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ABSTRACT

Work metabolism (WM) can be accurately estimated by oxygen consumption (VO_2), which is commonly assessed by heart rate (HR) in field studies. However, the VO_2–HR relationship is influenced by individual capacity and activity characteristics. The purpose of this study was to evaluate three models for estimating WM compared with indirect calorimetry, during simulated work activities. The techniques were: the HR-Flex model; HR branched model, combining HR with hip-worn accelerometers (ACC); and HR + arm-leg ACC model, combining HR with wrist- and thigh-worn ACC. Twelve participants performed five simulated work activities and three submaximal tests. The HR + arm-leg ACC model had the overall best performance with limits of agreement (LoA) of −3.94 and 2.00 mL/min/kg, while the HR-Flex model had −5.01 and 5.36 mL/min/kg and the branched model, −6.71 and 1.52 mL/min/kg. In conclusion, the HR + arm-leg ACC model should, when feasible, be preferred in wearable systems for WM estimation.

Practitioner Summary: Work with high energy demand can impair employees' health and life quality. Three models were evaluated for estimating work metabolism during simulated tasks. The model combining heart rate, wrist- and thigh-worn accelerometers showed the best accuracy. This is, when feasible, suggested for wearable systems to assess work metabolism.

Abbreviations: ACC: accelerometer; EE: energy expenditure; HR: heart rate; LoA: limits of agreement; RAS: relative aerobic strain; REE: resting energy expenditure; RHR: resting heart rate; VO2: oxygen consumption; WM: work metabolism

1. Introduction

Researchers and practitioners have for a long time been using self-reports and observations to assess and analyse work activities and the related risk factors, with a gradual increase of technical methods over the years (Li and Buckle 1999; David 2005; Shephard and Aoyagi 2012). Several researchers have emphasised the need for an increased use and development of technical measurement methods in order to achieve assessment with higher reliability and validity, and better mapping of relationships between exposures and work-related ill health, especially musculoskeletal disorders (Winkel and Mathiassen 1994; Forsman 2017;

Holtermann et al. 2017). Technology advances in sensor technologies, textile electrodes, data storage and analytics with smart mobile devices offer possibilities of integrating wireless miniature sensors into wearable systems which can communicate and analyse the data in real time. This has already been explored in many other areas, such as the military and sports (Buttussi and Chittaro 2008; Coyle et al. 2009; Seoane et al. 2014; Mohino-Herranz et al. 2015). There is an ongoing research effort aiming at developing smart wearable systems for automatic risk assessment at work, which facilitate risk identification, communication and interventions for better work environments (Yang, Grooten,

and Forsman 2017; Abtahi et al. 2017; Lind et al. 2019; Eklund and Forsman 2018; Yang et al. 2018). One step towards this aim is to evaluate methods that are applicable for estimating work metabolism (WM) with wearable sensors.

Work with high metabolic demand can lead to physical and mental fatigue, increase in work injuries and decrease in work performance, higher risk for cardiovascular diseases and early retirement (Karpansalo et al. 2002; Krause et al. 2007; Wigaeus Tornqvist 2011; Wultsch et al. 2012; Krause et al. 2014). The International Labour Organisation (ILO) recommends that the relative aerobic strain (RAS) level, which is calculated as the ratio between average oxygen consumption at work and the individual's maximal aerobic capacity (VO_{2max}), should not exceed 33% for an 8-h workday (Smolander and Louhevaara 2011). Considering the various characteristics of muscular work, task-dependent RAS levels have been suggested as below 30–35% for mixed physical work including manual materials handling (Jorgensen 1985), and proposed limits vary between 18.5 and 29% for lifting tasks (Legg and Myles 1981; Genaidy et al. 1985; Asfour, Genaidy, and Mital 1988).

WM can be assessed by various methods, including observations, self-reports, motion sensing, monitoring of heart rate (HR), minute ventilation or oxygen consumption (VO_2) (Shephard and Aoyagi 2012). Among them, HR monitoring has been used in many field studies for workload assessment because of its usability and relatively high accuracy (Kemper et al. 1990; Bernmark et al. 2006; Vogel and Eklund 2015; Preisser et al. 2016). The estimation is based on the fact that there is a strong positive relationship between HR and VO_2, and WM can be calculated with reasonable accuracy from VO_2 data in occupational studies, where the subjects metabolise mostly non-protein for energy and reach a steady state of gas exchange during the occupational activities (Shephard and Aoyagi 2012). However, difficulties using HR to assess VO_2 include that (i) the relationship between HR and VO_2 varies between persons depending on their endurance capacity; (ii) the slope of the relationship changes depending on how and what muscle groups are utilised; and (iii) HR is also affected by other factors, such as stress, food intake and environmental conditions (Haskell et al. 1993; Faria and Faria 1998; Leonard 2003; Åstrand et al. 2003). By doing calibration tests, the individual relationship between HR and VO_2 under certain conditions can be obtained, but the feasibility suffers because of increased need for time and resources. Motion sensors, e.g. accelerometers (ACC), have

