classes 'walking upstairs' and 'walking downstairs' were changed to 'cycling' and 'walking stairs'. Finally, adjustments were made to calculate features over all signals measured from both sensors.
The features Bunkheila selected to use in his algorithm were also used in this research. Time-domain features included average of total acceleration (i.e. sum of static and dynamic acceleration) and root mean square of body acceleration (i.e. dynamic acceleration). Both features aid in distinguishing static from dynamic features and classification of postures. Frequency-domain features,

for recognising type of dynamic activity, include autocorrelation (height of main peak, height and position of second peak), spectral peaks (height and position of first six peaks) and spectral power (total power in five adjacent and pre-defined frequency bands). These five features are all included in the overview presented by Janidarmian et al. [51]. In attempt to improve the algorithm, the following features were added: median of total acceleration, standard deviation of body acceleration, median absolute deviation and signal magnitude area of both total acceleration and body acceleration. These added features are also included in the overview presented by Janidarmian et al. [51]. Only time-domain features were added for the sake of preserving computation costs. Features were calculated for all three acceleration components of both sensors, resulting in a total of 160 features.
Based on an open-source Matlab script [63], NCA was performed in Matlab to determine weights of these 160 features. NCA was executed on features calculated on data collected from all patients in the labelling measurement of the clinical pilot study (Section 2.8.1). Features with feature weight of zero were eliminated. This resulted in feature selection of a subset of 59 features (Appendix F Table 24). For the sake of computation time, the neural network using only these 59 features was applied in the clinical pilot study to classify physical activity of patients after cardiac surgery (Results Section 3.3.3).

2.6 Signal processing

OmGui software was used to initiate and stop measurements, and to download data from the AX3 devices. Data was downloaded as .cwa files. Matlab was used to convert the .cwa files and to perform all other signal processing in this research. The AX3 devices collected tri-axial acceleration data set at a sampling rate of 100Hz and sensitivity range of $\pm$ 8 g. Signals were preprocessed for noise reduction with a third order median filter and a third order low-pass Butterworth filter with a 20Hz cutoff frequency [57]. The measured acceleration data, contains gravitational and body motion components. Body acceleration was obtained by passing the acceleration signal through a high-pass filter with a cutoff frequency of 0.8Hz. Measured data was divided into subsequent segments of 256 samples (2.56 seconds), using fixed-size sliding window method [57]. Thus, the neural network determined a classification every 2.56 seconds. The window size was similar to the window size determined in [57], based on a person's average walking cadence, which is at least 1.5 steps per second [64]. A full walking cycle of two steps is preferred on each window sample. Data used for training of the algorithm was divided into segments using a fixed-size overlapping sliding window method. Window size was 256 samples and overlap was 128 samples (50%). Overlap creates an artificial increase in the number of available training samples. Fixed-size sliding window methods are common and overlap between adjacent windows is effective in classification problems using wearable sensors [51], [65], [66].

2.7 Experimental methods

As mentioned in Section 2.3, sensors can be placed on the upper arm and and upper leg in the case of patients after cardiac surgery. An experiment was performed to determine optimal sensor placement on these body segments. Four able-bodied subjects participated in the experiment, two male and two female. Age ranged between 21 and 27 years, height between 169 and 184 cm, and weight between 63 and 76 kg. Due to the restrictive measures imposed by the COVID-19 pandemic, the experiment was performed in both indoor and outdoor setting (i.e. inside and outside one single house). The experiment was performed for measurement purposes and no invasive actions were imposed to the subjects. By verbal informed consent, all subjects gave permission for usage of personal data (gender, age, length, and weight) and measurement data in this research. The subjects performed static and dynamic activities according to a fixed protocol. They were asked to subsequently stand, sit on a chair, and lie on a bench (on the back, right side and left side). Each posture was held for 30 seconds. Transition time between posture was approximately 10 seconds. Afterwards, the subjects were asked to perform three dynamic activities subsequently: walking back and forth in a hallway, cycling laps around a courtyard and walking stairs in the

house. The length of the hallway was approximately ten meters. All subjects cycled in the same direction and on the same bicycle, without adjustments to the saddle or handlebar height. The staircase consisted of approximately fifteen steps and was both ascended and descended. The dynamic activities were performed at slow, comfortable, and fast speed (the different speeds were instructed using similar terms). All speeds were performed for a minimal duration of 30 seconds and were alternated with 10 seconds of standing still. The experiment also contained short parts of free movement (e.g., walking through the house from the static activities to outdoors for the dynamic activities). The fixed protocol was repeated twice. For each subject, the experiment had a duration of approximately 35 minutes. Eight tri-axial AX3 accelerometers were mounted to the subjects using Tegaderm^{TM} patches (Figure 6). Four devices were placed on both the right upper leg and the right upper arm. Device placement was anteroproximal (AP), lateroproximal (LP), anterodistal (AD) and laterodistal (LD) on both body segments.

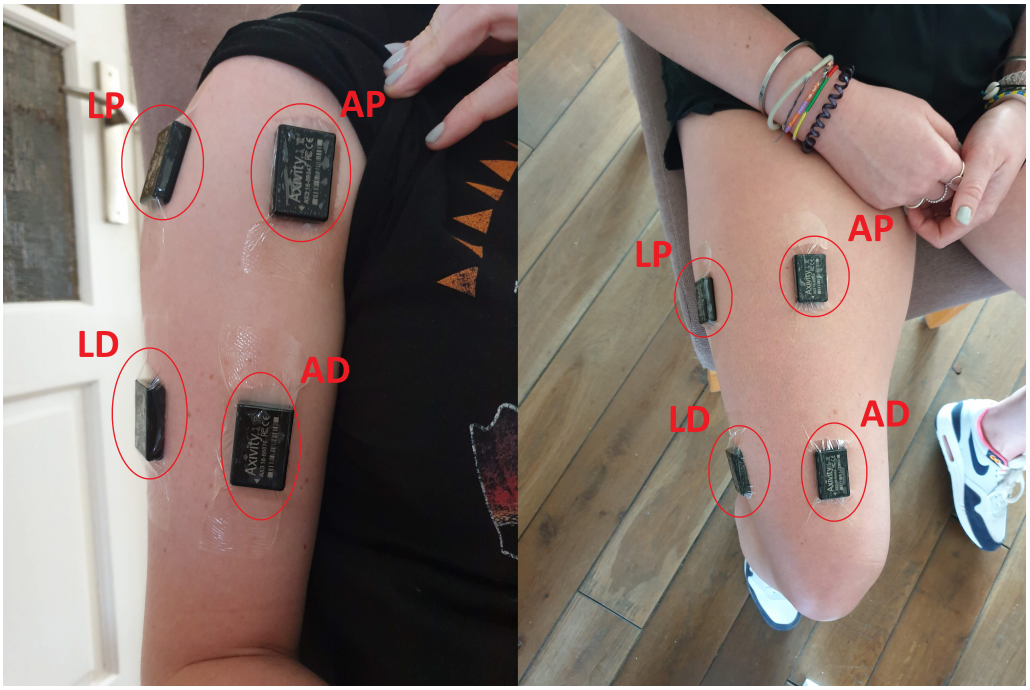


Figure 6: *Right upper arm and right upper leg sensor locations: anteroproximal (AP), lateroproximal (LP), anterodistal (AD) and laterodistal (LD).*

Segments of measured data were manually labelled as being lying, sitting, standing, walking, cycling or walking stairs. The process of data labelling was done via hard coding. The measured data was plotted with Matlab (Appendix C Figures 17 and 18). Through visual inspection of the plots, data samples were labelled as one of the six activities. The labelled data was used to train the neural network algorithm and determine its performance using sixteen possible sensor placement configurations. Performance was determined using results on overall classification accuracy from K-fold (K = 10) cross-validation and LOSO-validation (n = 4 subjects). The sensor configuration with highest accuracy, averaged from both validation methods, was used in clinical measurements of this research. Results of the experimental methods are presented in Section 3.2.

2.8 Clinical pilot

A clinical pilot study was conducted as part of this research. This study is reported as per the STROBE recommendations on the quality of reporting observational studies [67].

2.8.1 Study design and population

Physical activity of inpatients after cardiac surgery was measured with AX3 accelerometers in order to obtain objective quantification of inpatient mobilisation. The accelerometers were applied in dual configuration, placed lateroproximal on the right upper arm and anterodistal on the right upper leg (Appendix D Figure 19). This placement configuration was regarded optimal from results of the experimental methods (Section 3.2.).

This single centre, exploratory study was conducted at TCT (MST Hospital, Enschede, The Netherlands), a tertiary nonacademic teaching hospital. The study was exempted from the Medical Research Involving Human Subjects Act by the Medical Ethics Committee Twente (METC Twente) and approved by the local institutional review board. The study received number K20-14 and was named MOVeMeNTT.
Patients were recruited from 2 June to 31 July 2020. Patients did not make additional hospital visits, therefore, conform to the hospital measures during the COVID-19 pandemic. Adult patients undergoing Coronary Artery Bypass Grafting (CABG) surgery, valve surgery and CABG plus valve surgery were included. Patients with a Katz Index of Independence in Activities of Daily Living functioning (KATZ-ADL) score larger than 2 before surgery (i.e. patient is not independent in daily life mobilisation) [68], patients with an ICU stay longer than 72 hours, patients with post-operative Cerebro Vasculair Accident (CVA) and patients mentally incompetent were excluded from the study.
Patient inclusion occurred during the day of hospital admission. After approval with informed consent, a short (ten-fifteen minutes) measurement was performed (protocol in Appendix D), the so called "labelling measurement". During labelling measurement, patients performed six activities of interest with the AX3 devices attached to the intended locations. Activities were lying, sitting, standing, walking, cycling and walking stairs. Implementation and sequence of activities was as spontaneous as possible. Tegaderm^{TM} patches were used for sensor attachment. The purpose of this measurement was to collect data suitable for labelling. Data was labelled in similar manner as described in Section 2.7. The labelled data was used to train the neural network (Section 3.3.2), resulting in an algorithm able to classify postoperative physical activity of these same patients.
All patients were admitted to ICU after surgery. Measurements of postoperative mobilisation started after patient transfer from the ICU to the surgical ward. After arrival, AX3 devices were attached at identical locations as during the labelling measurement, again using Tegaderm^{TM} patches. The devices were to be worn for an entire postoperative clinical phase with a maximum of seven days.

Primary outcome was daily amount of time in activities of interest between 7 a.m.-11 p.m. Secondary outcomes included length of ICU stay and surgical ward stay. Baseline characteristics were determined based on Body Mass Index (BMI) (kg/m2) and The European System for Cardiac Operative Risk Evaluation II (EuroSCORE II) definitions [69].

Both sensor attachment and starting measurements were performed by the author. Problems with fixation of the AX3 devices were reported to this same person and resolved when nursing was unable to do so. Dedicated physiotherapists trained for cardio-thoracic physiotherapy practice participated in the study. Physiotherapists recorded patient activity on forms developed for this purpose, the so called "activity forms" (Appendix D Figure 20). Activity type, time and duration were noted. An A3-poster with study instructions for nursing was placed in patient rooms and at the surgical ward coffee room (Appendix D Figure 21).

2.8.2 Statistical analysis

Statistical analysis on patient characteristics and patient physical activity was performed with GraphPad Prism 5 (GraphPad Software Inc, San Diego, CA). Results were considered statistically significant at the 5% level. Continuous variables were presented as mean with standard deviation (SD) or median with interquartile range (IQR) depending on the distribution. Depending on the distribution, groups of continuous variables were compared using unpaired t-tests or Mann-

Whitney tests. Continuous variables were tested for normality with inspection of skewness and kurtosis measures. In addition, normality was tested using the Kolmogorov-Smirnov test, Shapiro-Wilk test, and D'Agostino-Pearson test. If necessary, normality test were supplemented by visual inspection of histograms. Categorical variables were presented as number with corresponding percentages and compared between groups using Chi-square or a Fisher Exact Test. Kruskal-Wallis tests were used to assess whether the amount of patient physical activity differed over the days measured. Dunn's multiple comparison post hoc test was used to pinpoint which day differed significantly from others and to determine whether activity differed significantly per day between genders.

3 Results

This section demonstrates results from device selection and findings concerning optimal sensor placement configuration. Results from the clinical pilot study are also presented, including patient characteristics, neural network performance after training and postoperative physical activity of patients after cardiac surgery.

3.1 Device selection

Based on specifications, a total of eighteen devices were subjected to the requirements (Appendix B Tables 18-23). Three devices were eligible for use in clinical setting. It concerned the AX3, ActiGraph and MOX1. The other fifteen devices were discarded as they were unable to meet the first technical requirement concerning classification of activities of interest. The AX3, ActiGraph and MOX1 are relatively equivalent devices and, therefore, met the device requirements to an equal extent (Appendix B Tables 18-19). The decisive factors on which final device selection is based were sample rate with corresponding battery capacity and price (Table 4). Both the AX3 and ActiGraph offer sufficient battery capacity of fourteen days at a sample rate of 100Hz. The MOX1 battery capacity is less than seven days when measuring with necessary sample rates of 60-100Hz. The MOX1 was therefore considered inferior. Based on the price (per one device), a selection was made between the AX3 and the ActiGraph. The AX3 price is less and above all within budget, which was not the case for the Actigraph. Therefore, device selection has led to the AX3.

Table 4: *Decisive factors for device selection: sampling rate, battery capacity and price.*

	AX3	**ActiGraph**	**MOX1**
Sampling rate	12.5-3200Hz [24]	30-100Hz [70]	25-100Hz [71]
Battery capacity	14 days at sampling rate of 100Hz [72]	16 days at sampling rate of 100Hz [73]	7 days at sampling rate of 25Hz [71]
Price	€123*	€225**	€195**

* Software costs nonexistent
** Software costs excluded

3.2 Experimental methods

Neural network performance with sixteen different sensor placement configurations, from combinations of AX3 sensors placed on the upper arm and on the upper leg, is reported in Table 5 and Table 6. Data from four subjects was available. The configuration using lateroproximal (LP) upper arm location and anterodistal (AD) upper leg location demonstrated highest overall classification accuracy (98.1%) determined by 10-fold cross-validation (Table 5). Configurations consisting of anterodistal (AD) or lateroproximal (LP) upper arm location, and anterodistal (AD) upper leg location demonstrated highest overall classification accuracy (93.3%) determined by LOSO-validation (Table 6). The sensor placement configuration using the lateroproximal (LP) upper arm location and the anterodistal (AD) upper leg location was considered optimal as its average value calculated from estimated classification accuracy of both validation methods was highest.

Table 5: *Overall classification accuracy of the neural network trained with experimental data from sixteen sensor placement configurations. Activities classified were lying, sitting, standing, walking, cycling, and walking stairs. Accuracy was determined by averaging results from K-fold cross-validation (K = 10).*

AX3 location	**Right upper leg**			
	Anteroproximal	**Lateroproximal**	**Anterodistal**	**Laterodistal**
Right upper arm				
Anterodistal	96.5 [94 100]	95.0 [93 98]	96.5 [92 100]	93.9 [87 97]
Laterodistal	94.8 [89 100]	97.7 [95 100]	95.2 [87 100]	95.9 [91 100]
Anteroproximal	93.9 [90 97]	93.4 [87 100]	96.8 [92 100]	93.6 [88 99]
Lateroproximal	97.0 [93 99]	96.5 [89 100]	**98.1** [94 100]	96.5 [92 100]

Data are percentages [Min Max]

Table 6: *Overall classification accuracy of the neural network trained with experimental data from sixteen sensor placement configurations. Activities classified were lying, sitting, standing, walking, cycling, and walking stairs. Accuracy was determined by averaging results from LOSO-validation (n = 4 subjects).*

AX3 location	**Right upper leg**			
	Anteroproximal	**Lateroproximal**	**Anterodistal**	**Laterodistal**
Right upper arm				
Anterodistal	92.3 [90 97]	84.9 [84 85]	**93.3** [91 97]	89.6 [87 94]
Laterodistal	86.6 [83 89]	83.3 [76 86]	87.4 [85 89]	84.7 [83 87]
Anteroproximal	85.9 [70 95]	78.5 [69 84]	85.1 [69 95]	85.8 [69 91]
Lateroproximal	91.7 [91 92]	87.0 [86 89]	**93.3** [91 95]	92.3 [91 95]

Data are percentages [Min Max]

3.3 Clinical pilot

Out of 75 patients selected for eligibility, in total 44 patients were excluded based on, inability to perform the labelling measurement (n=18), patient transfer from ICU to surgical ward planned during weekend days (n=9), no available sensors (n=8), patients referred from other hospitals (n=6), or patients unwilling to participate (n=3). Thus, 31 patients were included for the pre-operative labelling measurement. It concerned 24 male patients and 7 female patients of which labelled data was used for neural network training. Out of 31 patients, two male patients were excluded from the postoperative physical activity measurement. Exclusion was based on prolonged ICU-stay over 72 hours. Postoperative data of 29 patients was classified and analysed regarding time per activity. A flow diagram of the process is visualised in Appendix E Figure 22.

3.3.1 Patient characteristics

Patients had a median age of 70 [64-75] years, a BMI of 27 [25-29] kg/m2, 42% had multivessel disease and 7% a recent myocardial infarction. There were no significant differences between men and women for baseline or in-hospital characteristics (Tables 7-9). ICU stay was 1 [1-2] day for male patients and 2 [1-2] days for female patients. Surgical ward stay was 5 [3-6] days for men and 5 [2-6] days for women (Table 9). No complications such as wound infection, sternum dehiscence, or ventricular tachycardia related to early mobilisation were reported.

