Original Paper

Walking cadence required to elicit criterion moderate-intensity physical activity is moderated by fitness status

Grant Abt[a], James Bray[a], Tony Myers[b], Amanda C Benson[c]

[a]Department of Sport, Health and Exercise Science, The University of Hull, Kingston upon Hull, United Kingdom

[b]Faculty of Arts, Society and Professional Studies, Newman University, Birmingham, United Kingdom

[c]Department of Health and Medical Sciences, Swinburne University of Technology, Melbourne, Australia

Address for correspondence:

Grant Abt PhD

Email: g.abt@hull.ac.uk

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Abstract

The aims of this study were to estimate the walking cadence required to elicit a VO_2reserve (VO_2R) of 40 % and determine if fitness status moderates the relationship between walking cadence and %VO_2R. Twenty participants (10 male, mean(*s*) age 32(10) years; VO_2max 45(10) mL·kg^{-1}·min^{-1}) completed resting and maximal oxygen consumption tests prior to 7 x 5-min bouts of treadmill walking at increasing speed while wearing an Apple Watch and measuring oxygen consumption continuously. The 7 x 5-min exercise bouts were performed at speeds between 3 and 6 km·h^{-1} with 5-min seated rest following each bout. Walking cadence measured at each treadmill speed was recorded using the Apple Watch 'Activity' app. Using Bayesian regression, we predict that participants need a walking cadence of 138 to 140 steps·min^{-1} to achieve a VO_2R of 40 %. However, these values are moderated by fitness status such that those with lower fitness can achieve 40 % VO_2R at a slower walking cadence. The results suggest that those with moderate fitness need to walk at ~40 % higher than the currently recommended walking cadence (100 steps·min^{-1}) to elicit moderate-intensity physical activity. However, walking cadence required to achieve moderate-intensity physical activity is moderated by fitness status.

Keywords: wearable electronic devices, exercise, oxygen consumption, walking, Bayes theorem.

Introduction

Low cardiorespiratory fitness (CRF) is independently associated with increased chronic disease and mortality risk (Blair et al., 1989). Regular exercise improves CRF, with small (1 MET, 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$) increases in CRF shown to reduce all-cause mortality risk in the order of 8-14% (Dorn, Naughton, Imamura, & Trevisan, 1999). Given that improvements in CRF are influenced by the intensity of exercise (Swain & Franklin, 2006), and that government guidelines make explicit reference to the achievement of 'moderate-to-vigorous' intensity physical activity (MVPA), the measurement of physical activity intensity is therefore important.

Recently, a walking cadence of $\geq$ 100 $steps \cdot min^{-1}$ in adults has been recommended as sufficient to meet the requirements of MVPA (Tudor-Locke et al., 2018). However, this estimate is based on studies that have used accelerometry (an external measure of exercise intensity), together with the use of metabolic equivalents (an indirect measure of exercise intensity). To overcome these limitations, a recent study (Serrano, Slaght, Sénéchal, Duhamel, & Bouchard, 2017) used oxygen consumption reserve (VO_2R) to estimate the walking cadence required to achieve moderate-intensity. A VO_2R of 40 % is considered to be the lower bound of moderate-intensity (Riebe, 2018). These authors (Serrano et al., 2017) reported that a mean (*s*) walking cadence of 115 (10) $steps \cdot min^{-1}$ was required to achieve a VO_2R of 40 %, suggesting that an external measure of exercise intensity (accelerometry) underestimates the walking cadence required to achieve MVPA when compared to an individualized and relative measure (VO_2R). However, Serrano et al (2017) didn't explore the effect of fitness status on the walking cadence required to elicit 40 % VO_2R. Given that the participants in their study had a mean (*s*) age of 69 (8) years and VO_2peak of 24 (women) and 29 (men) $mL \cdot kg^{-1} \cdot min^{-1}$, fitness status is likely to have had an effect on the walking cadence required to elicit 40 % VO_2R. It is also unclear how these walking cadence values (100 (Tudor-Locke et al., 2018) and 115 (Serrano et al., 2017) $steps \cdot min^{-1}$) translate to modern consumer wearable devices that measure step counts.