also been explored in estimating energy expenditure (EE) during daily activities and showed good applicability for monitoring physical activities (Tapia 2008; Bonomi et al. 2009; Bonomi 2013; Altini, Penders et al. 2015). This type of method using solely ACCs can be performed with (i) counts-based estimation model, (ii) activity recognition with EE lookup tables or (iii) activity recognition with activity specified regression models (Altini, Penders et al. 2015). However, ACC has its inherent limitations in not being able to detect different resistance or exerted effort (Tapia 2008), which are important factors in estimating physical workload and the related risks. It is also not feasible to validate models using ACC for activity recognition of all work tasks, which have high variation within and between occupations. Moreover, the different physiological response of different individuals performing the same task cannot be assessed by ACC itself.

Several techniques using HR to estimate WM have been proposed to improve the estimation accuracy. The HR-Flex method was first proposed by Spurr et al. and thereafter has been tested for its validity and reliability (Spurr et al. 1988; Ekelund et al. 2002; Leonard 2003). By identifying an HR threshold point (known as the 'flex-HR') between resting and active levels, the period below flex-HR is estimated using resting energy expenditure (REE, calculated as mean EE spent while lying, sitting and standing), and the period above flex-HR is estimated based on the HR–VO_2 equation. Therefore, the method has shown to improve the estimation during low activity levels when the HR–VO_2 relationship often deviates from the calibration equation (Leonard 2003). However, the HR-Flex method has a limitation in that it may underestimate EE in daily living activities (Johansson et al. 2006). Another type of method using combined motion data with HR has been explored by researchers proposing various models, such as multiple regression analysis (Haskell et al. 1993); the branched equation model, a decision tree combining HR with one hip-worn ACC (Brage et al. 2004); or the HR + arm-leg ACC model, a decision tree combining HR with one wrist-worn and one thigh-worn ACC (Strath et al. 2001). The limitations of these methods include the complexity required for data analysis and the need of individual calibration tests that represent the type of activities accordingly. Several studies have tested and validated these HR and ACC combined models in laboratory settings during physical exercises or in the field during free-living activities, showing significantly improved accuracy compared to HR alone (Haskell et al. 1993; Strath, Brage, and Ekelund 2005; Strath et al. 2002; Johansson et al. 2006;

Thompson et al. 2006; Brage et al. 2007; Brage et al. 2015). However, no studies have yet evaluated them during occupational activities, when different tasks are performed with different muscle mass, i.e. using mainly arm, mainly leg or mixed muscle groups, and with various characteristics of static or dynamic movements.

The main aim of this study was to evaluate different modelling techniques for WM estimation during occupational activities using HR combined with or without ACC signals. A second aim was to evaluate different calibration procedures used in these models.

2. Methods

2.1. Participants

Twelve participants (three women and nine men) were involved in a laboratory study. All participants were informed of the general aims of the study and provided written informed consent. Ethical approval for the study was obtained from the Regional Ethics Committee in Stockholm (Dnr 2016/724-31/5).

The participants were met in the morning and asked to refrain from eating, smoking, drinking tea, coffee or alcohol for at least 2 h, and to refrain from exercise for 12 h, before the study. The participants' characteristics are shown in Table 1, the VO_{2max} of which were obtained by a submaximal treadmill test as described in Section 2.3.

2.2. Equipment

The participants were asked to wear a set of wearable sensors, including: (i) a commercial HR belt (Zephyr HxM BT, Zephyr Technology Corporation, Annapolis, USA), (ii) sport trousers with two ACCs (AX3, Axivity Ltd, Newcastle, UK) fixed in small pockets on the front of the right mid-thigh and the left waist, and (iii) two ACCs of the same model worn on both wrists with rubber wrist bands. The VO_2 was measured by a computerised metabolic system (Jaeger Oxycon Pro, Hoechberg, Germany) with a facemask, as a gold standard method.

2.3. The experimental protocol

The protocol consisted of three main components: resting, work task simulations and submaximal tests. To start with, the participants were asked to rest for 20 min while lying, 5 min while sitting and 5 min while standing. Then the participants performed five different simulated work tasks according to the instruction

Table 1. Descriptive characteristics of the participants (median [range]).

	Men ($N = 9$)	Women ($N = 3$)	All ($N = 12$)
Age (year)	27 (21–65)	44 (25–61)	27 (21–65)
Height (cm)	181.5 (171–199)	169.5 (164–173)	176.7 (164–199)
Weight (kg)	77.0 (51–89)	59.3 (58–62)	75.0 (51–89)
BMI (kg/m^2)	22.8 (17.4–25.6)	21.2 (20.7–22.0)	22.5 (17.4–25.6)
VO_{2max} (mL/min/kg)	42.9 (32.1–54.6)	30.9 (27.8–40.3)	39.9 (27.8–54.6)

(see Table 2). Each task lasted 8–10 min with breaks for around 5–10 min in between, to allow HR to return to within 10% of the resting heart rate (RHR).