Table 7: *Baseline patient characteristics. P values represent absence or presence of statically significant differences between genders. No significant differences were found.*

Variable	**Total (n = 31)**	**Male (n = 24)**	**Female (n = 7)**	**P value**
Age, years	70 [64-75]	72 [64-75]	68 [56-75]	0.52
Body Mass Index, kg/m2	27 [25-29]	26 [25-29]	29 [24-35]	0.64
Diabetes	6 (19%)	3 (13%)	3 (43%)	0.11
Multivessel disease	13 (42%)	11 (46%)	2 (29%)	0.67
Recent myocardial infarction	2 (7%)	2 (8%)	0 (0%)	1.00
Left Ventricular Function	...	...	...	0.23
- Poor, <30%	4 (13%)	4 (17%)	0 (0%)	
- Moderate, 30-50%	14 (45%)	9 (37%)	5 (71%)	
- Good, >50%	13 (42%)	11 (46%)	2 (29%)	
COPD	1 (3%)	1 (4%)	0 (0%)	1.00
Extracardiac arteriopathy	3 (10%)	3 (13%)	0 (0%)	1.00
Neurological dysfunction	3 (10%)	2 (8%)	1 (14%)	0.55
Previous cardiac surgery	0 (0%)	0 (0%)	0 (0%)	...
NYHA class	...	...	...	0.37
- I	12 (39%)	8 (33%)	4 (57%)	
- II	8 (26%)	6 (25%)	2 (29%)	
- III	11 (35%)	10 (42%)	1 (14%)	
- IV	0 (0%)	0 (0%)	0 (0%)	
Urgency	...	...	...	0.29
- Elective	25 (81%)	18 (75%)	7 (100%)	
- Urgent	6 (19%)	6 (25%)	0 (0%)	
- Emergency	0 (0%)	0 (0%)	0 (0%)	
- Salvage	0 (0%)	0 (0%)	0 (0%)	
EuroSCORE I, log	3.5 [1.5-6.3]	3.8 [1.7-6.4]	3.5 [1.2-6.3]	0.72
EuroSCORE II, log	1.4 [0.9-2.2]	1.5 [0.9-2.6]	1.0 [0.7-1.5]	0.21

COPD = Chronic Obstructive Pulmonary Disease
NYHA = New York Health Association
Data are medians [IQR] or numbers (proportions)

Table 8: *Periprocedural patient characteristics. P values represent absence or presence of statically significant differences between genders. No significant differences were found.*

Variable	**Total (n = 31)**	**Male (n = 24)**	**Female (n = 7)**	**P value**
Type of surgery	...	...	...	0.78
- CABG	15 (48%)	12 (50%)	3 (43%)	
- Valve surgery	10 (32%)	7 (29%)	3 (43%)	
- CABG + valve surgery	6 (20%)	5 (21%)	1 (14%)	
Surgical approach	...	...	...	1.00
- Median sternotomy	27 (87%)	21 (88%)	6 (86%)	
- Anterolateral mini-thoracotomy	4 (13%)	3 (12%)	1 (14%)	
Cardiopulmonary bypass	24 (77%)	18 (75%)	6 (86%)	1.00
Cardiopulmonary bypass time, min	99 [84-134]	96 [83-125]	116 [82-163]	0.53

CABG = Coronary Artery Bypass Grafting
Data are medians [IQR] or numbers (proportions)

Table 9: *Postoperative patient characteristics. P values represent absence or presence of statically significant differences between genders. No significant differences were found.*

Variable	**Total (n = 31)**	**Male (n = 24)**	**Female (n = 7)**	**P value**
ICU stay, days	2 [1-2]	1 [1-2]	2 [1-2]	0.29
Surgical ward stay, days	5 [3-6]	5 [3-6]	5 [2-6]	0.88
Discharge to	...	...	...	1.0
- Home	23 (74%)	18 (75%)	5 (71%)	
- Referring hospital	8 (26%)	6 (25%)	2 (29%)	

ICU = Intensive Care Unit
Data are medians [IQR] or numbers (proportions)

3.3.2 Neural network training

The neural network was trained using labelled data from 31 patients (24 male patients and 7 female patients). For each patient an average of eleven minutes of labelled data was used. The amount of activity classes in data used for training were not balanced, while classes in data used to test classification performance of the algorithm were balanced. Neural network performance after training is reported in Table 10. The classification accuracy of the neural network with increase in the number of patients is shown in figure 7. Neural network performance after feature selection is reported in Table 11.

The algorithm demonstrated 98% overall accuracy, determined by 10-fold cross-validation (Table 10). Recall was highest for cycling (100%) and lowest for walking stairs (94%). Precision was highest for both standing and cycling (100%) and lowest for walking (94%). Overall accuracy determined by LOSO-validation was 96% (Table 10). Recall was highest for both standing and cycling (99%) and lowest for sitting and walking stairs (93%). Precision was highest for both standing and cycling (99%) and lowest for lying (93%). Estimations from LOSO-validation showed an increased [Min Max] range, compared to results from K-fold validation. Decrease of minimum values caused the increase of this range. Additional information on performance is visualised in confusion matrices in Appendix F Figure 23.

Table 10: *Precision and recall per activity and overall classification accuracy of the neural network trained with patient data from the labelling measurement (number of features = 160). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	97 [92 99]	98 [95 99]	94 [59 100]	93 [53 100]
Sitting	98 [95 100]	98 [93 99]	93 [12 100]	94 [71 100]
Standing	99 [98 100]	100	99 [91 100]	99 [85 100]
Walking	98 [96 100]	94 [91 96]	97 [82 100]	94 [82 100]
Cycling	100	100	99 [86 100]	99 [76 100]
Walking stairs	94 [90 96]	98 [97 99]	93 [42 100]	97 [85 100]
Accuracy		**98 [97 98]**		**96 [85 100]**

Data are percentages [Min Max]

As the number of patients in the training data set increased, overall classification accuracy of the neural network remained fairly constant (Figure 7). Both the total patient group and the male patient group demonstrated accuracies starting at 98% and sustaining between 96-97%. Accuracy of the female patient group ranged from 96% to 95%. Appendix F Figure 24 provides insight in the development of precision and recall per activity with increasing number of patients.

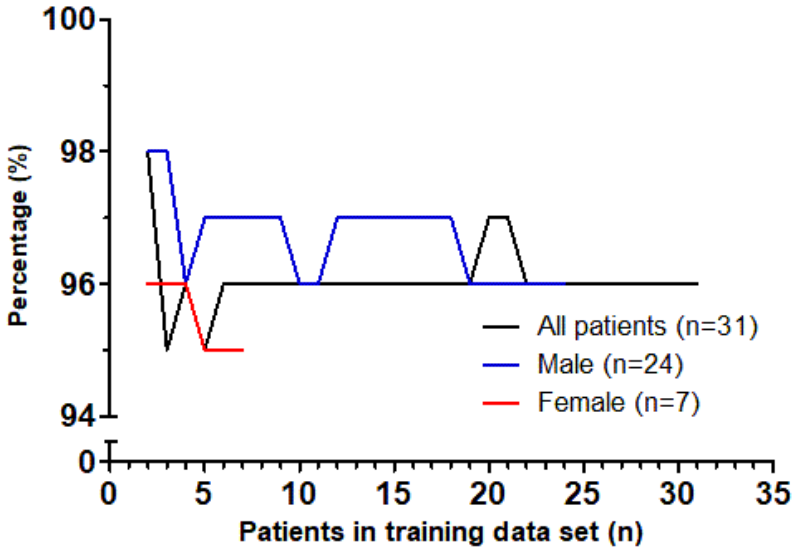


Figure 7: *Overall activity classification accuracy with n number of patients (starting from n = 2) in the data set used for training of the neural network. Classification accuracy was determined by averaging results from LOSO-validation over n number of patients. Activities classified were lying, sitting, standing, walking, cycling, and walking stairs.*

Overall classification accuracy was 98% after feature selection, determined by 10-fold cross-validation (Table 11). Recall was highest for cycling (100%) and lowest for walking (95%). Precision was highest for cycling (100%) and lowest for walking stairs (96%). Overall accuracy determined by

LOSO-validation was 96% (Table 11). Recall was highest for cycling (100%) and lowest for sitting (92%). Precision was highest for cycling (100%) and lowest for lying (91%). Again estimations from LOSO-validation showed an increased [Min Max] range, caused by lower minimal values. Additional information on performance is visualised in confusion matrices in Appendix F Figure 25.

Table 11: *Precision and recall per activity and overall classification accuracy of the neural network trained with patient data from the labelling measurement (number of features = 59). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	99 [96 99]	98 [96 100]	94 [66 100]	91 [53 100]
Sitting	98 [98 100]	99 [97 99]	92 [12 100]	94 [75 100]
Standing	99 [98 100]	99 [98 100]	99 [91 100]	99 [87 100]
Walking	95 [96 99]	98 [92 98]	97 [77 100]	93 [82 100]
Cycling	100 [99 100]	100 [99 100]	100 [93 100]	100
Walking stairs	98 [92 99]	96 [96 100]	93 [75 100]	96 [83 100]
Accuracy		**98 [98 99]**		**96 [85 100]**

Data are percentages [Min Max]

Tables 10 and 11 demonstrate equal overall classification accuracies using 160 features and 59 features. Also, estimations on average recall and average precision are similar with small shifts over the activities. A large amount of the minimal values for recall and precision are equal or lower using 160 features compared to using 59 features.

Results on training the algorithm on both upper arm sensor data and upper leg sensor data only is presented in Appendix F Tables 25 and 26. Using upper arm data yielded accuracies of 80% and 74%, respectively determined by K-Fold and LOSO-validation. For upper leg sensor data this was 95% and 92%. For experimental purposes, classification performance of the algorithm was also determined using segments larger than 256 samples. It concerned segments of 512 samples and 1024 samples, both yielded high overall classification accuracy (Appendix F Tables 27 and 28).

3.3.3 Postoperative physical activity

Patient physical activity was measured in 29 patients for a median [IQR] of 4 [2-5] days. The minimum and maximum time lying, sitting, standing, walking, cycling and walking stairs between 7 a.m.-11 p.m. were respectively 1-811 minutes, 45-858 minutes, 0-131 minutes, 0-68 minutes, 0-67 minutes and 0-25 minutes. Minimum and maximum percentage of time spent lying, sitting, standing, walking, cycling and walking stairs were 0-93% , 11-92%, 0-25%, 0-12%, 0-8%, 0-3%, respectively. Daily, patients were lying for a median [IQR] time of 278 [212-380] minutes, sitting 336 [274-383] minutes, standing 26 [19-40] minutes, walking 7 [4-14] minutes, cycling 3 [1-6] minutes and walking stairs 2 [1-5] minutes. The days on which median time was greatest for these respective activities were, day 2, day 6, day 4, day 3, day 3, and day 4.

Figure 8 demonstrates the median percentage of time spent lying, sitting, standing, walking, cycling, and walking stairs during daytime on an hour-by-hour basis. Patients were lying mostly between 7 a.m.-7.59 a.m., 1 p.m.-1.59 p.m., and 10 p.m.-10.59 p.m. All other hours patients were mostly sitting. Percentages standing and walking are highest (both 1%) between 9 a.m.-9.59 a.m.

Cycling is highest between 9 .a.m.-10.59 a.m. Median percentage of time spent walking stairs was always 0%. Appendix G Figure 26 provides additional information on amount of minutes per activity during daytime on an hour-by-hour basis.

Figures 9 and 10 outline median amount of minutes and percentage of time spent in static activity (i.e. lying, sitting, or standing) and in dynamic activity (i.e. walking, cycling, or walking stairs) during daytime for each day at the surgical ward. Median amount of minutes and percentage of time spent in both static and dynamic activity differed significantly over the days measured. Median percentage of time lying at the first day at the surgical was 55%, and decreased to 23% on day five. Median percentage of time sitting on day one was 39%, which increased to 74% at day seven. Standing increased from 0% at day one to 7% at day six. Median percentage lying is highest on day one and lowest on both day five and seven. For both sitting and standing median percentage is lowest on day one, highest on day seven for sitting and on day six for standing. The median amount of minutes walking was 0 on day one, and increased to 13 at day three. Median minutes for both cycling and walking stairs increased from 0 to 3 over the first three days. Day one and day nine demonstrated the lowest median amount of minutes for all dynamic activities. Median amount of minutes walking was highest on day three. For both cycling and walking stairs median amount of minutes was highest on day three and four. Appendix G Figure 27 provides additional information on mean percentage of time per activity for all patients visualised in a stacked bars diagram.

Male patients demonstrated minimum and maximum amounts of 1-811 minutes laying, 45-858 minutes sitting, 0-179 minutes standing, 0-68 minutes walking, 0-67 minutes cycling, and 0-25 minutes walking stairs. Minimum and maximum percentages of time in activity were, 0-93% laying, 7-92% sitting, 0-25% standing, 0-12% walking, 0-8% cycling, and 0-3% walking stairs. For female patients, minimum and maximum time lying, sitting, standing, walking, cycling and walking stairs were respectively 24-626 minutes, 51-788 minutes, 0-131 minutes, 0-32 minutes, 0-13 minutes and 0-9 minutes. Minimum and maximum percentages were 8-80% lying, 19-83% sitting, 0-19% standing, 0-5% walking, 0-4% cycling, and 0-2% walking stairs.

Median amount of minutes and percentage of time spent in static activity and in dynamic activity during daytime for both male and female patients are demonstrated in Figures 11 and 12. Between genders, no significant daily differences were found. Median amount of minutes differed significantly over the days for all activities in male patients. Female patients demonstrated no significant difference for median minutes sitting. Median percentage of time lying, sitting, cycling and walking stairs for female patients did also not differ significantly over the days. However, percentages differed significantly for all activities in male patients. Median percentage lying is lowest on day five for females, and lowest on day nine for males. Males demonstrated highest median percentage sitting on day nine, and females on day six. The median percentage time spent standing is greatest on day five and seven for females an males respectively. For all dynamic activities, male patients showed highest median minutes on day three. Female patients showed highest median minutes on day five for walking and on day six for both cycling and walking stairs. Appendix G Figure 28 provides additional information on mean percentage of time per activity for males and females visualised in a stacked bars diagram.

Figure 13 shows the findings of concentrating on two equivalent patient cases, concerning a male patient and a female patient after elective mitral valve surgery via median sternotomy. These specific cases do not show obvious daily decrease in sedentary activities (i.e. lying and sitting) accompanied by increase in the other activities. In contrast to the male patient, increasing and decreasing trends were discerned for several activities in the female patient. The female patient showed a daily decrease in the percentage lying and an increase in percentages standing and walking. The male patient cycled on day three and five at the surgical ward, while the female patient only cycled on day five.

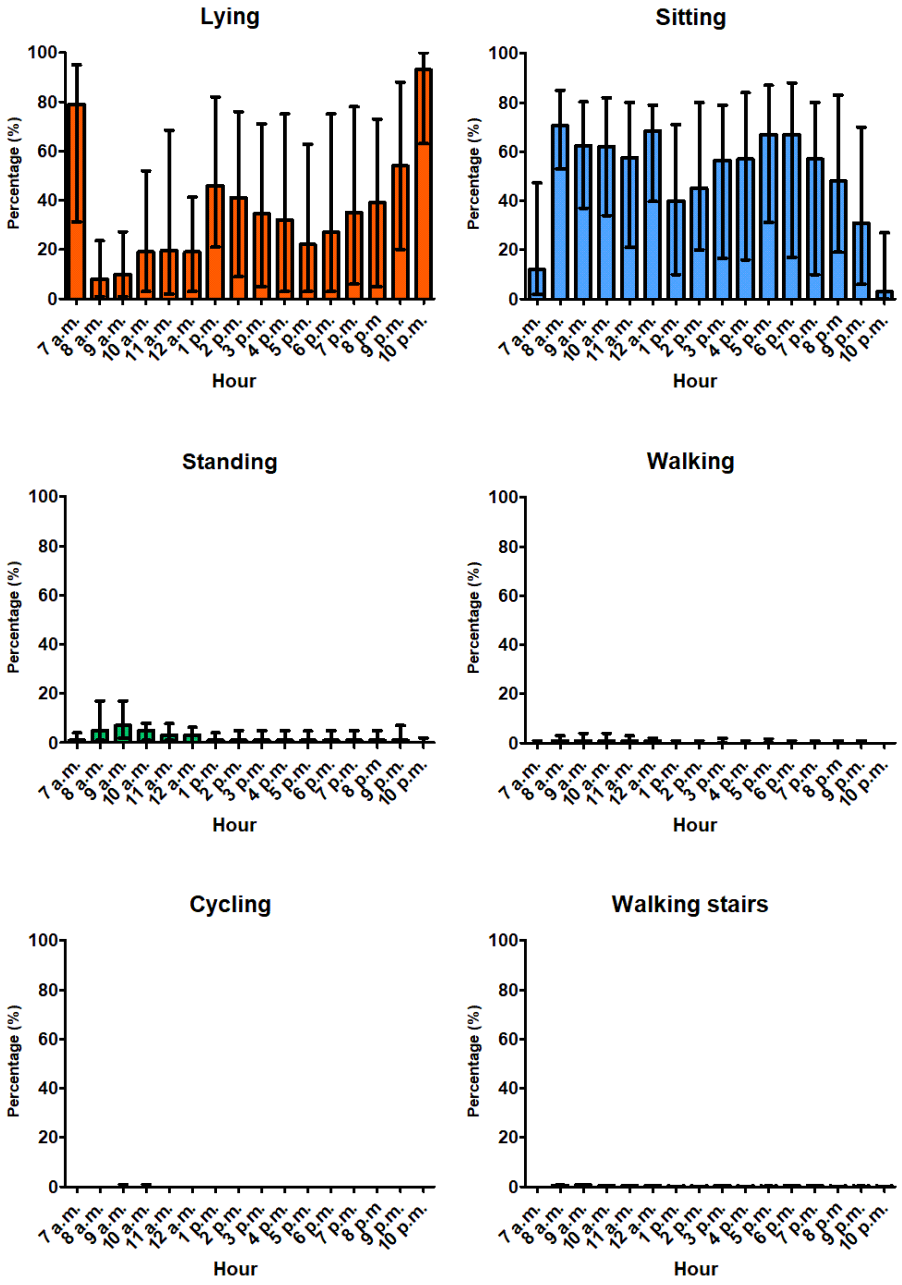


Figure 8: *Median percentage of time spent lying, sitting, standing, walking, cycling, and walking stairs per hour between 7 a.m. and 11 p.m. The 7 a.m. interval contains data measured between 7 a.m. and 7.59 a.m. Medians are determined using all patient data. Error bars represent IQR.*