We have recently reported that the Apple Watch underestimates the walking speed required to exercise at moderate intensity when measured using VO_2R (Abt, Bray, & Benson, 2018). Thompson et al. (2016) reported that because consumer wearable devices record all forms of activity, they typically overestimate the amount of MVPA achieved. This might suggest that a 100 or even 115 steps·min^{-1} thresholds are too low when measured using a consumer wearable device, and in those with higher fitness. The rapid growth in the consumer wearable market (Peake, Kerr, & Sullivan, 2018; Phillips, Cadmus-Bertram, Rosenberg, Buman, & Lynch, 2018) would suggest that this information is important if wearable devices are to be an effective component of physical activity promotion programmes. The Apple Watch is currently the highest selling smartwatch in the world, with global accumulated sales estimated at approximately 46 million units (Dediu, 2018). Given the public health messages that incorporate step count (Tudor-Locke et al., 2011; Yamamoto et al., 2018), it is important for researchers, exercise professionals and consumers to understand how target step counts translate into criterion measures of MVPA. Therefore, the aims of this study were to estimate the walking cadence required to elicit a VO_2R of 40 % (the lower bound of moderate-intensity) and determine if fitness status moderates the relationship between walking cadence and % VO_2R.

Methods

Our study used a cross-sectional design where each participant completed a series of brief exercise bouts within the same laboratory session. Prior to these exercise trials each participant had their maximal oxygen consumption (VO_2max) and resting oxygen consumption (VO_2rest) measured. Approval to conduct the study was granted by the Department of XXXX Ethics Committee (approval number 1516076) at XXXX. To approximate power and determine appropriate sample size, Bayesian power analysis was conducted using simulations from hypothesised posterior distributions (Kruschke, 2015). This involved simulating a random distribution of parameter values from hypothesised slope and intercept values based on previous research and pilot data for relationships between walking cadence and % VO_2R. These values were used to generate one thousand posterior estimates for each sample size from 10 to 40 (30,000 in total) using Integrated Nested Laplace Approximation (Rue, Martino, & Chopin, 2009). This analysis determined that measurements from 20 participants would result in a 0.8 probability of a positive relationship between walking cadence and % VO_2R.

Recruitment of low-risk participants (Riebe, 2018) aged between 18 and 50 years from the university and local community was undertaken using written promotional material and personal communication. The exclusion criteria were: 1) men and women classified as moderate or high-risk according to the ACSM risk classification criteria (Riebe, 2018), 2) those unable to walk on a motorized treadmill, 3) current smoker, 4) BMI ≥ 30 $kg{\cdot}m^2$, 5) currently taking medication that alters the heart rate response to exercise (e.g. beta blockers), 6) people with gait disturbances.

Prior to the measurement of body mass, participants were asked to ensure they had voided and then instructed to remove all clothing. The mean of two measurements of nude body mass was measured to the nearest 0.1 kg using digital scales (WB-100MA Mark 3, Tanita Corporation, Tokyo, Japan). A wall-mounted stadiometer (Holtain Ltd, Dyfed, Wales, UK) was used to measure stretch stature (Norton et al., 2000).

In a temperature-controlled laboratory, resting oxygen consumption was measured 30 minutes prior to, and in the same session, as VO_2max. This protocol has been previously described in detail (Abt et al., 2018), but briefly, participants lay supine on a bed with their head on a pillow with oxygen consumption measured continuously from expired air using a breath-by-breath online gas analysis system to calculate VO_2R based on a method reported by Miller et al (2012).

Participants completed an incremental protocol on a motorized treadmill (h/p/cosmos, Pulsar, Nussdorf-Traunstein, Germany) with oxygen consumption measured continuously from expired air using a breath-by-breath online gas analysis system (Cortex Metalyzer 3B, GmbH, Germany). The breath-by-breath analyzer was calibrated prior to each test using room air and known gas concentrations of O_2 and CO_2. Volume was calibrated using a 3 L syringe. The protocol commenced at 3 $km{\cdot}h^{-1}$ and a 1 % gradient and increased 0.5 $km{\cdot}h^{-1}$ in speed every 30 s until volitional fatigue. Maximal oxygen consumption was taken as the highest 30 s mean. Based on established criteria (volitional exhaustion; RER > 1.15; plateau in oxygen consumption < 150 $mL{\cdot}min^{-1}$), all participants were judged to have reached VO_2max (Howley, Bassett, & Welch, 1995).