In the end, the participants performed three submaximal tests, which were terminated if HR reached 80–85% of age-predicted maximal HR (calculated from $HR_{max} = 220 −$ Age) or if the participant was unable to continue. A break separated each submaximal test to allow HR to return to within 10% of RHR. The first submaximal test performed was the Chester step test (Sykes and Roberts 2004). The second was a submaximal arm ergometer test, consisting of successive 3-min stages at a constant cadence of 50 rev/min, following the protocol used by Strath et al. (2005). Briefly, the initial resistance of the arm ergometer was set at 0 kilograms (kg) and then increased by 0.25 kg for each stage. The third test was performed by walking on a treadmill consisting of continuous 3-min stages, also following the protocol by Strath et al. (2005). The initial speed was set at 4 km/h and then increased to 6 km/h, after which the speed remained while the grade was raised by 2% for each stage.

2.4. Data processing

The HR from the heart rate belt was registered every second and then averaged by every 15 s. The VO_2 was measured by Oxygen Pro using a mixing-chamber with breath-by-breath mode and registered in 15-s epochs. The accelerometer data were sampled at 100 Hz with a range of ±2.5 g and a 13-bit resolution. The total acceleration from three axes was calculated by $\sqrt{a_x^2 + a_y^2 + a_z^2}$ and then band-pass filtered with a pass band of 0.25–6 Hz. A mean value was taken for every 15 s.

Three models for estimating VO_2 were used and compared with the criterion measurement. The details of each model are described below, and the decision tree diagrams are shown in Figure 1.

2.4.1. The HR-Flex model

The HR-Flex model uses an individually calibrated linear HR–VO_2 relationship when the HR is above flex-HR

Table 2. Description of the simulated work activities.

| Work activities	Duration	Type of work	Description
1. Office work	10 min	Static, arm work	The participant sits beside a table and types in a text on a laptop computer
2. Painting work	10 min	Dynamic, arm work	The participant stands and raises up-and-down a painting pole with 0.5 kg weight on the top to mimic painting a wall at their own pace
3. Postal delivery work	10 min	Dynamic, leg work	The participant sits on a cycle ergometer and cycles at a pedal frequency of 60 rev/min with a resistance of 0.75 kg
4. Meat cutting work	4 + 4 min	Dynamic, arm work	The participant repetitively pulls a training resistance band towards the torso every 2 s following a metronome, starting with 4 min with the right arm and then 4 min with the left
5. Construction work	4 + 1+4 min	Dynamic, mixed arm and leg work	The participant repeats lifting and lowering a box (6 or 4.5 kg) by squatting from floor to table every 6 s for 4 min, marked as 'construction work – mix'. After 1 min break, the participant repeats lifting a box (9 or 6.5 kg) from side to side on a table every 5 s for 4 min, marked as 'construction work – arm'
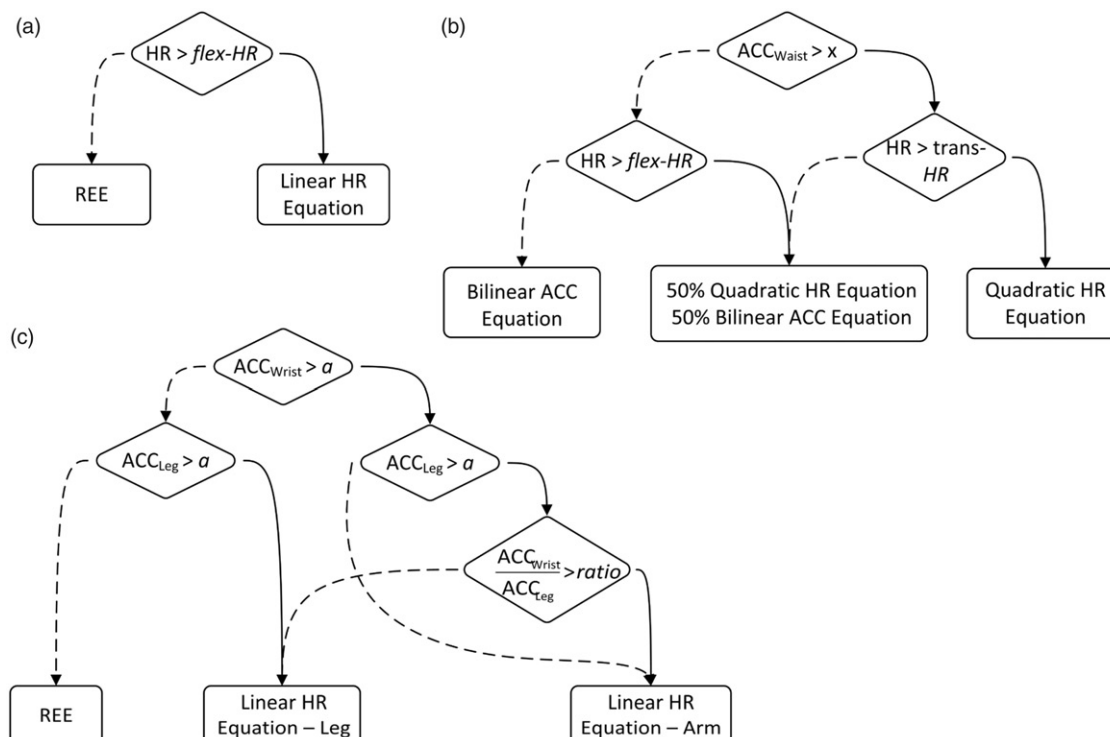
Figure 1. Model structure illustrations drawn as decision trees. The flow goes to the dashed branch if the decision condition is not met. (a) The HR-Flex model. (b) The HR branched equation model: the parameter x was set at 0.027g, and the flex-HR and transition-HR were individual calibrated. (c) The HR + arm-leg ACC model: the parameter a and ratio were set at 0.013 g and 1.5, which were adapted to our study. The HR and ACC equations were obtained from individual calibration tests. For more details, the readers are referred to the text, HR: heart rate; REE: resting energy expenditure; ACC_{body}: output from the accelerometer worn at the body part accordingly.