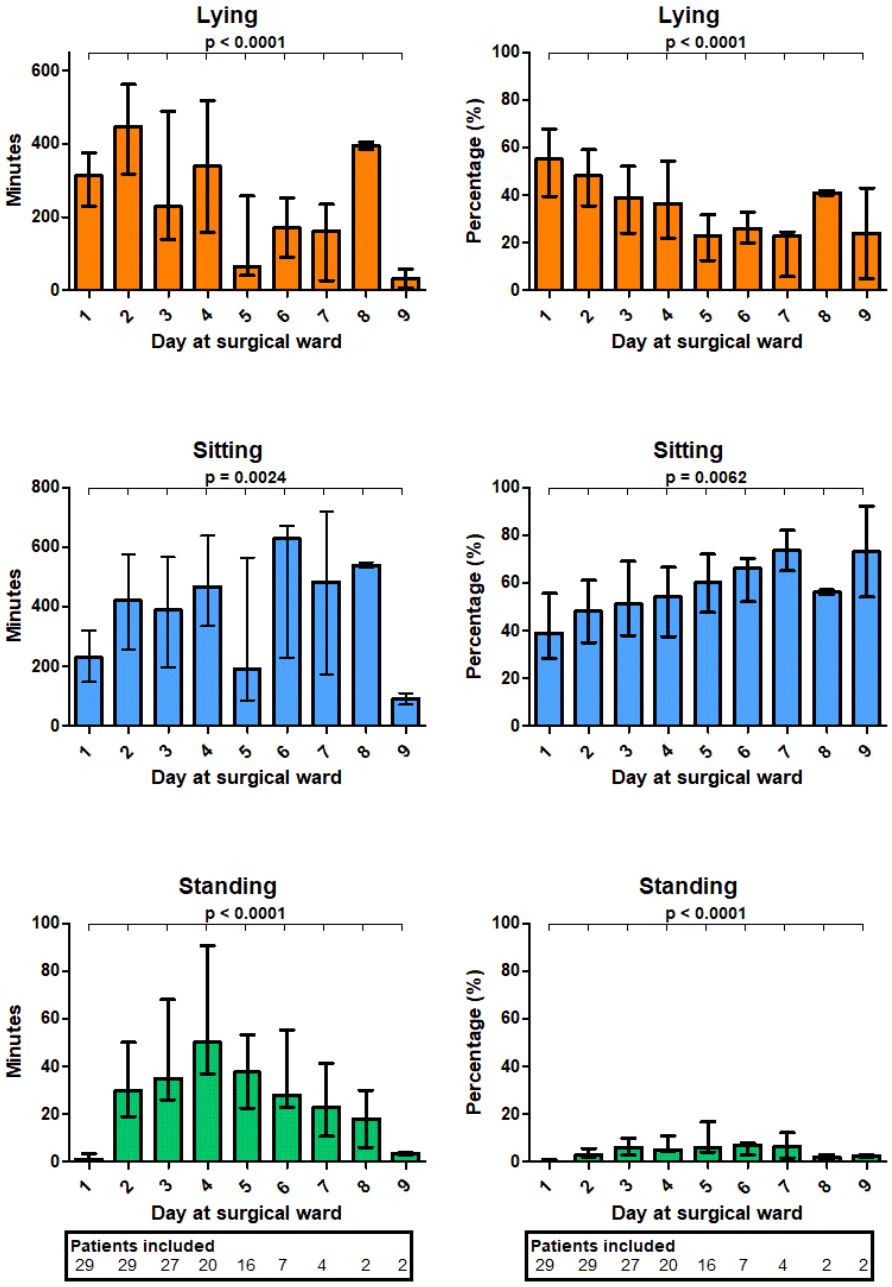


Figure 9: *Median amount of minutes and percentage of time spent lying, sitting, and standing for all patients. Daily intervals contain data between 7 a.m.-11 p.m. Error bars represent IQR. P values represent absence or presence of a statically significant difference between the days at the surgical ward.*

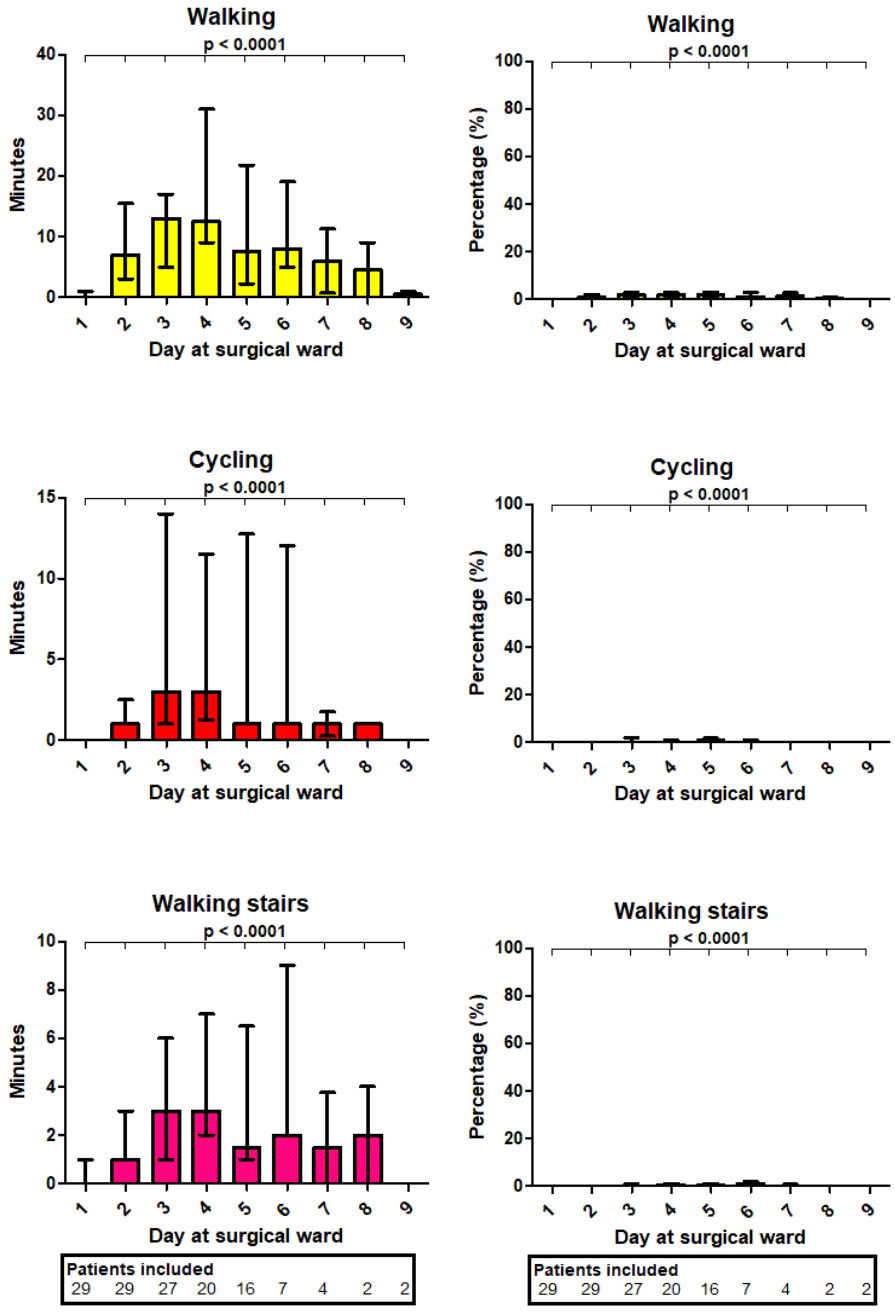


Figure 10: *Median amount of minutes and percentage of time spent walking, cycling, and walking stairs for all patients. Daily intervals contain data between 7 a.m.-11 p.m. Error bars represent IQR. P values represent absence or presence of a statically significant difference between the days at the surgical ward.*

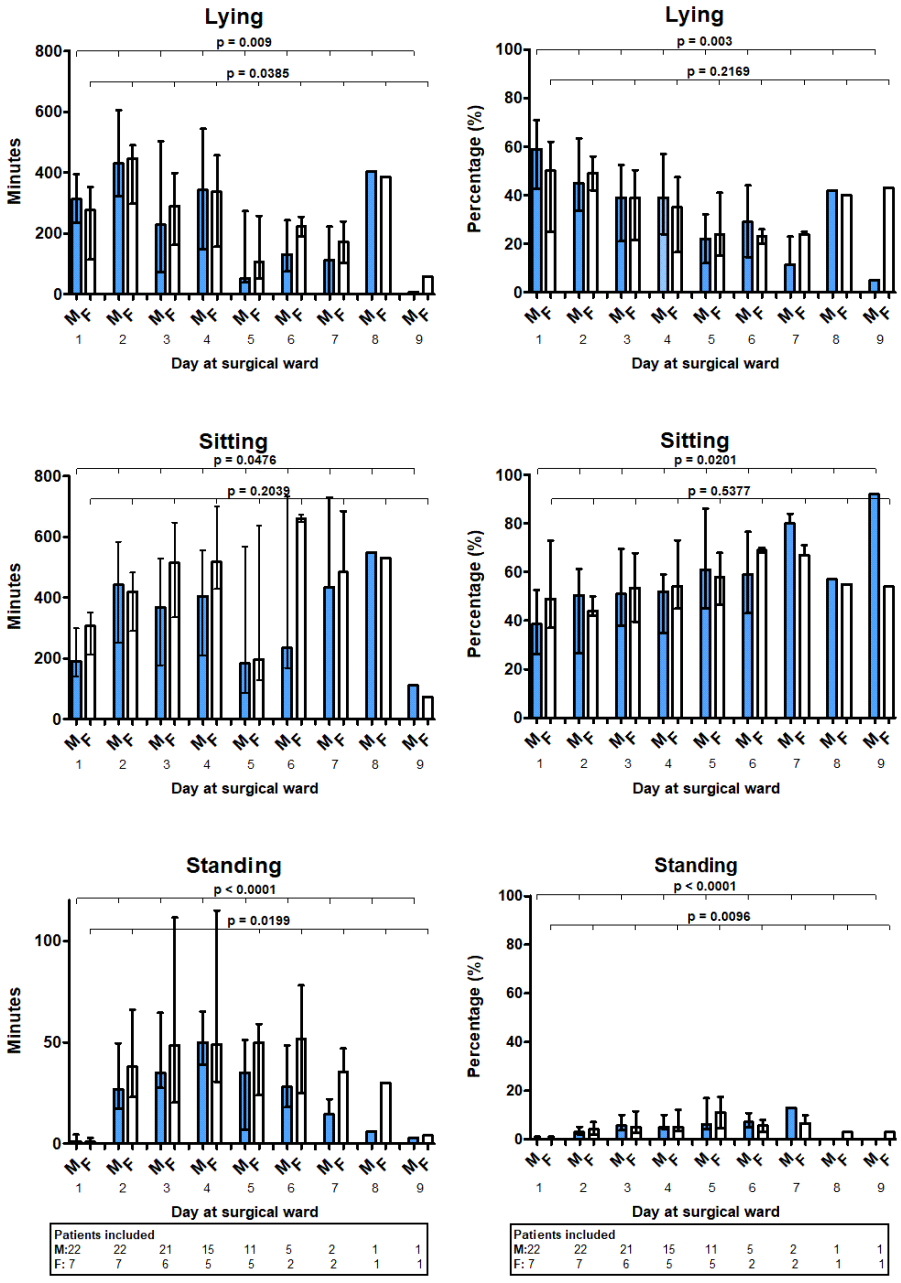


Figure 11: *Median amount of minutes and percentage of time spent lying, sitting, and standing for male (M) and female (F) patients. Daily intervals contain data between 7 a.m.-11 p.m. Error bars represent IQR. P values represent absence or presence of a statically significant difference between the days at the surgical ward.*

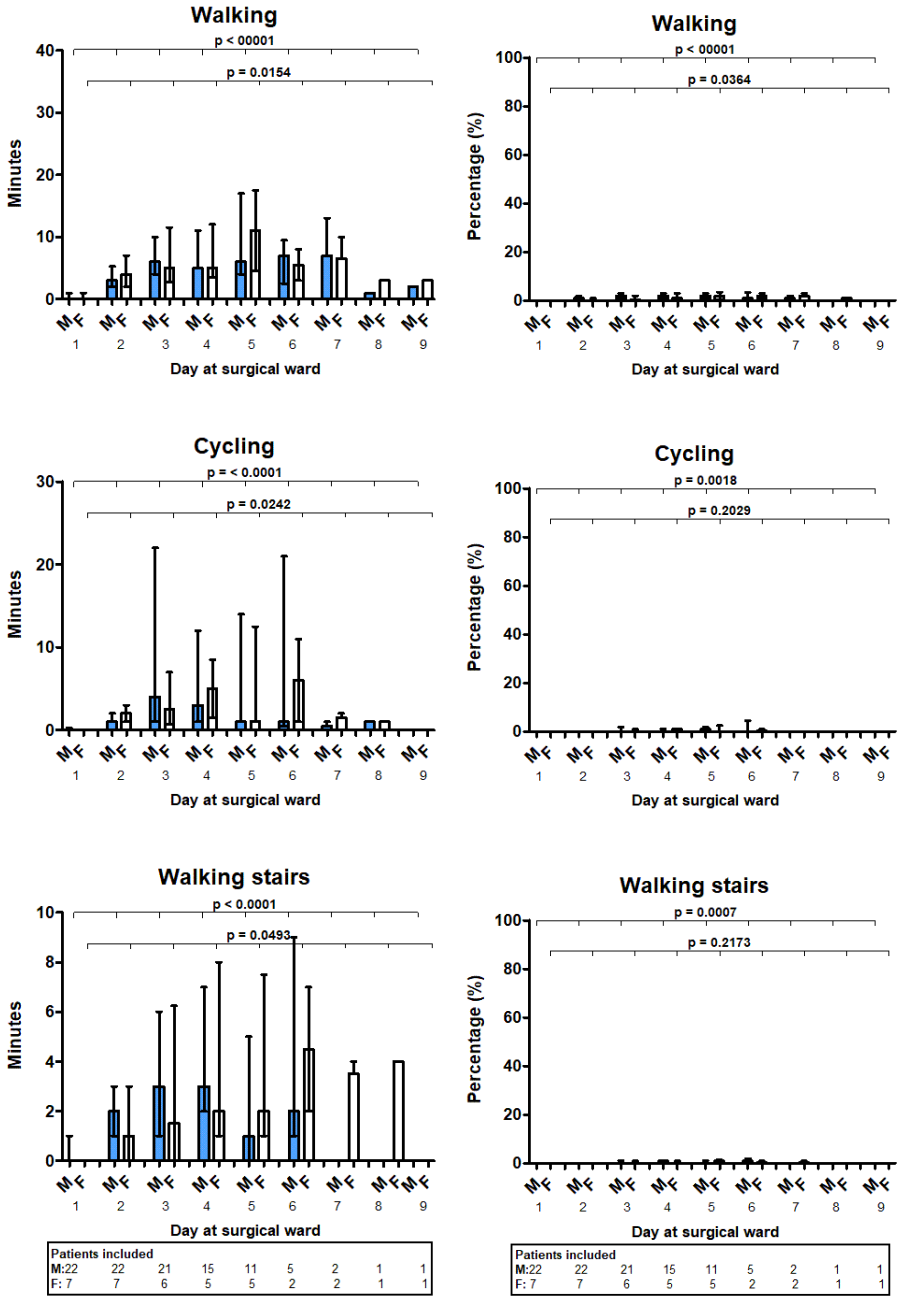


Figure 12: *Median amount of minutes and percentage of time spent walking, cycling, and walking stairs for male (M) and female (F) patients. Daily intervals contain data between 7 a.m.-11 p.m. Error bars represent IQR. P values represent absence or presence of a statically significant difference between the days at the surgical ward.*

Variable	Male	Female
Age, years	64	65
Body Mass Index, kg/m2	25	35
Diabetes	No	Yes
Left Ventricular Function	Good, >50%	Moderate, 30-50%
NYHA class	I	II
EuroSCORE I, log	2.1	3.1
EuroSCORE II, log	1.5	1.0
Cardiopulmonary bypass time, min	122	131
ICU stay, days	2	2

NYHA = New York Health Association
ICU = Intensive Care Unit

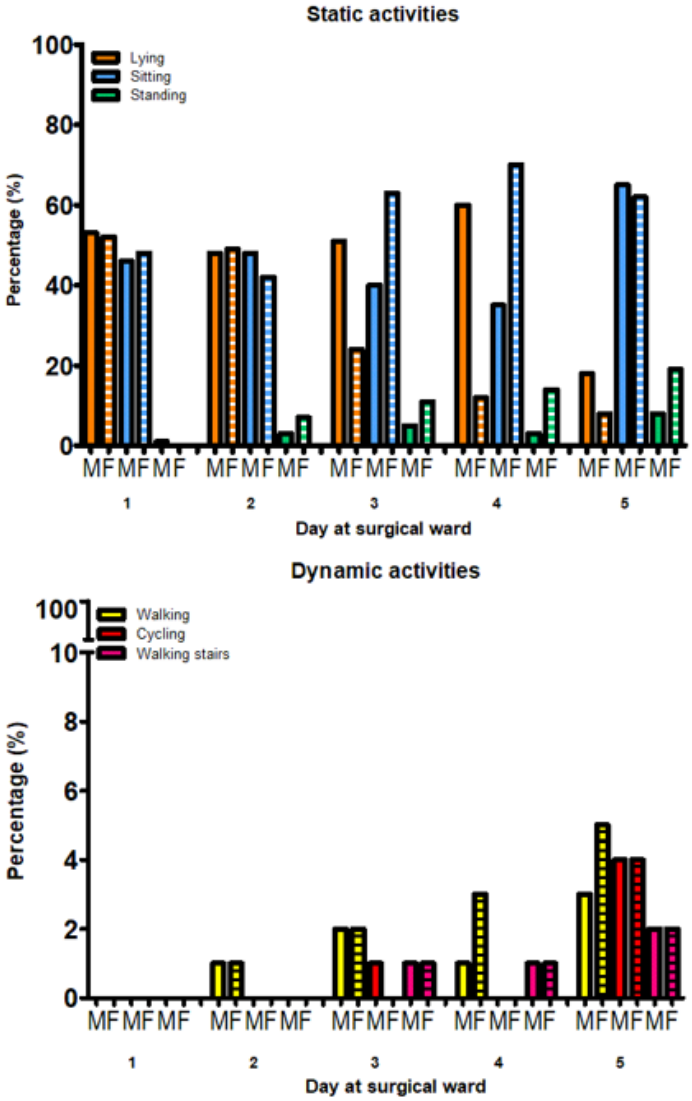


Figure 13: *Focus on two equivalent patient cases. It concerns a male patient and a female patient after elective mitral valve surgery via median sternotomy. Relevant patient characteristics and percentage of time spent in the static and dynamic activities for the male (M) and female (F) patient are presented. Daily intervals contain data between 7 a.m.-11 p.m.*

4 Discussion

This research aimed to determine a method to quantify in-hospital mobilisation objectively in patients after cardiac surgery. Several research questions were formulated to achieve this goal. These research questions focused on finding an approach and a suitable device to measure mobilisation objectively, and how these then could be deployed to conduct a clinical pilot study.
A method to automatic classification of physical activity to pursue objective quantification of in-hospital mobilisation of patients after cardiac surgery is described in this research. The technique of accelerometry combined with Machine Learning analysis was selected to measure and quantify physical activity objectively. The AX3 tri-axial accelerometer was regarded suitable as measurement tool based on requirements set. Towards conducting a clinical pilot study, a neural network algorithm has been developed to classify static and dynamic activities of interest. This algorithm is used to determine optimal sensor placement configuration based on experimental data. Ultimately, a clinical pilot study was conducted in which postoperative patient physical activity was quantified objectively. Results of the clinical pilot study were utilised to propose an answer to the research question regarding differences in mobilisation between men and women.
From execution of the clinical pilot, the method used to measure inpatient physical activity appeared feasible. There were no technical problems with the AX3 devices as measured data was for 100% usable, and the Tegaderm^{TM} patches did not unbind prematurely from any of the patient's skin. In addition, patients (except for one) did not experience any inconvenience or pain from wearing the sensors.
The strong point of this research is the combination of simultaneous use of two accelerometer sensors, specifically one placed on the upper leg and one on the upper arm, and usage of Machine Learning for classification of physical activity. To the best of our knowledge, no research has been performed in which similar approach has been used to objectify mobilisation especially in patients after cardiac surgery. Additionally, equivalent specific quantification of various types of physical activity in patients has not been reported before.