Familiarization on how to get on and off the treadmill, as well as walking at the prescribed speeds, was undertaken prior to the main trial. Participants were instructed to avoid exercise and maintain their normal diet for the 24 hours prior to the trial and avoid food and caffeinated drinks for three hours. The main trial consisted of participants completing a series of 5-min bouts of treadmill walking at a gradient of one percent at increasing speed while wearing an Apple Watch on both wrists (described below). Each bout was followed by 5-min of seated rest. The first 5-min walking bout was conducted at 3 $km \cdot h^{-1}$, with the treadmill speed increased for each successive 5-min bout by 0.5 $km \cdot h^{-1}$ (i.e. 3, 3.5, 4, 4.5, 5, 5.5, and 6 $km \cdot h^{-1}$). Participants were not permitted to hold the treadmill handrails and were instructed to maintain their normal walking gait during each 5-min bout of walking. During each 5-min bout, oxygen consumption and heart rate were recorded by an online gas analysis system (as described previously), a Polar chest strap (Polar T31, Polar Electro, OY, Finland) and an Apple Watch worn on each wrist. Steps measured at each treadmill speed were recorded using the Apple Watch Activity app.

Immediately after each 5-min exercise period was completed, the treadmill was stopped, and participants instructed to grasp the treadmill handrails and straddle the treadmill. Participants were required to sit motionless on a stationary chair placed on the treadmill belt with each hand resting on the treadmill handrail to ensure that no activity during the recovery period contributed to the step count. Five minutes of seated rest was provided to enable each Apple Watch to update the step count. The mean oxygen consumption from the last three minutes at each treadmill speed for each watch was used for later analysis.

Moderate intensity exercise and steps were estimated using two first-generation (Series 0) Apple Watches running watchOS 2.0.1. Each Apple Watch was paired to an iPhone 6 running iOS 9.1. Following each 5-min rest period the number of steps as measured by each of the Apple Watches was manually recorded from the Activity app. Moderate-intensity exercise was defined as that between 40 % and 59 % of VO_2R (Riebe, 2018). The VO_2R at each treadmill speed (exercise intensity in the equation) was calculated by rearranging equation 1 (Riebe, 2018). Target VO_2 was the measured oxygen consumption at each treadmill speed.

$$\text{Target } VO_2 = (VO_2max - VO_2rest) \times \text{exercise intensity} + VO_2rest \qquad (1)$$

Descriptive statistics were calculated and are presented as mean (*s*). To describe the relationship between treadmill speed and walking cadence, a series of Bayesian regression models were fitted to data from both right and left wrists. These modelled walking cadence as a linear function of speed, plus Gaussian noise using a standard linear model, a 2nd order polynomial, and a 3rd order polynomial. To determine the best model of the relationship, model fit was determined using Leave-One-Out cross-validation (LOO), a method of estimating pointwise out-of-sample prediction accuracy from fitted Bayesian models using log-likelihoods from posterior simulations of the parameter values (Vehtari, Gelman, & Gabry, 2017). The best model for describing the relationship between treadmill speed and walking cadence predicted by the Apple Watch worn on both left and right wrists was the a 2nd order polynomial regression.

To describe the relationship between walking cadence and % VO_2R, a series of Bayesian regression models were fitted. These walking cadences were used to predict percentage VO_2R. The models fitted included basic linear models, through 2nd and 3rd order polynomial models including multilevel models that allowed individual intercepts to vary, to multilevel non-linear models fitted using thin plate splines (Wood, 2003; Zhou & Shen, 2001). Each model was fitted with errors modelled using both normal and skew normal distributions. The final models selected for best out of sample predictions were a thin plate spline multilevel regression for the right wrist and a 2nd order polynomial model for the left wrist.

To explore differences between the estimated walking cadence at 40 % VO_2R and recommendations from the review by Tudor-Locke (2018), a random normal distribution of walking cadence values was generated (n = 200, mean = 100 (4)) in R (R Core Team, 2018). This simulated distribution captured the range of walking cadences presented in the review (90 to 114 steps·minute^{-1}) (Tudor-Locke et al., 2018). This distribution was compared to the estimated walking cadence at 40 % VO_2R for the right and left wrists using a Bayesian two-sample t-test. The probabilities calculated were the probability of a difference showing the percentage of the posterior distribution that falls above zero. In an attempt to explain, in part, the large variation between individual's percentage VO_2R, an additional model was fitted with VO_2max included as a covariate and the interaction between VO_2max and walking cadence explored using the best out of prediction models. To determine if including sex was an important factor in predicting the relationship between % VO_2R, an additional Bayesian regression model was fitted with sex as a predictor and then compared to the same model fitted without sex. In addition, predictions for % VO_2R were made using the model for both males and females to explore any differences directly.