and the REE value when the HR is below flex-HR (see Figure 1(a)). In our study, the flex-HR point was chosen as the average of the highest HR during the three resting periods and the lowest HR during walking on a treadmill after 30 s.

2.4.2. The branched equation model

The branched equation model uses a quadratic HR–VO_2 and a bi-linear ACC–VO_2 relationship obtained during individual calibration with different weightings applied in different conditions (Brage et al. 2004). Following its principles, when the HR is above RHR, a quadratic HR–VO_2 regression was used which was calibrated during the treadmill test and forced through the point of RHR and REE. When the HR is below RHR, the VO_2 was assumed to be equal to REE. For the ACC–VO_2 relationship, a bi-linear relationship was used, when the ACC was below the flex point (defined as 50% of the mean waist-worn ACC value during the first level treadmill test), the ACC–VO_2 regression was built between the flex-ACC point and the point of REE

Table 3. Estimates of oxygen consumption (mL/min/kg) during simulated work tasks using individual calibrated linear relationships between VO_2 and HR or hip-worn ACC under different submaximal test conditions.

Calibration conditions	Office work			Painting			Postal delivery			Meat cutting			Construction work			Average of all work tasks		
	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE	Mean±SD	Bias	RMSE
HR																		
Criterion	4.0±0.8	–	–	8.3±1.1	–	–	14.0±2.0	–	–	7.5±1.7	–	–	12.4±2.5	–	–	9.1±1.2	–	–
Chester step test	4.1±3.0	0.1	3.0	9.1±3.0	0.8	2.5	12.0±2.6	−1.9	2.8	10.7±3.2	3.2	4.1	13.6±3.2	1.3	2.7	9.5±2.6	0.4	2.3
Step + VO_2[a]	5.2±2.0	1.2	2.3	10.2±2.2	1.8	2.5	13.0±2.1	−0.9	2.1	11.7±2.3	4.2	4.4	14.6±2.4	2.3	2.6	10.5±1.7	1.4	2.0
Arm ergometer + VO_2[b]	2.4±1.6	−1.5	2.2	6.2±1.4	−2.1	2.3	8.5±1.5	−5.4	5.6	7.4±1.5	−0.1	0.9	9.8±1.8	−2.5	3.0	6.5±1.0	−2.6	2.7
Treadmill + VO_2[c]	3.9±2.5	−0.1	2.0	9.3±2.1	1.0	1.8	12.2±2.9	−1.7	2.2	10.8±3.0	3.3	4.0	13.9±3.5	1.5	2.4	9.6±2.4	0.5	1.6
ACC																		
Chester step test	3.4±0.6	−0.6	1.1	4.0±1.8	−4.3	4.7	5.6±3.4	−8.3	9.1	3.8±1.4	−3.6	4.2	4.9±2.8	−7.5	8.2	4.4±1.9	−4.7	5.2
Step + VO_2[a]	3.7±0.4	−0.2	0.8	5.2±1.2	−3.2	3.5	8.2±2.6	−5.7	6.8	4.8±1.0	−2.7	3.2	6.9±1.8	−5.4	6.1	5.8±1.2	−3.3	3.7

SD: standard deviation; RMSE: root mean square error; HR: heart rate; ACC: accelerometer
[a]Step + VO_2: individual calibration obtained during a submaximal step test with measured oxygen consumption.
[b]Arm ergometer + VO_2: individual calibration obtained during the submaximal test performed with an arm ergometer with measured oxygen consumption.
[c]Treadmill + VO_2: individual calibration obtained during the submaximal test performed on a treadmill with measured oxygen consumption.

and zero ACC. When the ACC was above the flex-ACC point, the regression was built during the step test using waist-worn ACC and measured VO_2. The *a priori* parameters in the original study were adapted to our study following its original criteria, where the x was set to 0.027 g (to ensure cycling was not classified below the cut-off), and y and z was set individually to the flex-HR and the transition HR between the second and third stage during the treadmill test (see Figure 1(b)).