Postoperative patient physical activity

The exploratory clinical pilot study illustrates time lying, sitting, standing, walking, cycling, and walking stairs of patients after cardiac surgery during postoperative hospital stay on the surgical ward. Patients daily spent most time sitting and lying. The decreasing daily time spent laying is largely due to increasing time spent sitting. Daily time in non-sedentary activities (i.e. standing, walking, cycling, or walking stairs) was low, with most time spent standing. Patients were most active between 8 a.m. and 12.59 a.m. Daily amounts of static and dynamic activities did not differ significantly between male and female patients. Where males showed significant different amounts per activity over the days measured, females did not. For females, time lying, sitting, cycling, and walking stairs did not differ significantly over nine days. This is believed to be due to the small number of female patients.
Notably, our results demonstrate an increasing trend in dynamic activities over day one to day three for males, females, and all patients (Figures 10 and 12). This trend is fluctuating or decreasing over the rest of the days. Possibly, due to decrease in number of patients in the data sample after day three, the proportion of "less active" patients increases. This might explain why the increasing trend does not continue after day three.
Another remarkable point is that, patient movements were classified as cycling (in males only) and walking stairs on day one. According to protocol, patients start cycling from day two and walk stairs before or on the day of discharge. The activity forms on which physical therapists noted patient activity supported this, as no cycling or walking stairs was reported on day one. The explanation for these deviating findings lies with misclassifications of the algorithm. Misclassifications can include transfers between activities and other atypical movement of one or body segments to which sensors are attached. The amount of these misclassifications is assumed to be similar for all days and patients.
Finally, it is worth mentioning that the amount of minutes lying is not highest on the first day at

the surgical ward. Given the patient's status shortly after transfer from the ICU, this would be expected. The explanation for this is that, on the first day measurements were started earliest at 11 a.m.

Comparison of results to the relevant literature

Absence of significant gender difference in our study is not in line with observations in previous research performed by Halfwerk et al. [19] performed in TCT. This study aimed on improving early-mobilisation after cardiac surgery and used ACSM-scores (American College of Sport Medicine) and TCT-scores (TCT Matrix of functional activities and frequency descriptors) to monitor mobilisation. Halfwerk et al. found higher ACSM scores for male patients than for female patients, indicating males being more active. Our results fail to demonstrate that male patients are significantly more active than female patients. This is due to the small data sample of patients (n=29) and the relatively large difference between subset males (n=22) and females (n=7). In addition, two female patients (29%) were transferred to referring hospitals. This was the case with four male patients (18%). Statistical methods used in this research could be a part of the explanation of the absence of significant difference between male and female patients. A Kruskal-Wallis test was used to assess whether the amount of physical activity differed over days measured and a Dunn's multiple comparison post hoc test was used to determine and whether male patients significantly differed from female patients. The influence of previously measured data on current data is was not factored in, as a repeated measures ANOVA test or Friedman test does. Our results are not totally dissimilar to the work by Halfwerk et al. They reported that patients were mostly lying in bed on day one at surgical ward, decreasing up to day five. They also reported an increasing time of patients sitting in a chair over the days. Similar trends are demonstrated in our research (Figure 9). They also showed that on days three to five patients spent highest amounts of time "on toilet", "on corridor", "on home trainer", and "on stairs". This is to some extent in line with our results showing that patients are most active on days three and four (Figure 10). The difference of one day is caused by the relatively large daily decrease in amount of patients in the data sample from day two. This decrease was largely caused by patients transferred to their referring hospital. In case of patient transfer to referring hospital, remaining recovery is performed there. Actual mobilisation data is therefore not measured.
Mungovan et al. [5] quantified physical activity in 83 patients during the first five days after cardiac surgery using the SenseWear Pro 3 Armband (BodyMedia, Inc, Pittsburgh, PA, USA). The study was conducted at Westmead Private Hospital (Sydney, Australia) and primary outcomes were step count and Metabolic Equivalent of Task (MET). These patients displayed at most 22 minutes of physical activity time in MET $\geq$ 3, indicating most of time was spent inactive or in light activity (i.e. walking slowly). Both time MET $\geq$ 3 and step count increased significantly over the days after surgery. They also demonstrated a significant difference between males and females in the rate of increase in both outcomes as males showed greater increase rates. Our research indicates to some extent that patients are increasingly active over the first five days after surgery (Figures 9 and 10), unfortunately the trend is not statistically significant demonstrated. Step count was also measured in research by Doppelbauer et al. [20] in patients after orthopaedic surgery. They found that male patients take a significantly higher number of steps on the day before hospital discharge than female patients. Levels of physical activity in patients before the day of discharge was not investigated in our study, so unfortunately nothing can be stated about this.
Koenders et al. [74] performed similar research on quantification of physical activity in patients admitted to the internal medicine or surgical nursing wards of the Radboud University Medical Centre (Nijmegen, the Netherlands). They measured time lying, sitting/standing and walking using HealthPatch sensors. Despite the difference in activities of interests, our results are comparable to those of Koenders et al. They visualised average percentages of time in activities per hour, between 7 a.m. and 12 p.m. The percentage lying first appeared to decrease, followed by an increase until the early afternoon. The remainder of the hours until 12 p.m. again showed a decrease and increase. Percentage sitting/standing showed an opposite tendency. Comparable

trends in time spent per activity on different daytime hours are demonstrated in our results (Figure 8).
Hussey et al. [75] measured postoperative mobilisation after oesophagectomy in patients at the Oesophageal and Gastric Cancer Centre at St James's Hospital (Dublin, Ireland). They measured postoperative physical activity objectively using the Actigraph GT3X+. Results from Hussey et al. are in line with our findings as they demonstrated that patients spent the majority of time (over 96%) sedentary. Their study showed that daily step count and amounts of light intensity activity in patients were low but did increase daily from the first to the fifth postoperative day. This trend is also in line with our findings.
Results from studies by Au et al. [76] and van der Meij et al. [77] demonstrate that patients were daily sedentary for approximately 90% and 78% of time in the first week after surgery. Au et al. measured physical activity in Canadian patients after radical prostatectomy using the Actiwatch 2 by Philips Healthcare. Van der Meij et al. used Actigraph wGT3X-BT accelerometers to measure physical activity in Dutch patients after laparoscopic abdominal surgery. The lower percentages in these two studies are due to the fact that patients were not required to, and did not, always wear the sensors.

4.1 Limitations

This research has limitations divided into general limitations and specific limitations of the clinical pilot study.

General limitations

General limitations of this research include the method of device selection. The number of devices tested is based on literature research conducted by a single person. Research into devices by more researchers could provide a more complete, and possibly less biased overview. In addition, specific attention could be given to devices working with the same technology (e.g. accelerometers). Technical and clinical device requirements set were based on advice from experts and general knowledge of (clinical) limitations of device application. A more valid list of requirements could have emerged if a complete group of stakeholders (i.e. patients, nurses, physiotherapists, and surgeons) was involved. The devices found were subjected to the requirements based on their specifications, again by one person. A more valid selection can be made when the devices are actually tested and benchmarked, preferably by multiple researchers.

Another limitation is the modest amount testing with other types of algorithms. In this research a relatively simple neural network was built for pragmatic reasons, however there are potentially better and/or more efficient algorithms. It is debatable whether the involvement of neural network classification does exceed the complexity of the activity classification problem. Based on physiological interpretation of measured data, a simple "classification tree" could have been made and used as an algorithm for classification. Static and dynamic activities can be distinguished by determining whether measured signals vary over time, thereby assuming that static activities yield constant accelerometer signals and dynamic activities time-varying signals. A measure of signal variation over time can be obtained by, respectively, high-pass filtering, rectifying, and low-pass filtering of the measured signal [40]. By applying a threshold to the resulting signal, activities can be classified as static or dynamic. Determination of accelerometer orientation can be used to distinguish type of static activity. Orientations of accelerometers can be estimated from the angle between accelerometer axes and the gravity vector when the measured signal is constant. Knowing sensor orientation provides information of body segment orientation and is, therefore, useful to detect postures. Dynamic activities are normally cyclical in nature and can differ in several facets: mean, signal morphology determined by the maximum correlation coefficients of cycles with templates from the different activities, cycle time, and standard deviation [40]. These differences can be used to determine type of dynamic activity such as walking (stairs) and cycling.

In addition, the construction of the neural network algorithm in terms of feature selection was

partially well-grounded. The same features as Bunkheila [56] proposed in his code were used as they yielded high overall classification accuracy. Additional features were added based on findings from the literature. Hence a limiting aspect of this research is the fact that a large number of features was used of which the actual individual added value per feature was not fully explored.

The experimental methods towards determining optimal sensor placement configuration were also fairly limited, with merely four subjects available for measurements. A number of twenty subjects would be advised. Sensor placement configuration using one sensor on the upper leg and one on the lower leg was not investigated while this also may enable classification of the static and dynamic activities of interest [78]. In addition, it would benefit validity of sensor configuration selection when the experimental methods were performed with actual patients.

Limitations of the clinical pilot

Limitations of the pilot study include unknown error margins of the neural network used for classification. Readers should note that outcomes regarding actual time spent per activity might differ. The neural network was trained based on semi-controlled preoperative data from 31 patients. It was not tested how the semi-controlled data relates to real life postoperative data measured. Inevitably, there are differences between both circumstances which raise the question to what extent the algorithm can be applied [79]. Although the environment and setting were similar for the patients in both pre- and postoperative phases, there were differences in postures and the way patients moved. For example, patients frequently lied with their head up at an angle instead of flat. The neural network might misclassify such as sitting, of which cases were found after inspecting the algorithm's classifications. Additionally, patients are likely to walk more slowly after surgery compared to before surgery and should start walking with a walker. During the labelling measurement all patients walked without any form of support. This could have caused a classification shift from walking to standing, thereby overestimating amounts standing and underestimating walking. As stated before, amounts of cycling and walking stairs are likely to be overestimated due misclassifications of data unrecognisable for the neural network.

A validation of correctness of classifications from the postoperative measurement was attempted via inspection of the activity forms. Adequate validation was not possible as the forms were filled in infrequently, incompletely and inaccurately. Nevertheless, data retrieved from the forms was reflected in the actual classifications. It mainly concerned periods of cycling and walking, since documentation on the other activities was scarce. These findings are positive concerning precision (or positive predictive value) of the neural network in recognising cycling and walking. In order to be more conclusive on the validity of the classifications, segments of classifications were inspected of which could be assumed that a patient was in a certain activity (e.g. laying at night time). Also, classifications on the first day at the surgical ward were inspected, as patients mostly lie or sit. Both inspections showed that cycling and walking stairs emerged in classifications. These observations are negative concerning recall (or true positive rate) of cycling and walking stairs. Actual amounts of cycling and walking stairs is therefore expected to be less.

In this study, postoperative physical activity of patients is classified using a neural network trained with preoperative data from these same patients. The setting and environment of training and application of the neural network can be considered as almost identical. In our case, this is beneficial, given that the algorithm is more likely to recognise certain data. It is therefore assumed that this has benefited classification accuracy. However, this aspect limits the generalizability of the algorithm in other patients, patient groups, or (hospital) setting. The group of patients used in this study does not represent all types of patients. We included only patients with KATZ-ADL score > 2 and able to perform the labelling measurement (including walking, cycling and walking stairs). This has resulted in training data biased towards more able-bodied patients. Application of our classification method in less able-bodied and/or disabled patients could lead to unreliable outcomes.

The number of patients included in the training data, specifically the small number of female pa-

tients, may be too small to cope with intraclass variability (i.e. a patient performs similar activity differently) and interclass variability (i.e. patients perform similar activity differently). In general, a larger number of subjects is important to perform pattern recognition [80], [81]. Jandidarmian et al. [51] aggregated a data set containing approximately 35 million acceleration samples from 228 subjects. This data set was stated as "most complete, realistic, and transparent" in the context of designing a HAR model working in realistic conditions. Research into HAR, in a broad sense, is challenging due to differences in and differences between individual's movement patterns [82]. It is challenging to make a statement on to what extent relevant variability exists between individuals for the static and dynamic activities measured in this research. Graphs in Figure 7 (Results Section 3.3.2) imply that an increase in patients has little influence on overall classification accuracy. This makes sense given the fact that several activity classes (e.g. postures) can be distinguished on purely physiological grounds and without training. The low number of female patients cannot justify the assumption of stagnation of accuracy. Therefore, addition of female patients is necessary. Ideally, amount of males and females should be equal to make a further statement. Appendix F Figure 24 reveals that an increase in patients influences recall and precision of lying, sitting, walking ans waking stairs. For all four of these activities additional data of new patients is necessary to investigate further development of these variables. Neural network performance after training demonstrated low minimum recall and precision values for various activities, determined with LOSO-validation (Results Section 3.3.2 Tables 10 and 11). Thus, as result of variability of certain patients the algorithm does not recognise movement patterns adequately. Testing the current algorithm's performance on labelled data from new patients should reveal whether the algorithm is able to accommodate to this variability. If so, no lower minimum recall and precision values will be found.

Statistical methods could also be considered as a limiting factor. For the sake of time, relatively simple statistical tests were applied. These tests did not specifically assess day-to-day statistical differences in amounts of activity and did not factor in that data is measured over increasing time (i.e. the influence of the increasing number of days after surgery). It is likely that the level of patient physical activity on the previous day(s) affects amount of physical activity on the current day as well as days in the future. A repeated measures ANOVA test or Friedman test can be used for improvement. In addition, when performing the statistical tests, no correction was made for the fact that the patient data sample decreased over the days. This resulted in varying patients in the daily data samples. Therefore, it would be relevant to split patients in groups based on postoperative hospital stay and compare within these groups or limit statistical analysis corresponding to the least amount of postoperative days measured.

Furthermore, a small sample of patients was included in this pilot study ($n<50$) [83]. The results on measured physical activity will need to be confirmed by larger studies. The number of female patients was also too small to make a thorough gender comparison. Doppelbauer et al. [20] have attempted to objectify mobilisation using Fitbit activity trackers. They performed measurements in of 50 male and 50 female patients after total hip arthroplasty. These numbers may be used as a guideline with regard to a suitable patient sample size. Moreover, the number of patients in our data sample decreased substantially after day three resulting in data represented by merely two patients. Such small numbers are not representative to make conclusions.

Finally, it could be possible that the Hawthorne Effect has influenced levels of patient physical activity positively [78], [84]. The Hawthorne Effect is the effect of an intervention (i.e. application of accelerometers) on participants that is solely due to their participation in research. Thus, the actual average amounts of physical activity of patients after cardiac surgery may be lower than shown in this study.

4.2 Clinical relevance

This research demonstrates the feasibility to quantify in-hospital patient mobilisation objectively. Classification of relevant static and dynamic activities of patients is achieved using two tri-axial

accelerometers. The degree of objectivity and specificity of the obtained results regarding physical activity of patients is rare and clinically relevant, directly enabling objective evaluation of interventions aimed to stimulate inpatients' mobilisation. Results of the clinical pilot study confirm that patients spend majority of their time sedentary during daytime. This is an important outset as it can be used to create more awareness in healthcare professionals of the actual amount of in-hospital patient physical activity, which can have a positive indirect effect on patient care. A higher degree of awareness can initiate processes generating changes for the benefit of the patient. An important clinically relevant insight is the daily distribution of physical activity. Where there is still some amount of physical activity in the morning, this is hardly the case in the afternoon. Research into the cause of this finding is relevant to adequately address it. A possible explanation could be fatigue and/or pain in patients after exercises in the morning [11]. Nevertheless, this finding indicates the need for further improving of current mobilisation strategy in TCT. Improvement should stimulate patients being more (frequently) active during the entire day. Physiotherapists in TCT generally only mobilise patients in the morning. Patients can reach a higher level of activity when nurses and/or physiotherapists would actively mobilise patients more frequently on a daily basis. For example, it would be advantageous to provide patients with regular supervised mobilisation both in the morning and in the afternoon. Mungovan et al. [5] found significant and strong correlation between exercise supervised by physiotherapists and independent patient physical activity which suggests that supervised physical activity fosters more independent physical activity in patients after cardiac surgery. Readjustment of schedules or hiring of more medical personnel would possibly be necessary to achieve standardised physiotherapist-supervised exercises twice a day. This might be a time-consuming process or significantly add to the costs. Therefore, a first step should be to instruct patients more emphatically to be active throughout the entire day. These instructions deserve more emphasis during preoperative patient education.
In order to reach higher levels of activity, intrinsic motivation in patients regarding mobilisation is beneficial [85]. This can be achieved by informing patients personally on their level of physical activity via a certain medium (e.g. an application on a smartphone or tablet). This information should be provided when patients are (or have been) sufficiently active and when this is not the case. Only sharing patient-specific objective information, and thereby increasing the patient's knowledge on its own recovery, is a first step. The shared information must also be converted into useful actions. For example, a medium could give stimulating notifications when the patient should start to be physically active and rewarding notifications when the patient has been sufficiently active. This medium should also provide patient-specific tips and exercises based on the level of activity of the patient. Aspects of 'serious gaming' could be integrated in this medium, as it is suggested to increase motivation in rehabilitating patients [86].