2.4.3. The HR + arm-leg ACC model

The HR + arm-leg ACC model uses two linear HR–VO_2 relationships obtained during an arm ergometer test and a treadmill test accordingly (Strath et al. 2001). The outputs from the wrist- and thigh-worn ACCs are used to classify the condition as inactivity, arm-mainly activity, leg-mainly activity or mixed activity (see Figure 1(c)). A modification was made implicitly later which included a lower limit of the estimated VO_2 as REE (Strath et al. 2005). In our study, following the model's modified principles, the value of threshold a was adapted to 0.013 g to differentiate periods of activity and inactivity, a ratio of 1.5 was used to decide if the arm or the leg activity was dominant, when both wrist and thigh ACC exceeded the threshold, and a lower limit of REE was included in both the arm and leg calibrated HR–VO_2 equations (Strath et al. 2001; Strath et al. 2005).

2.5. Statistical analysis

All data were analysed by 15-s average values. The mean and standard deviation of the estimated oxygen consumption from the three models were compared against the criterion for all participants during each work task, of which the first 2 min were left out. The bias and root-mean-square errors (RMSEs) were also calculated for each work task. Additionally, the total oxygen consumption for the five work tasks was summed up and compared. Bland-Altman plots were presented to show the bias and limits of agreement (LoA) between the criterion and the estimate for all work tasks from the models calibrated with two different tests, i.e. the treadmill submaximal test and Chester step test, for calibrating the individual HR–VO_2 equations.
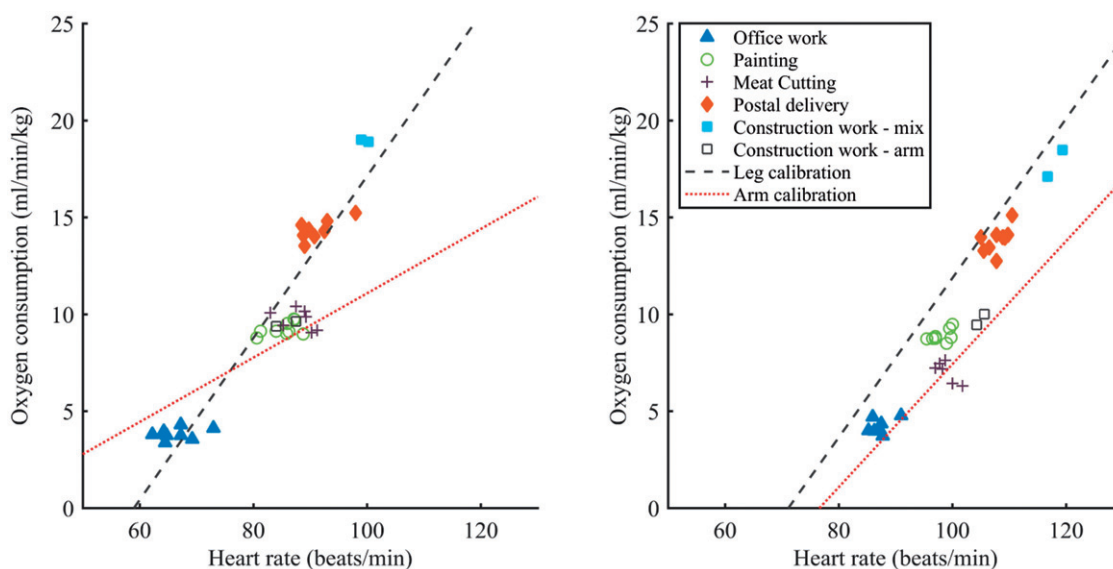
Figure 2. The relationships between heart rate (HR) and measured oxygen consumption (VO_2) during different work tasks in 1-min average values, with two simple linear regressions calibrated during submaximal tests performed with treadmill (leg calibration) and arm ergometer (arm calibration): (a) example of one participant with a clear distinction between types of work using arm, leg or mixed muscle groups following the respective calibration regression lines; (b) example of another participant showing a vague distinction between types of work tasks.

3. Results

3.1. Simple linear regression from individual calibrations

To better examine the characteristics of relationships between VO_2 and HR as well as between VO_2 and hip-worn ACC during various work tasks, criterion and estimates of oxygen consumption based on simple linear regression calibrated individually during submaximal tests are shown in Table 3. For calibration of HR–VO_2 relationships, the condition using the treadmill and measured VO_2 from indirect calorimetry had the highest accuracy during all work tasks, except meat cutting. The condition using arm ergometer had the highest accuracy during meat cutting (RMSE = 0.9 mL/min/kg) but worse accuracy during the other tasks.