4.3 Recommendations and future research

This research serves as a foundation for further research. There are several recommendations for research in future. First, it is important to validate the correctness of the algorithm's classifications during postoperative measurements. Validation can be performed in healthy subjects and in patients, of which the first option is easier to set up and the latter is more specific. In a group of new subjects and/or patients, physical activity could be measured using the AX3 sensors while simultaneous and accurate (in minutes) documentation is assembled on this activity. Simultaneous recording of video images is also an option, which is less labour intensive but could entail difficulties regarding privacy. Validation then relies on comparing classifications with the documentation or video images. Regardless of importance, validation seems to be a time consuming process. It is therefore advised to experiment with other instruments beforehand to optimise correctness of the classifications. A decision threshold approach can be applied to the output of the neural network. For each classification the network calculates a quantitative output of a score per activity. Setting thresholds scores may result in more realistic classification performance. Research showed that increasing thresholds lower the algorithm's sensitivity and higher specificity with limited effect on concordance of the classifications [87]. Another instrument is 'majority voting', whereby the largest number of classifications over a certain period is chosen as classification. This lowers the

classification resolution, but can reduce the number of misclassifications. A lower resolution is not a problem in a clinical context. A classifications every 2.56 seconds is not necessary to get an impression of patient mobilisation, this is also feasible with classifications per 10-60 seconds.

As already mentioned, there is a discrepancy in the way patients move pre- and postoperatively. Adequate training data should be collected to solve this problem. The same labelling measurement can be performed, supplemented with the necessary adjustments. Additional data for adequate training of the neural network can also be obtained from actual postoperative measurements, which optimises specificity of the data.

A topic discussed before, is the decision of using a neural network for classification and the feature selection. It would be interesting to investigate whether a less complex algorithm, developed based on physiological characteristics of the different activities, obtains sufficient classification performance. When the ML approach is continued, thorough feature evaluation and selection is advised. The algorithm makes predictions based on 160 features (59 after feature selection), which requires a significant amount of computing power and time. An evaluation of the added value of features used in this research, and eventually other features presented in the work by Janidarmian et al. [51], could result in a neural network performing equally well or even better using less features. This would ease algorithm incorporation into a system capable of continuous real-time classification. In the context of computation costs, it would be valuable to investigate classification performance on larger segments, and from data measured with lower sampling rates. Testing with segments of five and ten seconds yielded positive results (Appendix F Table 27 and 28). Regarding patient comfort, research should be devoted to activity classification using one sensor. Our research has demonstrated that the neural network is able to make classifications with over 90% overall accuracy, only using knee sensor labelling data (Appendix F Table 26). It is relevant to determine whether 90% accuracy is sufficient in clinical context and whether this accuracy also holds for the postoperative measurement.

Finally, further research aimed at converting clinical measurements into acts is essential. Despite the fact that measurements on physical activity offer valuable insights, they are not yet of direct use to the patient. As already discussed, patients should be informed on amount of physical activity, and be motivated to act accordingly. This is a process with several important facets. Firstly, the device for data collection needs to be improved. A device supporting wireless connection in order to provide real-time data analysis is needed, such as the Actigraph (Appendix B figure 14b). Subsequently, the measured data must be linked to a certain medium that can inform both clinicians and patients and offers patient-specific motivation. This medium can take various forms. For example, an application on a smartphone or tablet, eventually incorporating aspects of serious gaming, a band around the wrist that provides notifications, or a television screen that acts according to amount of patient activity. By informing clinicians, they receive a more complete objective impression of the patient's status and can intervene when necessary. Ultimately, future research should analyse effects of this medium as intervention to stimulate physical activity of patients after cardiac surgery.

5 Conclusion

Mobilisation of inpatients after cardiac surgery was successfully objectively quantified with the use of two body-worn tri-axial accelerometers and a Machine Learning classification approach. This current study proves that inpatients spent most of their time laying or sitting. The decreasing time spent laying is a result of an increase in time spent sitting. The amount of other forms of physical activity is low, mostly demonstrated between 8 a.m. and 11:59 a.m. This suggests sufficient scope to motivate inpatients to be more and more frequently active in order to raise overall daily level of patient mobilisation.
This research is a valuable first step serving as foundation for further research. Future work should focus on further development of the classification algorithm and the validation of its classifications on data measured in uncontrolled setting. Furthermore, it is important to devote research to using objective physical activity measurements for interventions directly affecting patient care.

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Appendix A

Table 12: *Overview of methods to assess patient mobilisation (part 1 of 2).*

Method	Outcomes	Principle	Patient population	Limitations	Research
Patient-reported					
Criteria of The Corpus Christi Heart Project (CCHP)	Activity level	Activity scoring (1-5) based on self-reporting assessment	Cardio-thoracic surgery	Not suited for in-hosptal Overestimates true activity Not specific enough	Van Laar et al., 2017 [88]
International Physical Activity Questionnaire -Short Form (IPAQ-SF)	Sitting time Walking time Moderate physical activity Vigorous physical activity Metabolic equivalent minutes per day	Outcomes derived from answers of questionnaire	Pelvic exenteration surgery	Under and/or overestimation of activity	Steffens et al., 2019 [89]
Activity diary	Post-operative dates	Dates on which patients were able to perform specific activities for the first time	Laparoscopic abdominal surgery	Not validated Subjective measure	Van der Meij et al., 2017 [77]
Professional scoring					
Functional milestones	Daily milestones Degree of dependance RPE scores	Daily recording of outcomes by observaton	CABG surgery	Observer dependent	Van der Peijl et al., 2004 [10]
AM-PAC "6-clicks" Basic Mobility	Basic mobility level	Daily scoring (1-4) of six activities	Internal medicine	Only includes basic mobility items	Geelen et al., 2019 [90]
6-min walk test (6MWT)	Distance (in meters) walked in six minutes	Submaximal excersise test entailing measurement of distance walked over a span of six minutes	CABG surgery Gastrointestinal cancer surgery Cardiac rehabilitation	Wound pain can be limiting No insight in mechanisms of exercise limitation	Hirschorn et al., 2008 [9] van der Leeden et al., 2016 [91] Alexiev et al., 2017 [92]
Behavioural mapping	Physical activity Persons attending Location Daily activity	Scoring acording to predefined items based on intermittent observation	General care ICU	Large workload Patient privacy	Valkenet et al., 2019 [93] Berney et al., 2015 [94]
the Johns Hopkins Highest Level of Mobility (JH-HLM)	Mobility milestones score	Capturing mobilty milestones with 8-point ordinal scale based on patient observation	General medicine	Data cannot fully describe total mobility and activity	Hoyer et al., 2016 [95]

Table 13: *Overview of methods to assess patient mobilisation (part 2 of 2).*

Method	Outcomes	Principle	Patient population	Limitations	Research
Wearable devices					
Actigraph wGT3X-BT	Wear time Step count Physical activity intensity	Tri-axial accelerometer worn around hip	Laparoscopic abdominal surgery	Wear location impedes full wearing compliance	Van der Meij et al., 2017 [77]
The Dynaport/ MoveMonitor	Sitting time Walking time Lying time Physical activity intensity Wear time	Tri-axial accelerometer worn on the lower back	CABG surgery General medicine Pelvic exenteration surgery Peripheral arterial disease	Wear location impedes full wearing compliance Detection of low amplitude movements is challenging	Van der Peijl et al., 2004 [10] Valkenet et al., 2019 [93] Steffens et al., 2019 [89] Fokkenrood et al., 2014 [96]
SenseWear Pro 3 Armband	Step count Physical activity intensity	Bi-axial accelerometer and multiple skin sensors	Cardiac surgery via median sternotomy	Overestimation of walking activities	Mungovan et al., 2017 [5]
Fitbit	Step count	Accelerometer worn around wrist or ankle	Metastatic peritoneal cancer Cardiac surgery Orthopedic surgery	Underestimation of steps for patients moving slowly or with assistance No validation for slow and assisted walking	Low et al., 2018 [21] Cook et al., 2013 [97] Dopperlbauer et al., 2019 [20]
MOX activity monitor	Sedentary time Standing time Physical activity intensity	Tri-axial accelerometer attached above the knee	Colorectal cancer	Limited reproducibility at moderate-to-vigorous intensity levels	Van Roekel et al., 2016 [98]
Step Activity Monitor (SAM)	Step count	Accelerometer attached at the ankle	Acute elderly care	Limited outcomes	Fisher et al., 2010 [99]
Active Style Pro HJA-350IT	Step count	Waist-mounted tri-axial accelerometer	Cardiac surgery	Limited outcomes	Takahashi et al., 2015 [100]

Appendix B

Table 14: *Expert discussions on inpatient mobilisation monitoring.*

Person	**Field of expertise**	**Topic**
(1) N. Wielens BSc	Physical therapist TCT	Relevant measures and outcomes. - Patient's posture over time - Step count - Physical activity intensity - Upper and lower body movement - Automatic activity detection
(2) Prof. J.S. Rietman PhD	Technology and rehabilitation	Devices for monitoring inpatient physical activity. Suggestion: McRoberts MoveMonitor
(3) Prof H.J. Hermens PhD	eHealth and telemonitoring	Feasibility of using the McRoberts MoveMonitor from own experience. Conclusion: considering patient comfort an alternative device is advised.
(4) M. Cabrita PhD	Personalized eHealth technology	Devices for monitoring inpatient physical activity. Suggestion: MOX Physical Activity Monitor (Maastricht Instruments bv). Important features: - Raw data - Product support - Patient comfort - Battery life - Price
(5) D. van Dartel MSc	Activity monitoring in patients after hip surgery	User experience of the MOX device. - Easy to use - Good patient comfort - Raw data analysis in Matlab - Good product support
(6) F. Boesten MSc	Product line manager Maastricht Instruments	Demonstration of the MOX devices. Points of interest: - Device is easy to use, not uncomfortable for patients and already used in hospitals - MOX1 saves raw data unable to stream the data - MOX2 does only stream filtered data but does not save the raw data - Posture detection with one sensor is not optimal, two sensors are needed

Table 15: *Specifications and properties of devices suitable for activity monitoring (part 1 of 3).*

	AX3 Axivity Ltd [27][101] [24] [72]	**ActiGraph wGT3X-BT** ActiGraph, LLC [70][102][73]	**MOX1** Maastricht Instruments BV [71][103]	**MoveMonitor** McRoberts BV [104][105]	**Fibion** Fibion Inc [106][107]	**Activ8 A8015 Bluetooth** Activity Tracker Remedy Distribution Ltd [108]
Technology	Tri-axial accelerometer Logarithmic light sensor Linear thermistor	Tri-axial accelerometer Capacitive touch sensor Ambient light sensor	Tri-axial accelerometer	Tri-axial accelerometer	Tri-axial accelerometer	Tri-axial accelerometer
Outcomes	Raw acceleration	Raw acceleration	Raw acceleration	Posture detection (lying, sitting, standing, walking, cycling, walking stairs)	Energy expenditure	Duration and intensity per activity class (sitting, standing, walking, cycling, running)
	Ambient light	Activity counts	Posture detection (sedentary and standing)	Physical activity intensity	Physical activity types (sitting, standing walking and cycling)	Energy expenditure
	Temperature	Energy expenditure	Physical activity intensity	Step count	Physical activity intensity (light, moderate and vigorous)	
		Step count	Physical activity classification (low, medium, high)			
		Physical activity intensity Activity time Sedentary time Body position				
Size (LxWxH)	23x33x9mm	46x33x15mm	35x35x10mm	106.6x58x11.5mm	30x32x10mm	30x32x10mm
& weight	11 grams	19 grams	11 grams	55 grams	20 grams	20 grams
Placement	Wrist Upper arm Waist Ankle	Wrist Waist Ankle Thigh	Thigh Hip Sacrum Arm	Lower back	Thigh	Upper leg Chest Wrist
Patient comfort	++	+	++	−	+	+
Raw/filtered data	Yes/No	Yes/Yes	Yes/Yes	No/Yes	No/Yes	Yes/Yes
Sampling rate	12.5Hz-3200Hz	30-100Hz	25-100Hz	100Hz	12.5Hz	12.5Hz
Data streaming	No	Yes	No	No	Yes	Yes
Data storage	512 Mb	4 Gb	1.5 Gb	1 Gb	?	?
Battery life	14 days	25 days	7 days	14 days	20 days	30 days
Waterproof	Yes	Yes	Yes	No	No	No
Validated	Yes	Yes	Yes	Yes	Yes	Yes
In-hospital use/	Yes/	Yes/	Yes/	Yes/	No/	Yes/
in MST use	No	No	No	No	No	No
Price	€123	€225	€195	€295	€298	€139

++ = causes no/minimal discomfort + = may cause light discomfort − = causes discomfort ? = specification or property unknown

(a) AX3 [24]

(b) ActiGraph [70]

(c) MOX1 [103]

(d) MoveMonitor [105]

(e) Fibion [107]

(f) Activ8 [108]

Figure 14: *Devices suitable for activity monitoring (part 1 of 3).*

Table 16: *Specifications and properties of devices suitable for activity monitoring (part 2 of 3).*

	activPAL	**VitalPatch disposable biosensor**	**Philips Health Watch**	**SenseWear Pro3 Armband**	**HeartGuide**	**Fitbit**
	PAL Technologies Ltd	VitalConnect	Philips	Micro Star Instruments Co. Ltd	Omron Healthcare Inc	Fitbit Inc
	[109][110][111][112]	[113]	[114]	[115]	[116]	[117][21][20][118]
Technology	Tri-axial accelerometer	Tri-axial accelerometer ECG electrodes Thermistor	Tri-axial accelerometer Optical heart rate sensor	Bi-axial accelerometer Skin temperature Galvanic skin response Heat flux sensor	Tri-axial accelerometer Photoplethysmography sensor Oscillometric blood pressure sensor	Tri-axial accelerometer Optical heart rate sensor
Outcomes	Energy expenditure Body posture time (sedentary and standing) Stepping time Step count	Time active Posture detection Single-lead ECG Heart rate Respiratory rate Body temperature	Step count Energy expenditure Distance covered Physical activity intensity Heart rate	Step count Energy expenditure Time lying Physical activity duration and intensity	Step count Energy expenditure Distance covered Heart rate Blood pressure	Step count Energy expenditure Distance covered Physical activity intensity Heart rate
Size (LxWxH)	35x53x7mm	120x40x9.5mm	36x3x12mm	?	48x30x14mm	48x19x10mm
& weight	15 grams	13 grams	?	80 grams	115 grams	8 grams
Placement	Thigh Thigh	Chest	Wrist	Triceps right	Wrist	Wrist Waist Ankle
Patient comfort	++	+	++	+	++	++
Raw/filtered data	No/Yes	No/Yes	No/Yes	?/Yes	No/Yes	No/Yes
Sampling rate	20Hz	62.5Hz	?	?	?	?
Data streaming	No	Yes	Yes	?	Yes	Yes
Data storage	?	10 hours	?	?	7 days	?
Battery life	14 days	5 days	4 days	14 days	2 days	Up to 7 days
Waterproof	No	Yes	No (IP44)	?	No	Potential
Validated	Yes	Yes	Yes	Yes	Yes	Yes
In-hospital use/	Yes/	Yes/	No/No	Yes/?	No/No	Yes/No
in MST use	No	No	No	No	No	No
Price	$450	€80	€250	$500	$499	From €90

++ = causes no/minimal discomfort + = may cause light discomfort − = causes discomfort ? = specification or property unknown

(a) activPAL [110]

(b) VitalPatch [113]

(c) Philips Health Watch [114]

(d) SenseWear Pro3 [115]

(e) HeartGuide [116]

(f) Fitbit [117]

Figure 15: *Devices suitable for activity monitoring (part 2 of 3).*

Table 17: *Specifications and properties of devices suitable for activity monitoring (part 3 of 3)*

	Garmin VivoSmart	**Alvita Ultimate HJ-325**	**Motiv Ring**	**wellsense vu**	**BCGMCU/SCA11H**	**E4 Wristband**
					Accelerometer-based ballistocardiographic sensor	
	Garmin [119]	Omron Healthcare Inc [120]	Motiv inc [121]	wellsense [122]	Murata Manufacturing Co., Ltd [123]	Empatica Inc [124]
Technology	Tri-axial accelerometer Optical heart rate senor	Tri-axial accelerometer	Tri-axial accelerometer Optical heart rate senor	Pressure sensor	Tri-axial accelerometer	Tri-axial accelerometer Photoplethysmography sensor Electrodermal activity sensor Infrared thermopile
Outcomes	Step count Energy expenditure Distance covered Physical activity intensity Heart rate	Step count Energy expenditure Distance covered	Step count Physical activity intensity Energy expenditure Distance covered Resting heart rate	Pressure map	Heart rate Heart rate variability Respiration rate Stroke volume Activity indication Bed occupancy status	Raw acceleration Electrodermal activity Heart rate Skin temperature
Size (LxWxH)	21x15x12mm	57x42x13mm	8x2.5mm	2315x1125mm	84x41x18mm	44x40x16mm
& weight	31 grams	23 grams	3 grams	3000 grams	?	25 grams
Placement	Wrist	Waist	Ring finger	Over mattress	Under matress	Wrist
Patient comfort	++	+	++	++	++	++
Raw/filtered data	?/Yes	No/No	No/Yes	?/Yes	?/Yes	Yes/Yes
Sampling rate	?	?	?	?	1Hz	32Hz
Data streaming	Yes	No	Yes	No	Yes	Yes
Data storage	?	7 days	?	?	?	60 hours
Battery life	5 days	6 months	3 days	?	?	20 hours
Waterproof	Potential	No	Yes	Yes	No	No
Validated	Yes	Yes	No	Yes	?	Yes
In-hospital use/	Yes/	Yes/	No/	Yes/	?/No	-/No
in MST use	No	No	No	No	No	No
Price	From €90	$30	From €90	Over €10000	From €150	$1690