This effect of different types of muscular work on HR–VO_2 relationships is further illustrated for two subjects in Figure 2, where the HR and measured VO_2 are shown during simulated work tasks together with two calibration lines obtained from the arm ergometer (marked as 'Arm calibration') and treadmill (marked as 'Leg calibration') submaximal tests. Individual differences were observed among subjects. A clear distinction between the work tasks that use mainly the arm, leg or mixed muscle groups can be observed in Figure 2(a), where the tasks using mainly the arm followed the arm calibration and the rest followed the leg calibration. However, there are also individual differences in the physiological response when participants performed the simulated work tasks. For example, no clear distinction between arm or leg muscle work is observed for the participant in Figure 2(b).

The relationships between VO_2 and hip-worn ACC had worse accuracy in all work tasks except office work. The estimated VO_2 were distinctively underestimated, especially in tasks at higher intensities such as postal delivery (RMSE = 9.1 mL/min/kg for calibration by step test) and construction work (RMSE = 8.2 mL/min/kg).

3.2. Models using HR or combined HR and ACC

The criterion and estimates of oxygen consumption during simulated work tasks using three models based on HR or both HR and ACC, as described in Section 2.4 are shown in Table 4. The HR-Flex had the highest accuracy during office work (RMSE = 0.7 mL/min/kg) and painting (RMSE = 2.1 mL/min/kg). The HR branched equation combining HR and hip-worn ACC had a distinctive underestimation during postal delivery (bias and RMSE: −3.5 and 4.0 mL/min/kg) and construction work (bias and RMSE: −3.4 and 4.1 mL/min/kg). The HR + arm-leg ACC model had the highest accuracy in postal delivery, meat cutting and construction work (RMSE = 2.2, 0.9 and 2.1 mL/min/kg accordingly).

Table 4. Estimates of oxygen consumption (mL/min/kg) during simulated work tasks using three models including HR-Flex, HR branched equation and HR + arm-leg ACC model.

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

RMSE: root mean square error; HR-Flex: heart rate flex model

HR branched equation: Heart rate branched equation model combining HR and one accelerometer placed on the hip.

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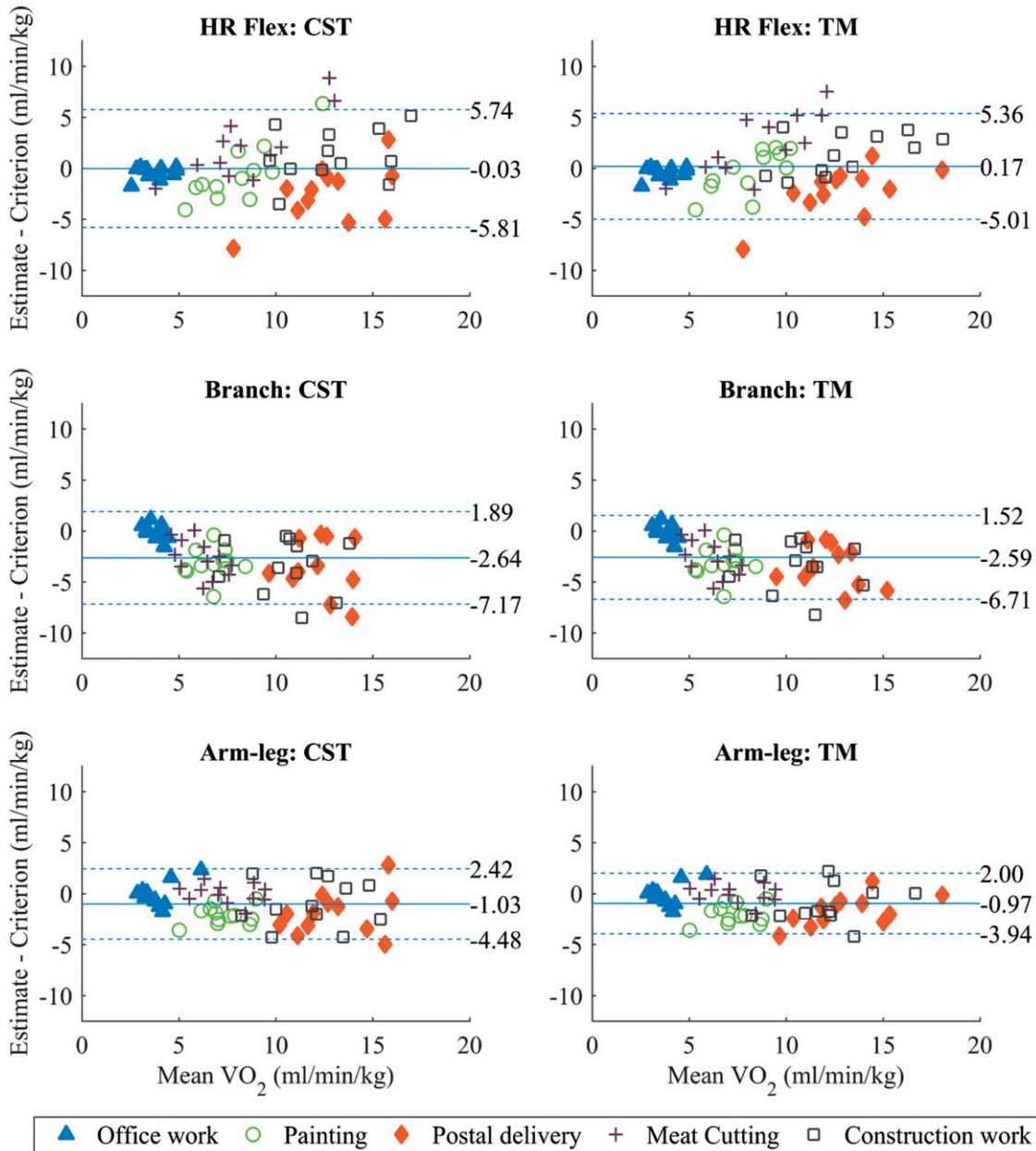

Figure 3. Bland–Altman plots of the oxygen consumption (VO₂) estimated by three models with two different calibration procedures, in five simulated work tasks. Two calibration methods were used, the Chester step test (CST, to the left in each model row), and a submaximal treadmill test (TM, to the right in each model row); the three estimation models were, top to bottom row, the HR flex model (HR-Flex), the HR branched equation (Branch) and the HR + arm-leg ACC model (Arm-leg).

Bland–Altman plots are presented to further illustrate the estimation from the three models against the criterion VO_2 during five simulated work tasks with different calibration procedures (see Figure 3). The HR-Flex model calibrated with Chester step test had the smallest bias (-0.03 mL/min/kg) while quite a large LoA (-5.81 and 5.74 mL/min/kg). The HR branched equation underestimated under both of the conditions calibrated with Chester step test (-2.64 mL/min/kg) and treadmill (-2.59 mL/min/kg). The HR + arm-leg ACC model calibrated with treadmill test had the smallest LoA (-3.94 and 2.00 mL/min/kg) while a slight underestimation (-0.97 mL/min/kg).

4. Discussion

In this study, three models for estimating WM by using HR alone or combined with ACC were compared with the gold standard measurement using indirect calorimetry during simulated work activities. The results showed that the HR + arm-leg ACC model provided the most accurate estimation, especially in work tasks involving dynamic arm and/or leg muscle activities. The HR-Flex method had a larger variance in its estimation accuracy regarding different types of work tasks, but a small bias when looking at the total oxygen consumption for the five work tasks. It might be used as an alternative for studies performed on a larger scale when laboratory calibration is not accessible. The HR branched equation had a remarkable underestimation in four out of five work activities and hence might not be suitable for estimating WM.

The associations between HR and VO_2 have been studied and used for estimating oxygen consumption in sports, daily activities or at work. The characteristics of muscular work, i.e. small or large muscle groups and static or dynamic components are important factors to consider, which influence the relationships between HR and VO_2, as can be observed in Figure 2(a). In occupational settings, activities involving arm or static work are quite common, and, therefore, the influence on the estimation becomes more significant. It was shown that by considering arm or leg work in the estimation model, i.e. using the HR + arm-leg ACC model, the accuracy was improved in several simulated work activities (see Table 4), compared to the HR-Flex or HR branched equation. The results agree with that of Strath et al. (2002) who compared the HR + arm-leg ACC model with the HR-Flex in free-living activities. However, this result was contradictory to Brage et al. (2015), who showed that the HR branched equation had a more accurate estimation than the HR-

Flex model in daily activities. The difference can be explained because different types of activities were included in the studies. The HR branched equation intended to improve the estimation by compensating the errors from the HR equation with the ones from the ACC equation (Brage et al. 2004; Crouter, Churilla, and Bassett 2008). In Brage et al. (2015), the focus was on daily activities during free-living conditions and the overall intensity was low – as stated about 62% of the time the HR was below the flex-HR point. In our study, the estimation using the ACC equation substantially underestimated the VO_2 in most of the working tasks (as shown in Table 3), since most of the movements involving arm and/or leg could not be detected by the hip-worn ACC. Therefore, with the *a priori* parameters used in the HR branched model, it may not compensate the errors from the HR equation using the ACC equation in a different type of activity, e.g. occupational activities. This was in agreement with Edwards et al. (2010) who showed that the performance of HR branched model might be limited by the heterogeneity in daily living activities.