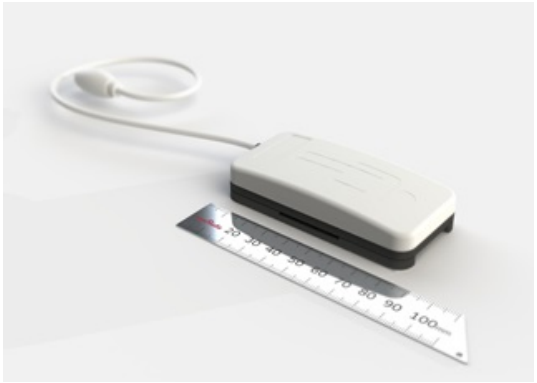
++ = causes no/minimal discomfort + = may cause light discomfort − = causes discomfort ? = specification or property unknown

(a) VivoSmart [119]

(b) Alvita Ultimate [120]

(c) Motiv Ring [121]

(d) wellsense vu [122]



(e) BCGMCU/SCA11H [123]

(f) E4 Wristband [124]

Figure 16: *Devices suitable for activity monitoring (part 3 of 3).*

Table 18: *Results of device subjection to the technical requirements (part 1 of 3).*

	AX3	ActiGraph	MOX1	MoveMonitor	Fibion	Activ8
1. Activity classification						
- Lying	✓*	✓*	✓*	✓	×	×
- Upper body movement	✓** [125]	✓** [126]	✓** [127]	×	×	×
- Sitting	✓*	✓*	✓*	✓	✓	✓
- Standing	✓	✓	✓	✓	✓	✓
- Walking	✓	✓	✓	✓	✓	✓
- Bicycling	✓	✓	✓	×	✓	×
- Walking stairs	✓	✓	✓	×	×	×
	In-device analysis: N/A [101]	In-device analysis: - Posture: lying, sitting and standing [70]	In-device analysis: - Posture: standing and sedentary [71]	In-device analysis: - Posture: lying, sitting and standing - Activity: walking and cycling [104]	In-device analysis: - Posture: sitting and standing - Activity: walking and cycling [106]	In-device analysis: - Posture: sitting and standing - Activity: walking, cycling and running [108]
2. Sampling rate	✓(12.5-3200Hz) [24]	✓(30-100Hz) [70]	✓(25-100Hz) [71]	✓(100Hz) [105]	× (12.5Hz) [106]	× (25Hz) [108]
3. Exportable data / raw data	✓/ ✓ [24]	✓/ ✓ [102]	✓/ ✓ [71]	✓/ × [105]	✓/ × [107]	✓/ × [108]
4. Battery life	✓(14 days at sampling rate of 100Hz) [72]	✓(approximately 16 days at sampling rate of 100Hz) [73]	× (7 days at sampling rate of 25Hz) [71]	✓(14 days) [105]	✓(30 days) [106]	✓(30 days) [108]
5. Data storage / streaming	✓(14 days)/ × [72]	✓(93 days) / ✓ [73]	✓(up to 14 days) / × [103]	✓/ × [105]	✓/ × [107]	✓/ ✓ [108]

✓= device does meet requirement × = device does not meet requirement
* Classification of lying and sitting separately only possible using two sensors
** Detection of upper body movement requires a sensor attached to upper arm/shoulder

Table 19: *Results of device subjection to the clinical requirements (part 1 of 3).*

	AX3	ActiGraph	MOX1	MoveMonitor	Fibion	Activ8
1. No discomfort and hindrance in mobilisation	✓[101]	✓[70]	✓[71]	✓[105]	✓[107]	✓[108]
2. No tissue deformation	✓[101]	✓[70]	✓[71]	×* [105]	✓[107]	✓[108]
3. Device placement outside wound area	✓[101]	✓[70]	✓[71]	✓[105]	✓[107]	✓[108]
4. Patient privacy	✓	✓	✓	✓	✓	✓
5. No impediment of daily care	✓[101]	× [70]	✓[71]	✓[105]	× [107]	× [108]
6. CE certification	✓[72]	✓[70]	✓[71]	✓[105]	✓[107]	?
7. Costs	✓[24]	× [128]	✓	×	✓[107]	✓[108]
8. Analysis software	✓[101]	✓[70]	✓[71]	✓[105]	✓[107]	✓[108]

✓= device does meet requirement × = device does not meet requirement ? = unknown whether device meets requirement
* Stress on lower back when lying supine due to sensor location

Table 20: *Results of device subjection to the technical requirements (part 2 of 3).*

	activPAL	**VitalPatch**	**Philips Health Watch**	**SenseWear Pro3**	**HeartGuide**	**Fitbit**
1. Activity classification:						
- Lying	×	×	×	×	×	×
- Upper body movement	×	×	×	×	×	×
- Sitting	×	×	×	×	×	×
- Standing	✓	✓	×	×	×	×
- Walking	✓	×	✓	✓	✓	✓
- Bicycling	×	×	×	×	×	×
- Walking stairs	×	×	×	×	×	×
	In-device analysis: - Posture: standing and sedentary - Activity: walking [109]	In-device analysis: - Posture: standing and sedentary [113]	In-device analysis: - Activity: walking [114]	In-device analysis: - Activity: walking [115]	In-device analysis: - Activity: walking [116]	In-device analysis: - Activity: walking [21][20][118]
2. Sampling rate	× (20Hz) [109]	✓(62.5Hz) [113]	?	?	?	?
3. Exportable data / raw data	✓/ × [110]	✓/ × [113]	✓/ × [114]	✓/ × [115]	✓/ × [116]	✓/ × [117]
4. Battery life	✓(14 days) [110]	✓(5 days) [113]	× (4 days) [114]	✓(14 days) [115]	× (2 days) [116]	✓(up to 7 days) [117]
5. Data storage / streaming	✓/ × [111]	×/ ✓ [113]	✓/ ✓ [114]	? / × [115]	✓/ ✓ [116]	✓/ ✓ [117]

✓= device does meet requirement × = device does not meet requirement ? = unknown whether device meets requirement

Table 21: *Results of device subjection to the clinical requirements (part 2 of 3).*

	activPAL	**VitalPatch**	**Philips Health Watch**	**SenseWear Pro3**	**HeartGuide**	**Fitbit**
1. No discomfort and hindrance in mobilisation	✓[110]	✓[113]	✓[114]	✓[115]	✓[116]	✓[117]
2. No tissue deformation	✓[110]	✓[113]	✓[114]	?	✓[116]	✓[117]
3. Device placement outside wound area	✓[110]	×* [113]	✓[114]	✓[115]	✓[116]	✓[117]
4. Patient privacy	✓	✓	✓	✓	✓	✓
5. No impediment of daily care	× [110]	✓[113]	× [114]	× [115]	× [116]	✓[117]
6. CE certification	✓[110]	✓[113]	✓[114]	?	✓[116]	✓[117]
7. Costs	×	?	✓[114]	×	× [116]	✓[117]
8. Analysis software	✓[110]	?	✓[114]	✓[115]	?	✓[117]

✓= device does meet requirement × = device does not meet requirement ? = unknown whether device meets requirement
* Close to sternum

Table 22: *Results of device subjection to the technical requirements (part 3 of 3).*

	Garmin VivoSmart	Alvita Ultimate	Motiv Ring	wellsense vu	BCGMCU/SCA11H	E4 Wristband
1. Activity classification						
- Lying	×	×	×	✓	✓	×
- Upper body movement	×	×	×	×	×	×
- Sitting	×	×	×	×	×	×
- Standing	×	×	×	×	×	×
- Walking	✓	✓	✓	×	×	×
- Bicycling	×	×	×	×	×	×
- Walking stairs	×	×	×	×	×	×
	In-device analysis: - Activity: walking [119]	In-device analysis: - Activity: walking [120]	In-device analysis: - Activity: walking [121]	In-device analysis: N/A [122]	In-device analysis: N/A [123]	In-device analysis: N/A [124]
2. Sampling rate	?	?	?	?	?	× (32Hz) [124]
3. Exportable data / raw data	✓/ × [119]	× / × [120]	? / × [121]	? / × [122]	✓/ × [123]	✓/ ✓ [124]
4. Battery life	✓(5 days) [119]	✓(6 months) [120]	× (3 days) [121]	✓(power supply without battery)[122]	✓(power supply without battery) [123]	× (20 hours) [124]
5. Data storage / streaming	✓/ ✓ [119]	✓/ × [120]	✓/ ✓ [121]	? / × [122]	✓/ × [123]	×/ ✓ [124]

✓= device does meet requirement × = device does not meet requirement ? = unknown whether device meets requirement

Table 23: *Results of device subjection to the clinical requirements (part 3 of 3).*

	Garmin VivoSmart	Alvita Ultimate	Motiv Ring	wellsense vu	BCGMCU/SCA11H	E4 Wristband
1. No discomfort or hindrance in mobilisation	✓[119]	✓[120]	✓[121]	✓[122]	✓[123]	✓[124]
2. No tissue deformation	✓[119]	✓[120]	✓[121]	✓[122]	✓[123]	✓[124]
3. Device placement outside wound area	✓[119]	✓[120]	✓[121]	✓[122]	✓[123]	✓[124]
4. Patient privacy	✓	✓	✓	✓	✓	✓
5. No impediment of daily care	✓[119]	× [120]	✓[121]	✓[122]	✓[123]	× [124]
6. CE certification	✓[119]	✓[120]	✓[121]	✓[122]	✓[123]	✓[124]
7. Costs	✓[119]	✓[120]	✓[121]	× [122]	✓[123]	× [124]
8. Analysis software	✓[119]	× [120]	✓[121]	?	✓[123]	✓[124]

✓= device does meet requirement × = device does not meet requirement ? = unknown whether device meets requirement

Appendix C

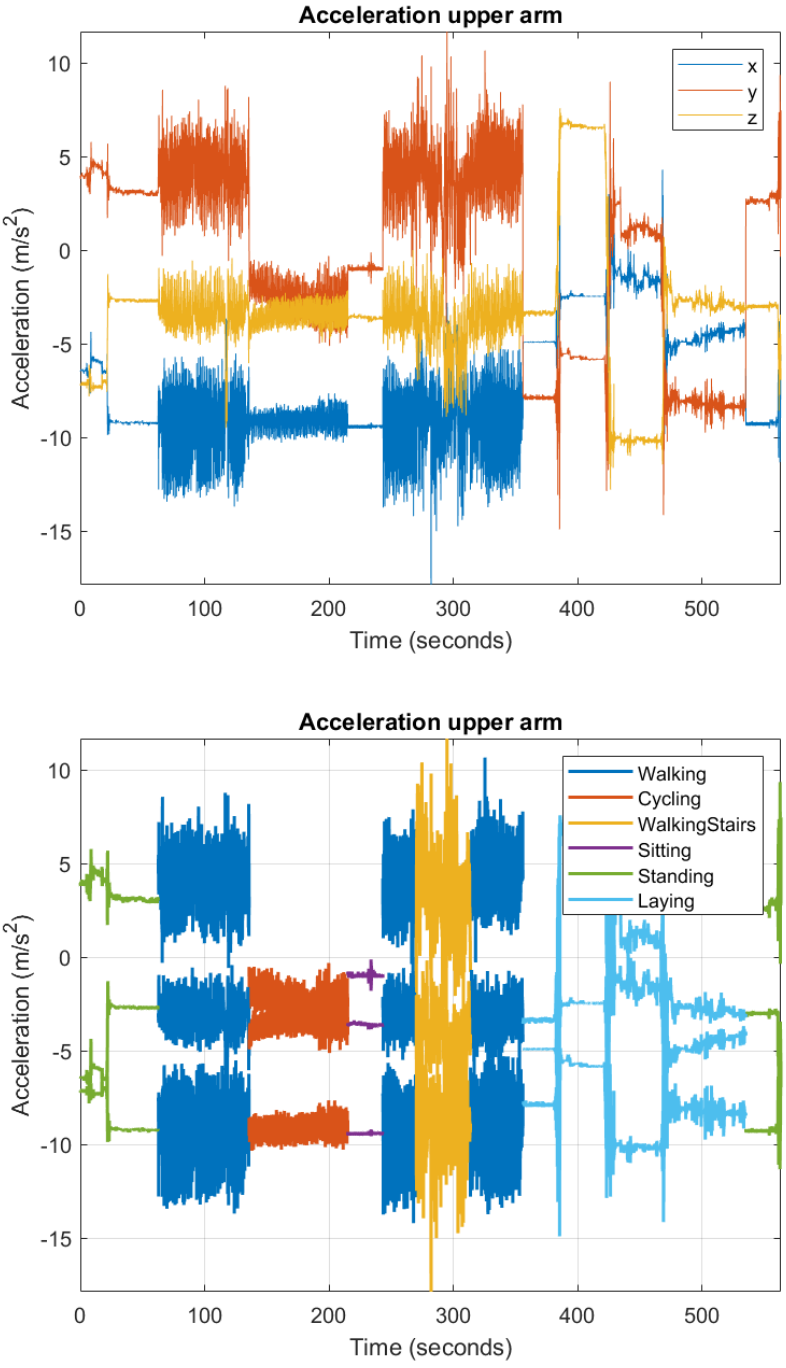


Figure 17: *An example of accelerometer data captured with the AX3 attached to the right upper arm, with and without colour marking per activity.*

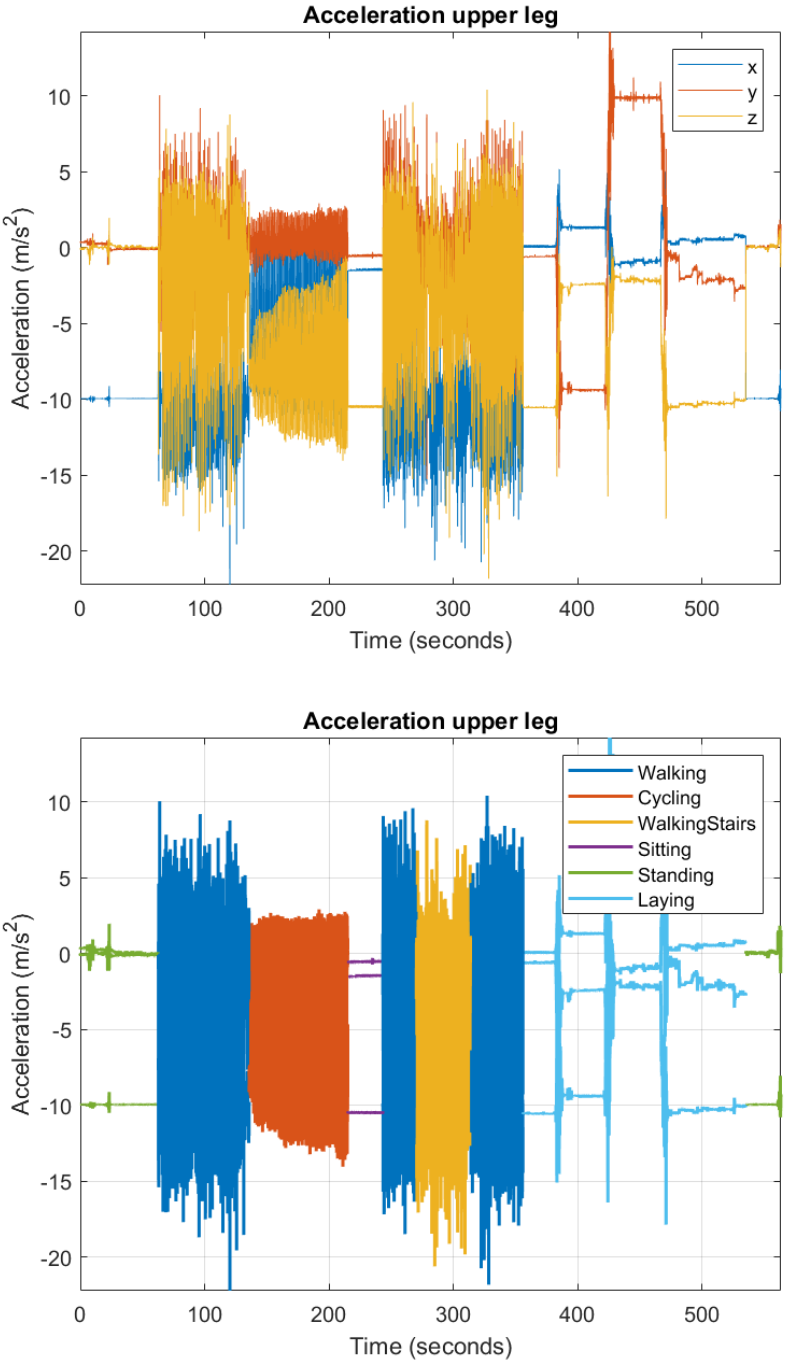


Figure 18: *An example of accelerometer data captured with the AX3 attached to the right upper leg, with and without colour marking per activity.*

Appendix D

Protocol labelling measurement

Below an example of a standardised protocol of the labelling measurement. Implementation and sequence of activities was as spontaneous as possible and, therefore, differs for each patient. The static activities were held for a minimum of 30 seconds, and the dynamic activities for at least 60 seconds (except of walking stairs). With a stopwatch and notations, the exact moment of execution of the various activities was recorded.

1. Attachment of AX3 devices according to figure 19.
2. Patients start the labelling measurement sitting or standing.
3. Patients stand or sit.
4. Patients walk from their room to the home trainers.
5. Patients immediately start cycling or sit on a chair before cycling.
6. After cycling, patients stand still.
7. Patients walk to the stairwell where one staircase consisting of about 15 steps is walked up and down at least twice.
8. After walking stairs, patients stand again still and subsequently walk back to their room.
9. Once arrived in the room, patients lie in bed, on the back and on both sides.
10. The labelling measurement is concluded with sitting on the edge of the hospital bed.