The individual differences of the physiological response to different tasks were observed among participants, some of whom did not show a clear distinction between arm or leg work (as shown in Figure 2). These differences might have multiple sources. First, participants performed the tasks under the same instruction but in their own style, and this difference in the working technique had an influence on how they used the muscles and how much force was exerted. Second, the work tasks were at different intensity levels to different participants, especially comparing those who have a high fitness level and those who have not. For the participants who have high aerobic capacities, the simulated work tasks were at a low to medium level with a small difference in HR values, and therefore less distinction was observed between the leg or arm work activities.

The calibration procedure using the treadmill with measured VO_2 had smaller LoA in the estimation from all models compared to Chester step test without measured VO_2 (as shown in Figure 3). This was expected, while it also required more time and resources to perform the treadmill test than the Chester step test. It is worth noticing that the calibration using treadmill also led to an underestimation of VO_2 during postal delivery (performed on a cycling station), as shown in Tables 3 and 4, which can be explained by the different muscle activities involved in these two movements.

During simulated painting, however, the VO_2 was closer to the estimation based on the leg calibration, which was obtained during the treadmill test, rather than the arm calibration obtained during arm ergometer test (see Table 3). This was unexpected and led to estimation errors (as shown in Table 4). Since the wrist-worn ACC had much higher output than the thigh-worn ACC (with a ratio >1.5) during painting, this work task was classified as arm-mainly activity and used the arm calibration equation in the HR + arm-leg ACC model. This deviation might be caused by higher activity in trunk muscles, which have larger muscle mass than arm muscles. Moreover, the participants were instructed to perform the painting task with their own style and pace, which led to the larger variance of how the tasks were carried out among the individuals.

The limitations of this study included the limited number and duration of the simulated work activities, which represented a variety of work tasks but still did not cover the wide range of occupations. The simulated work tasks were more constrained compared to real occupational activities. Moreover, the study was performed in a laboratory setting where other non-physical factors which influence HR, such as heat, stress, and food or caffeine intake, were controlled. However, in real life scenarios, those factors will have a larger influence. Therefore the estimation based on HR–VO_2 relationship would suffer, while the estimation models combined with ACC might have a buffering effect, especially in low-intensity work activities. Dubé et al. looked at a method of removing the thermal component from heart rate to improve the estimation accuracy of work VO_2 in forest workers (Dubé et al. 2015, 2016), which showed significant improvement of the estimation when four 10-min rest pauses were performed and analysed. This method can be further explored to combine with the other methods evaluated in this study, e.g. the HR + arm-leg ACC model, to improve the estimation performance in field settings.

Another limitation of the study was the difference in the choices of the calibration procedures and the sensors when compared with the previous studies. The calibration procedure used in this study was based on Strath et al. (2002), which differed from the one used by Brage et al. (2004). This difference might introduce additional error in the estimation from the HR branched equation. For the choice of the sensors, the thresholds and parameters used in previous studies were device-dependent, i.e. the ACC counts were calculated differently by different manufacturers, such

as the Actigraph used by Brage et al. (2004) and Strath et al. (2001), and the Actiheart used by Crouter, Churilla, and Bassett (2008) and Brage et al. (2015). In our study, we calculated the thresholds based on the raw acceleration signals and adapted the parameters used by the original studies to ours (as shown in Figure 1). It is worth considering the choices of the frequency range and parameters when applying these models to different sensors.

One recent study showed that respiratory signals including respiratory volume and rate could contribute to the estimation of VO_2 during daily physical activities (Gilgen-Ammann et al. 2017). In the present experiments, respiratory signals were also collected. The method combining HR, ACC and respiratory signals using a neural network to estimate the VO_2 during occupational activities was investigated in another study (Lu et al. 2018). Kolus et al. (2015) presented a machine learning model using personal demographic variables and resting HR to predict HR-Flex parameters and VO_2 without individual calibration. Moreover, Altini, Casale et al. (2015) described a Bayesian model using HR and ACC calibrated during daily activities for EE estimation, which avoided the need for laboratory protocol calibration. There is still a need for future researches to look into the applicability and validity of these models in occupational settings before they can be used for assessing WM in practice.

5. Conclusion

In this study, three methods using HR with or without ACC were compared with the standard measurement of WM during simulated work tasks. The HR-Flex model calibrated by Chester step test showed a small bias for the total WM for all work tasks and offered a good alternative for field studies on a large scale when recourses for individual calibration are limited. The method of combining HR with hip-worn ACC showed significant underestimations, especially in tasks involving dynamic arm and/or leg movements. Therefore, the HR branched model is not recommended for estimation of WM in occupational settings. The method of using HR in combination with ACC placed on wrist and thigh showed good accuracy in most of the work tasks and provided a valid estimation when calibration resources are provided. For the development of smart wearable systems, these two models, i.e. the HR-Flex and the HR + arm-leg ACC model, are suitable for estimating the WM and assessing the RAS level. The choice of

models depends on the need for the accuracy level and resources and opportunities to perform calibrations in the field.

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