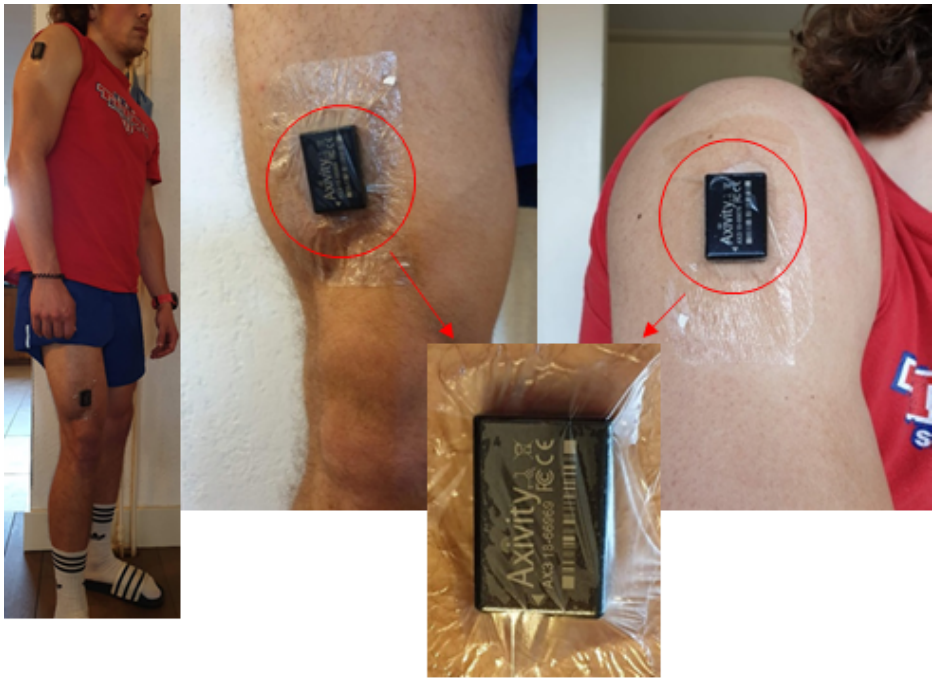


Figure 19: *Final AX3 application in dual arrangement, placed lateroproximal on the right upper arm and anterodistal on the right upper leg. This exact sensor placement configuration was used in the clinical pilot study.*

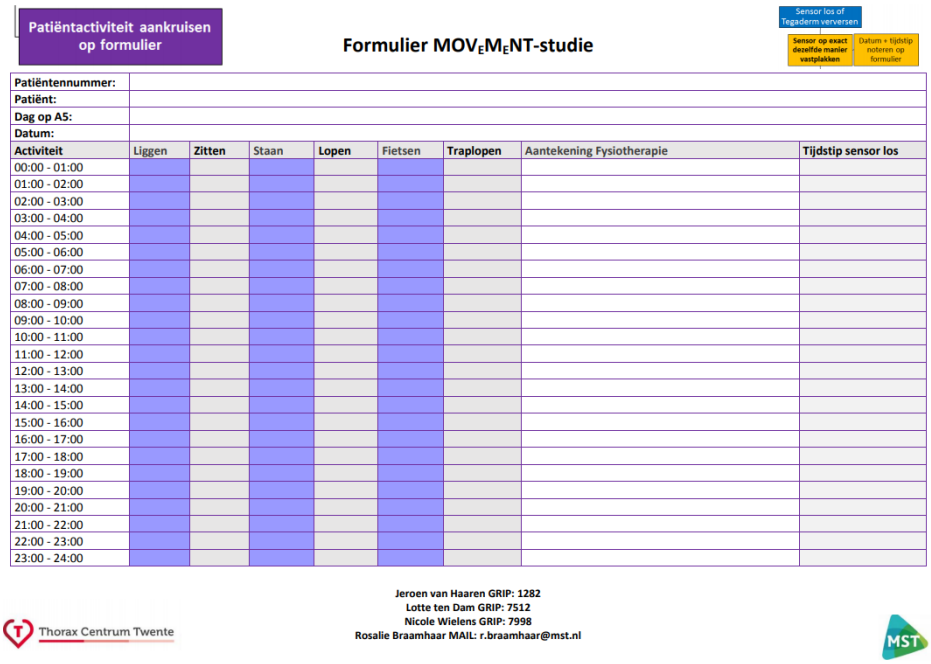


Figure 20: *The "activity forms" on which physiotherapists reported patient physical activity. Text is in dutch.*

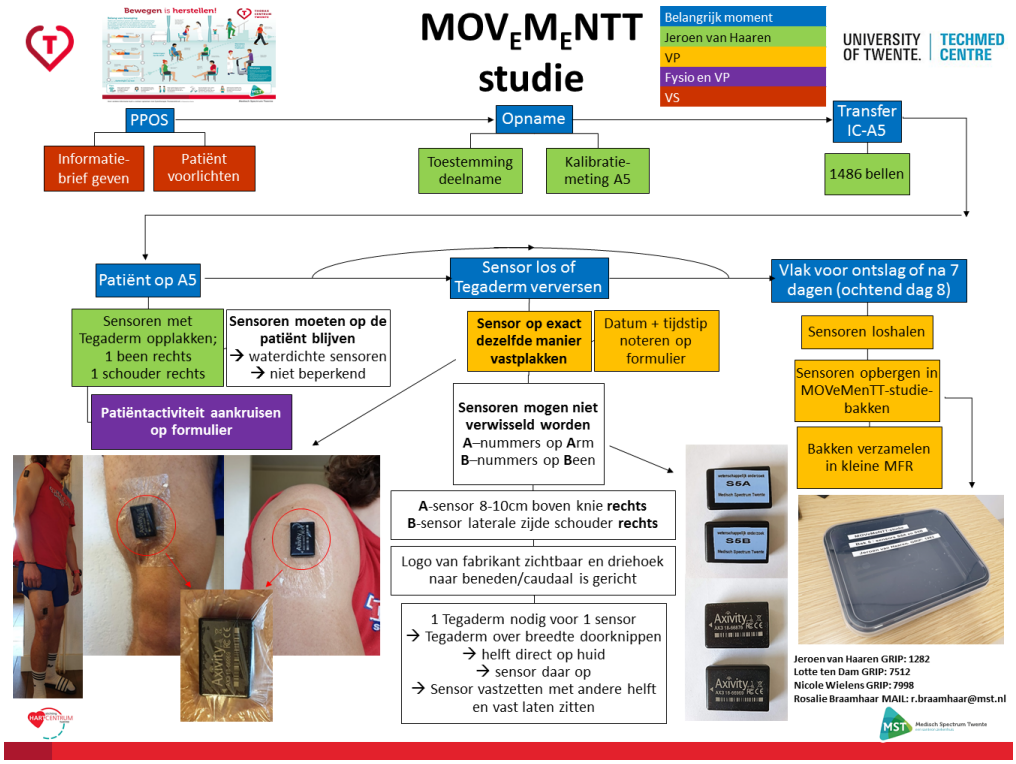


Figure 21: *A3-poster with study instructions for nursing. Text is in dutch.*

Appendix E

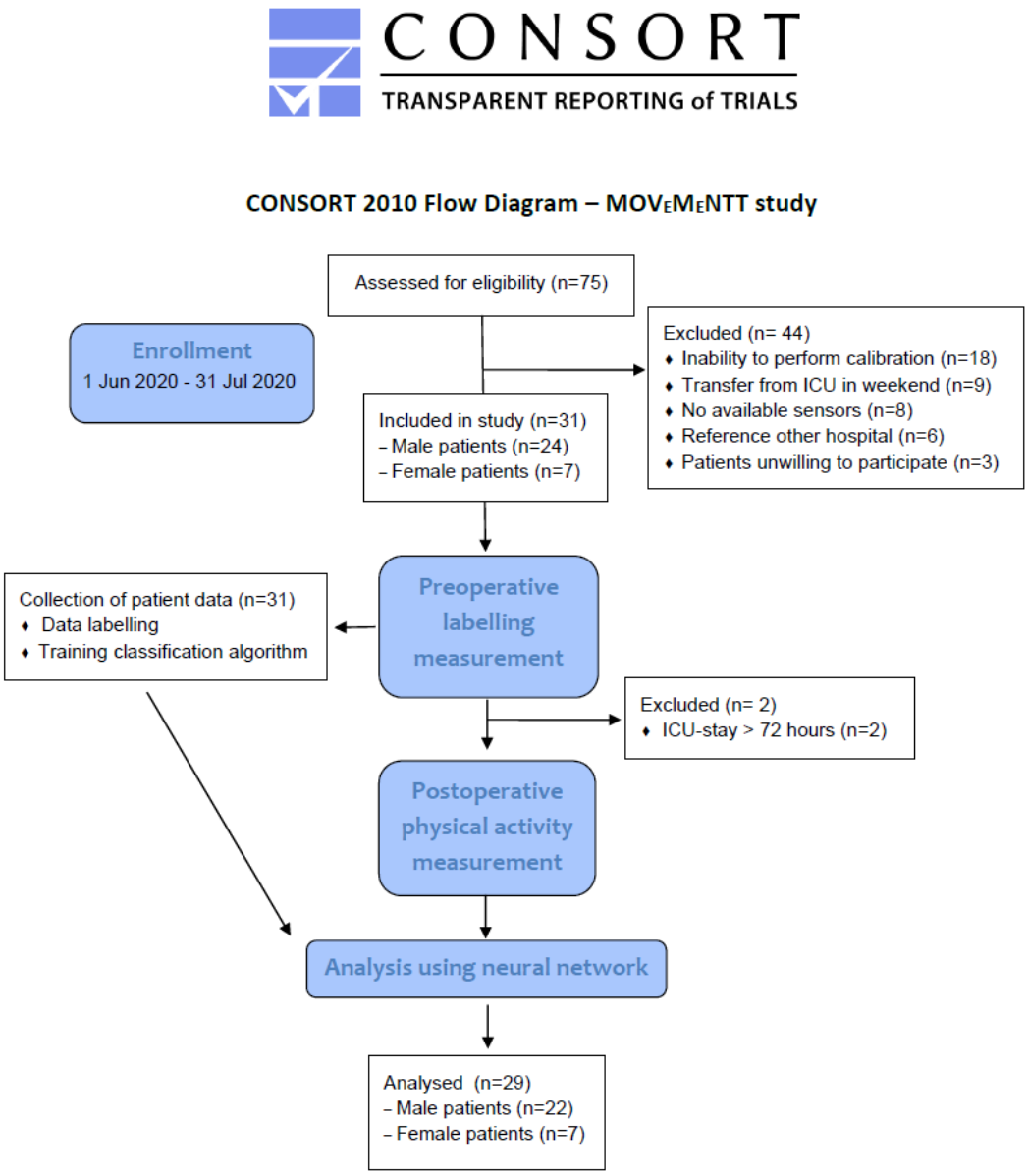
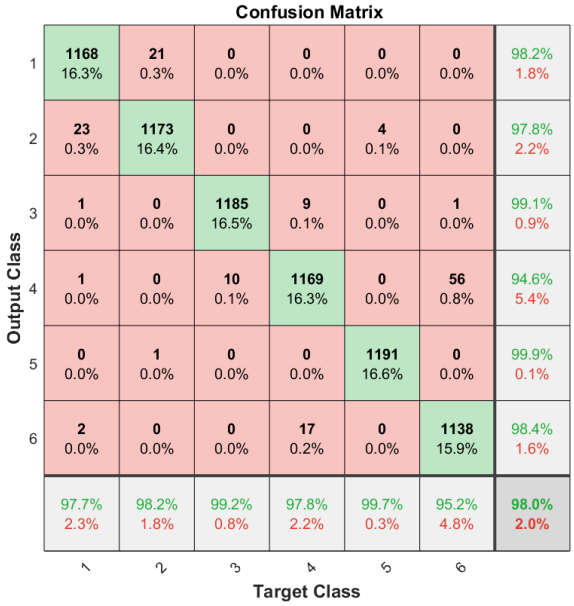
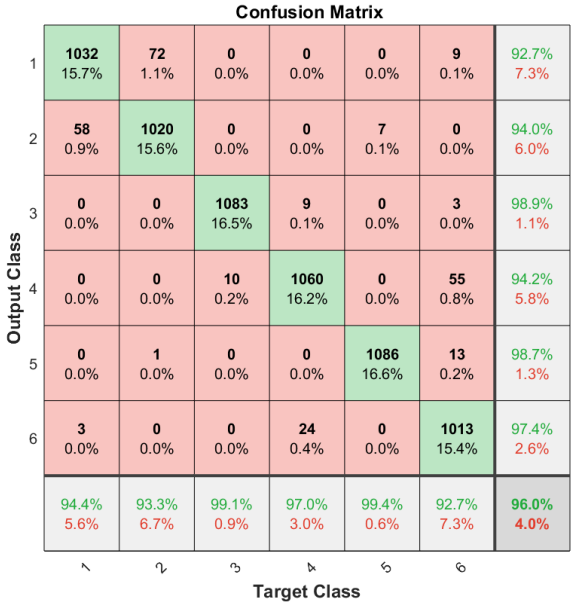


Figure 22: *Flow chart of the clinical pilot study.*

Appendix F



(a) K-fold cross-validation



(b) LOSO-validation

Figure 23: *Confusion matrix for the true labels targets and predicted labels outputs after K-fold cross-validation and LOSO-validation using 160 features. 1 = lying, 2 = sitting, 3 = standing, 4 = walking, 5 = cycling, and 6 = walking stairs. The column on the far right of the plot shows the precision (or positive predictive value) and false discovery rate. The row at the bottom of the plot shows the recall (or true positive rate) and false negative rate. The cell in the bottom right of the plot shows the overall classification accuracy.*

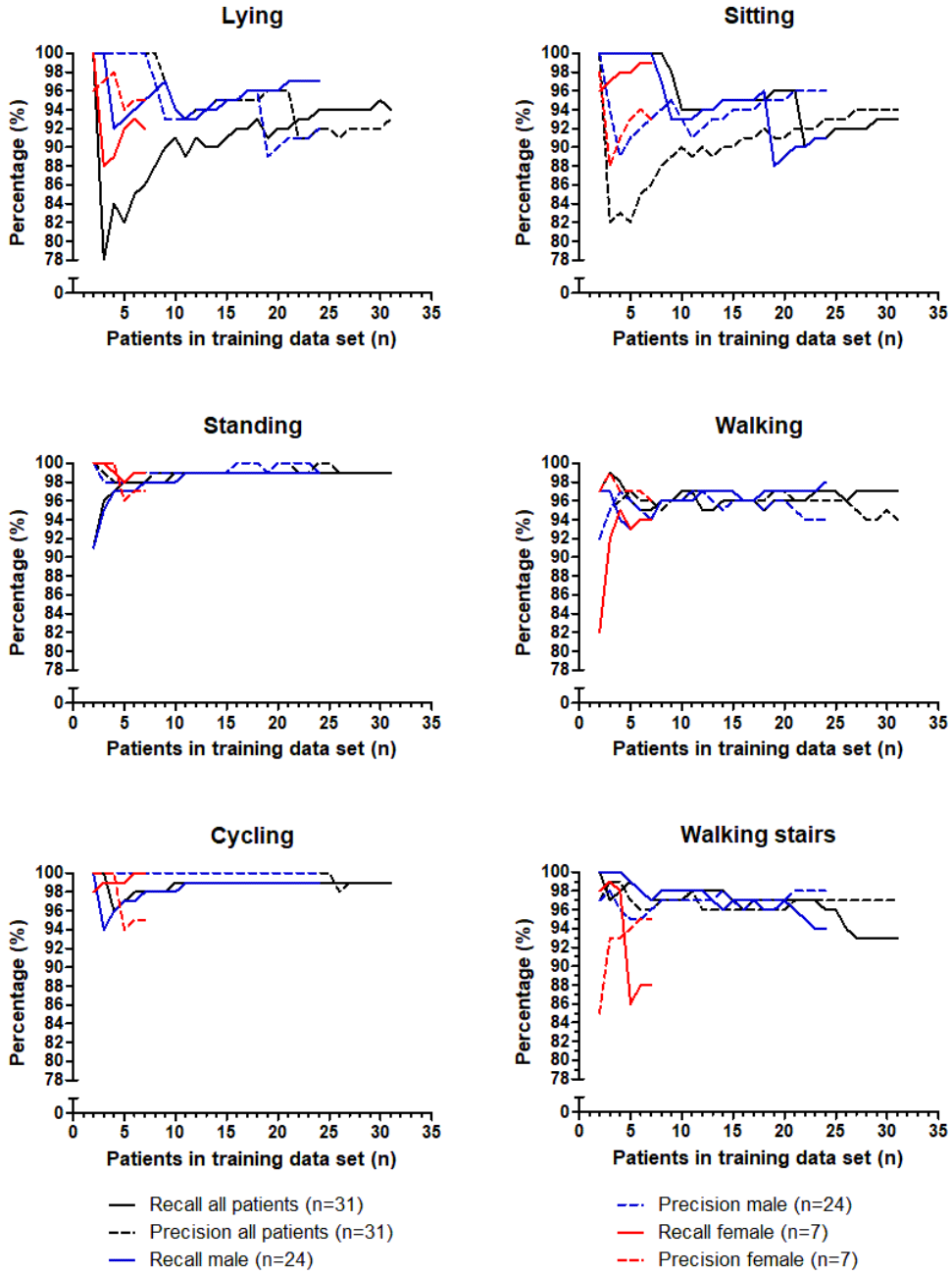
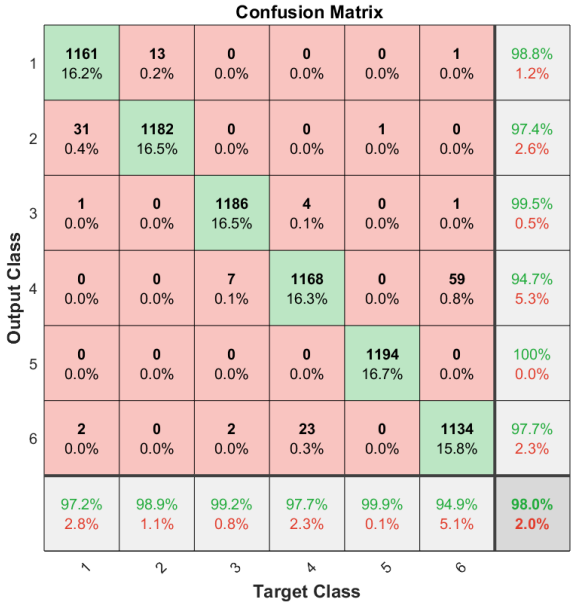


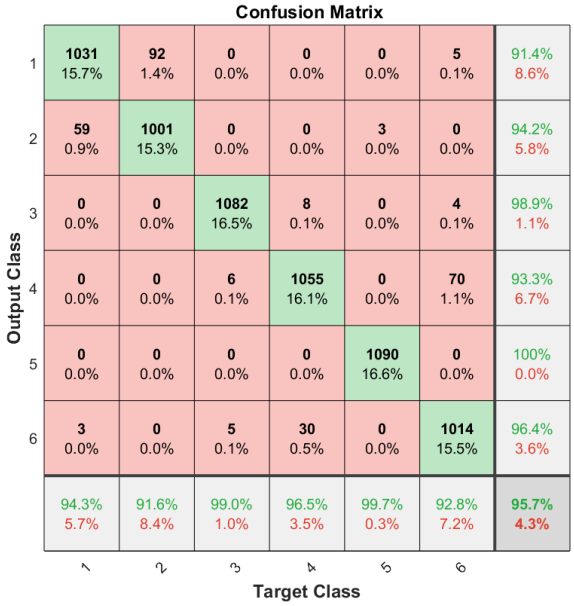
Figure 24: *Neural network precision and recall per activity using n number of patients (starting from n = 2) in training data set. Precision and recall were determined by averaging results from LOSO-validation over n number of patients.*

Table 24: *Overview of features used after feature selection. Demonstrated are name of the features with the corresponding type of acceleration, sensor, sensitive axis, and variable computed.*

Feature name	Acceleration	Sensor	Sensitive axis	Computed variable
$'TotalAccXMeanshoulder'$	Total	Upper arm	X	Mean
$'TotalAccYMeanshoulder'$	Total	Upper arm	Y	Mean
$'TotalAccZMeanshoulder'$	Total	Upper arm	Z	Mean
$'TotalAccXMeanknee'$	Total	Upper leg	X	Mean
$'TotalAccYMeanknee'$	Total	Upper leg	Y	Mean
$'TotalAccZMeanknee'$	Total	Upper leg	Z	Mean
$'BodyAccXRMSshoulder'$	Body	Upper arm	X	Root Mean Square
$'BodyAccYRMSshoulder'$	Body	Upper arm	Y	Root Mean Square
$'BodyAccZRMSshoulder'$	Body	Upper arm	Z	Root Mean Square
$'BodyAccYRMSknee'$	Body	Upper leg	Y	Root Mean Square
$'BodyAccZRMSknee'$	Body	Upper leg	Z	Root Mean Square
$'BodyAccXCovZeroValueshoulder'$	Body	Upper arm	X	Autocorrelation, height of main peak
$'BodyAccYCovFirstPosshoulder'$	Body	Upper arm	Y	Autocorrelation, position of second peak
$'BodyAccZCovFirstPosshoulder'$	Body	Upper arm	Z	Autocorrelation, position of second peak
$'BodyAccYCovFirstPosknee'$	Body	Upper leg	Y	Autocorrelation, position of second peak
$'BodyAccXSpectPos5shoulder'$	Body	Upper arm	X	Spectral Peaks, position of fifth peak
$'BodyAccYSpectPos5shoulder'$	Body	Upper arm	Y	Spectral Peaks, position of fifth peak
$'BodyAccXSpectPos4knee'$	Body	Upper leg	X	Spectral Peaks, position of fourt peak
$'BodyAccXSpectPos5knee'$	Body	Upper leg	X	Spectral Peaks, position of fifth peak
$'BodyAccYSpectPos1knee'$	Body	Upper leg	Y	Spectral Peaks, position of first peak
$'BodyAccYSpectPos3knee'$	Body	Upper leg	Y	Spectral Peaks, position of third peak
$'BodyAccYSpectPos4knee'$	Body	Upper leg	Y	Spectral Peaks, position of fourth peak
$'BodyAccYSpectPos5knee'$	Body	Upper leg	Y	Spectral Peaks, position of fifth peak
$'BodyAccYSpectPos6knee'$	Body	Upper leg	Y	Spectral Peaks, position of sixth peak
$'BodyAccXPowerBand2shoulder'$	Body	Upper arm	X	Spectral Power, total power in second band
$'BodyAccXPowerBand3shoulder'$	Body	Upper arm	X	Spectral Power, total power in third band
$'BodyAccYPowerBand3shoulder'$	Body	Upper arm	Y	Spectral Power, total power in third band
$'BodyAccZPowerBand2shoulder'$	Body	Upper arm	Z	Spectral Power, total power in second band
$'BodyAccXPowerBand2knee'$	Body	Upper leg	X	Spectral Power, total power in second band
$'BodyAccXPowerBand3knee'$	Body	Upper leg	X	Spectral Power, total power in third band
$'BodyAccYPowerBand1knee'$	Body	Upper leg	Y	Spectral Power, total power in first band
$'BodyAccYPowerBand2knee'$	Body	Upper leg	Y	Spectral Power, total power in second band
$'BodyAccYPowerBand3knee'$	Body	Upper leg	Y	Spectral Power, total power in third band
$'BodyAccYPowerBand4knee'$	Body	Upper leg	Y	Spectral Power, total power in fourth band
$'BodyAccZPowerBand2knee'$	Body	Upper leg	Z	Spectral Power, total power in second band
$'BodyAccZPowerBand3knee'$	Body	Upper leg	Z	Spectral Power, total power in third band
$'BodyAccZPowerBand4knee'$	Body	Upper leg	Z	Spectral Power, total power in fourth band
$'TotalAccXMedianshoulder'$	Total	Upper arm	X	Median
$'TotalAccYMedianshoulder'$	Total	Upper arm	Y	Median
$'TotalAccZMedianshoulder'$	Total	Upper arm	Z	Median
$'TotalAccXMedianknee'$	Total	Upper leg	X	Median
$'TotalAccYMedianknee'$	Total	Upper leg	Y	Median
$'TotalAccZMedianknee'$	Total	Upper leg	Z	Median
$'BodyAccXStdshoulder'$	Body	Upper arm	X	Standard Deviation
$'BodyAccYStdshoulder'$	Body	Upper arm	Y	Standard Deviation
$'BodyAccZStdshoulder'$	Body	Upper arm	Z	Standard Deviation
$'BodyAccYStdknee'$	Body	Upper leg	Y	Standard Deviation
$'BodyAccZStdknee'$	Body	Upper leg	Z	Standard Deviation
$'BodyAccXMadknee'$	Body	Upper leg	X	Mean Absolute Deviation
$'BodyAccYMadknee'$	Body	Upper leg	Y	Mean Absolute Deviation
$'BodyAccZMadknee'$	Body	Upper leg	Z	Mean Absolute Deviation
$'TotalAccSMAshoulder'$	Total	Upper arm	All	Signal Magnitude Area
$'TotalAccSMAknee'$	Total	Upper leg	All	Signal Magnitude Area
$'TotalAccXMadshoulder'$	Total	Upper arm	X	Mean Absolute Deviation
$'TotalAccYMadshoulder'$	Total	Upper arm	Y	Mean Absolute Deviation
$'TotalAccZMadshoulder'$	Total	Upper arm	Z	Mean Absolute Deviation
$'TotalAccXMadknee'$	Total	Upper leg	X	Mean Absolute Deviation
$'TotalAccYMadknee'$	Total	Upper leg	Y	Mean Absolute Deviation
$'TotalAccZMadknee'$	Total	Upper leg	Z	Mean Absolute Deviation



(a) K-fold cross-validation



(b) LOSO-validation

Figure 25: *Confusion matrix for the true labels targets and predicted labels outputs after K-fold cross-validation and LOSO-validation using 59 features. 1 = lying, 2 = sitting, 3 = standing, 4 = walking, 5 = cycling, and 6 = walking stairs. The column on the far right of the plot shows the precision (or positive predictive value) and false discovery rate. The row at the bottom of the plot shows the recall (or true positive rate) and false negative rate. The cell in the bottom right of the plot shows the overall classification accuracy.*

Neural network performance Upper arm sensor and Upper leg sensor only

Table 25: *Precision and recall per activity and overall classification accuracy of the neural network trained with patient data from the upper arm sensor (number of features = 80). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	94 [91 96]	60 [51 65]	93 [39 100]	81 [17 100]
Sitting	78 [70 84]	70 [64 75]	71 [0 100]	64 [25 100]
Standing	71 [64 78]	81 [77 85]	66 [0 100]	77 [0 100]
Walking	92 [85 96]	69 [60 75]	84 [0 100]	65 [51 100]
Cycling	86 [79 90]	87 [83 92]	76 [0 100]	79 [0 100]
Walking stairs	60 [51 65]	89 [84 94]	53 [34 60]	83 [59 100]
Accuracy		**80 [77 83]**		**74 [17 95]**

Data are percentages [Min Max]

Table 26: *Precision and recall per activity and overall classification accuracy of the neural network trained with patient data from the upper leg sensor (number of features = 80). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	93 [88 96]	87 [83 90]	89 [46 100]	80 [42 100]
Sitting	86 [80 90]	93 [89 95]	78 [0 100]	88 [0 100]
Standing	99 [97 100]	99 [97 100]	99 [91 100]	99 [89 100]
Walking	98 [96 99]	92 [88 94]	96 [51 100]	91 [69 100]
Cycling	100 [99 100]	100	100 [93 100]	100 [92 100]
Walking stairs	92 [88 95]	98 [96 99]	91 [55 100]	96 [68 100]
Accuracy		**95 [94 95]**		**92 [76 100]**

Data are percentages [Min Max]

Neural network performance using data divided in larger segments

Table 27: *Precision and recall per activity and overall classification accuracy of the neural network using patient data divided in segments of 512 samples (number of features = 160). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	98 [93 100]	99 [96 100]	95 [66 100]	94 [53 100]
Sitting	99 [95 100]	98 [93 100]	93 [13 100]	95 [74 100]
Standing	100 [98 100]	99 [93 100]	99 [88 100]	100 [94 100]
Walking	99 [98 100]	98 [93 100]	99 [91 100]	97 [82 100]
Cycling	100 [98 100]	100	100 [93 100]	100 [95 100]
Walking stairs	98 [94 100]	99 [98 100]	98 [72 100]	99 [91 100]
Accuracy		**99 [98 100]**		**97 [85 100]**

Data are percentages [Min Max]

Table 28: *Precision and recall per activity and overall classification accuracy of the neural network using patient data divided in segments of 1024 samples (number of features = 160). Variables were determined by averaging results from K-fold cross-validation (K = 10) and LOSO-validation (n = 31 subjects).*

	K-fold		**LOSO**	
	Recall	**Precision**	**Recall**	**Precision**
Lying	96 [79 100]	98 [95 100]	97 [90 100]	92 [52 100]
Sitting	98 [95 100]	96 [85 100]	93 [9 100]	96 [75 100]
Standing	100 [96 100]	100	99 [71 100]	100
Walking	100	98 [89 100]	99 [71 100]	96 [67 100]
Cycling	100	100	97 [50 100]	100
Walking stairs	98 [90 100]	96 [96 100]	91 [50 100]	97 [50 100]
Accuracy		**99 [98 99]**		**97 [83 100]**

Data are percentages [Min Max]

Appendix G

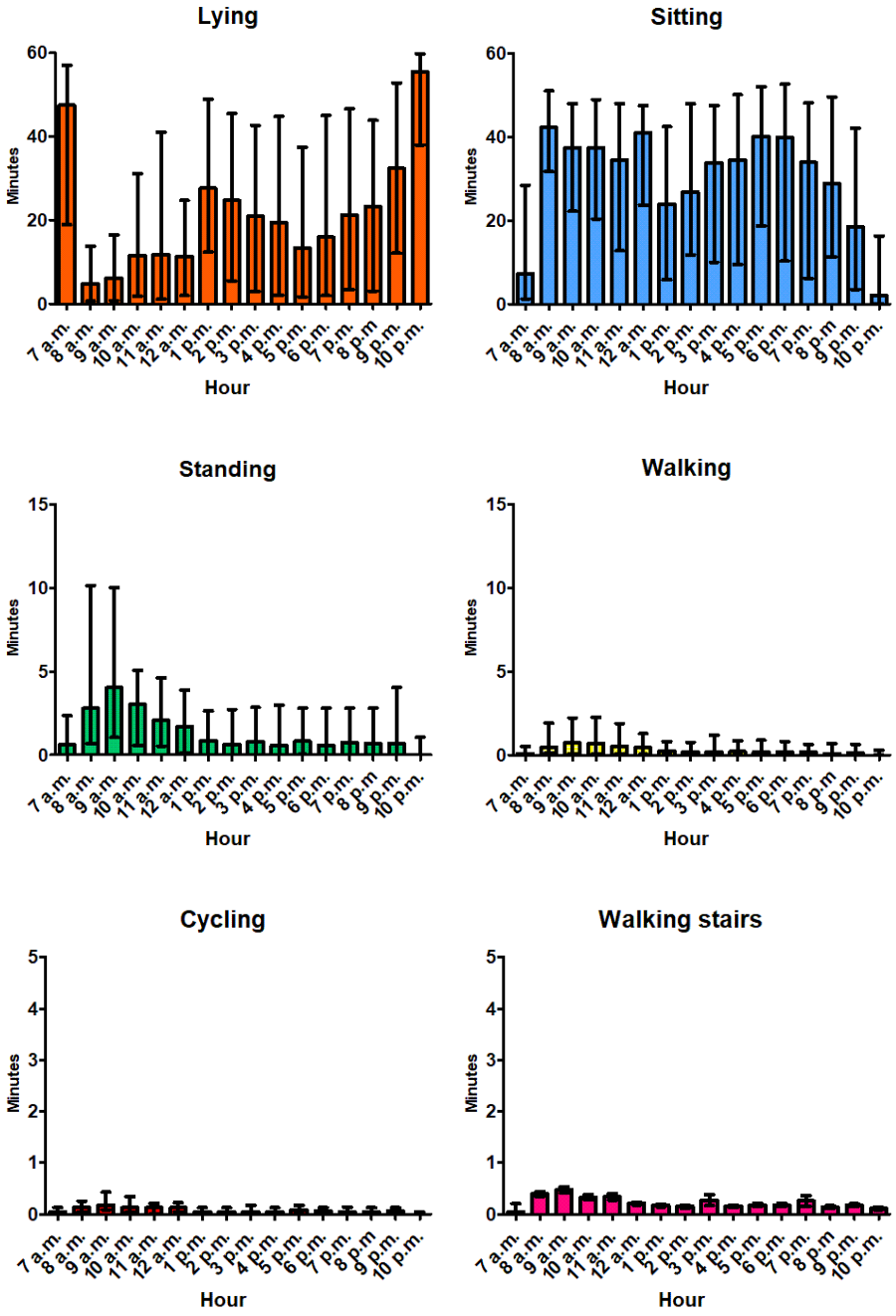


Figure 26: *Median amount of minutes lying, sitting, standing, walking, cycling, and walking stairs per hour between 7 a.m. and 11 p.m. The 7 p.m. interval contains data measured between 7 a.m. and 7.59 a.m. Medians are determined using all patient data. Error bars represent IQR.*

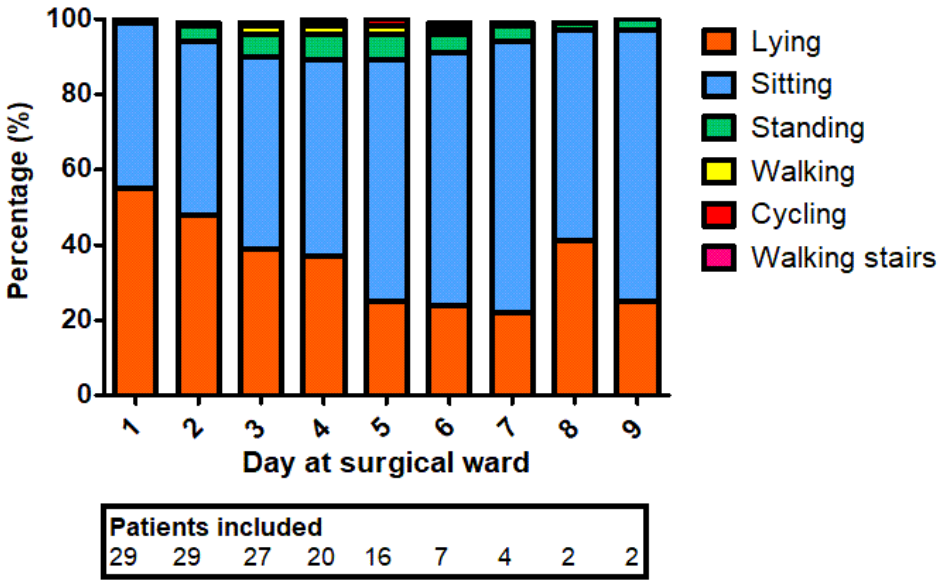


Figure 27: *Stacked bars diagram of mean percentage time spent per activity for all patients. Daily intervals contain data between 7 a.m.-11 p.m.*

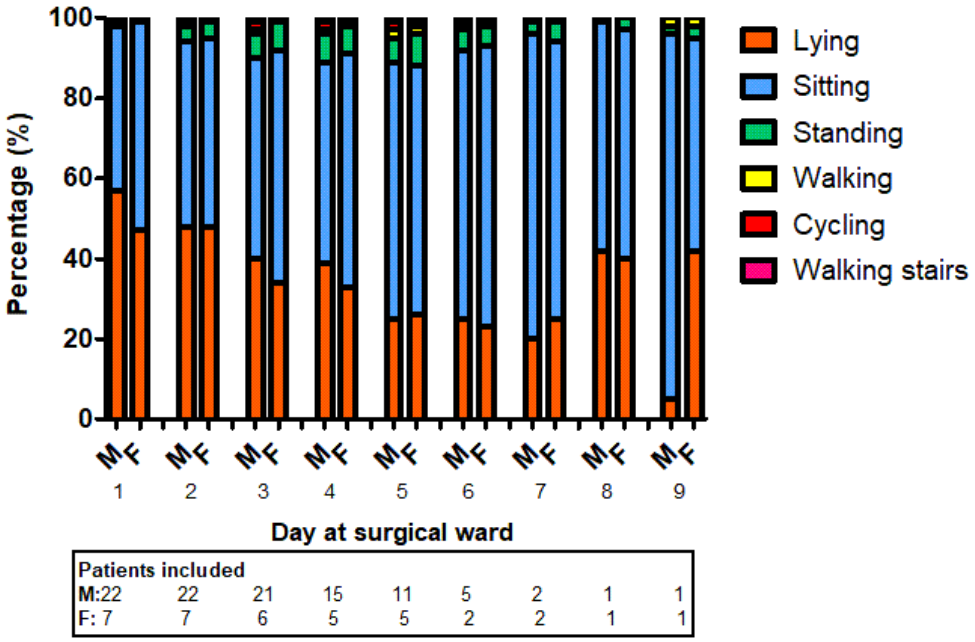


Figure 28: *Stacked bars diagram of mean percentage time spent per activity for male (M) and female (F) patients. Daily intervals contain data between 7 a.m.-11 p.m.*