All analyses were conducted using R (R Core Team, 2018) and with the Bayesian Regression Models using 'Stan' (brms) package (Bürkner, 2017) (Stan Development Team, 2018) to implement a Hamiltonian Markov Chain Monte Carlo (MCMC) with a No-U-Turn Sampler. Weakly informative priors were used to regularize the models and avoid unreasonable parameter estimates. All models were checked for convergence ($\hat{r} = 1$), with the graphical posterior predictive checks showing that simulated data under the best fitted models compared well to the observed data with no systematic discrepancies (Gabry, Simpson, Vehtari, Betancourt, & Gelman, 2019). Uncertainty in all of the estimates are reported as 95 % credible intervals.

Results

Written informed consent was obtained from twenty low-risk (Riebe, 2018) participants (Table 1).

TABLE ONE ABOUT HERE

Walking cadence estimated by the Apple Watch worn on right and left wrists increased from a mean (both wrists combined) of 94 steps·min^{-1} at 3 km·h^{-1} to 130 steps·min^{-1} at 6 km·h^{-1}, with maximum walking cadence reached by one participant recorded as 144 steps·min^{-1}. Oxygen consumption increased from a mean of 16 % VO_2R at 3 km·h^{-1} to 34 % VO_2R at 6 km·h^{-1} (Table 2).

TABLE TWO ABOUT HERE

The curvilinear relationship found between treadmill speed and walking cadence estimated by the Apple Watch when worn on both the right and left wrists can be best described by 2nd order polynomial (quadratic) regressions. The relationship between treadmill speed and walking cadence estimated by an Apple Watch worn on the right wrist produces the following equation: $y = 40.91 + 22.08x - 1.21x^2$. The relationship between treadmill speed and walking cadence estimated by an Apple Watch worn on the left wrist produces the equation: $y = 26.61 + 26.44x - 1.54x^2$.

The Bayesian multilevel thin plate spline regression suggests that the relationship between percentage VO_2R and walking cadence estimated by the Apple Watch on the right wrist is curvilinear (Figure 1). The regression suggests that 93 % of the variance in percentage VO_2R is explained by the model, with 87 % of the variance being between participants, and 13 % of the variance being within participants. This model predicts that the mean walking cadence required to illicit 40 % VO_2R is 138 steps·min^{-1} with a range between individuals from 126 to 147 steps·min^{-1}. The Bayesian multilevel 2nd order orthogonal regression suggests that the relationship between % VO_2R and walking cadence estimated by the Apple Watch on the left wrist is also curvilinear. Ninety two percent of the variance in percentage VO_2R is explained by the model as a whole, with 86 % of the variance being between participants, and 14 % of the variance being within participants. The model predicts that the mean walking cadence required to illicit 40 % VO_2R is 140 steps·min^{-1} with a range between individuals from 126 to 147 steps·min^{-1}.

FIGURE ONE ABOUT HERE

Including VO_2max as a covariate did not improve the R^2 or the out of sample prediction (LOO). Nonetheless, this analysis provides an interesting insight into how an individual's fitness moderates the walking cadence required to achieve 40 % VO_2R. Those with a higher VO_2max need a higher walking cadence to achieve 40 % VO_2R (Figure 2). For example, an individual whose VO_2max is 50 mL·kg^{-1}·min^{-1} needs to walk at an estimated cadence of 141 steps·min^{-1} when wearing an Apple Watch on their right wrist to achieve 40 % VO_2R. In contrast, an individual whose VO_2max is 30 mL·kg^{-1}·min^{-1} can walk at a cadence of 131 steps·min^{-1} to achieve 40 % VO_2R. A similar effect is observed with the Apple Watch worn on the left wrist. However, while these walking cadence predictions are most probable for predicting 40 % VO_2R, uncertainty in the predictions of % VO_2R are high, with a 95% chance that the true % VO_2R predicted by walking cadence is 40 % VO_2R ± 18 % on average. Sex differences in predicted % VO_2R in relation to walking cadence are displayed in Table 3 and Figure 3. Sex did not improve either data fit (Bayesian R^2) or out of sample prediction (LOO). While predictions from the model showed that the same walking cadence produced lower % VO_2R on average for males compared to females, the credible intervals suggested these differences are highly uncertain.

FIGURE TWO ABOUT HERE

TABLE THREE ABOUT HERE

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The Bayesian two sample t-test used to estimate differences between walking cadence estimated to elicit 40 % VO_2R and the recommendations from the review by Tudor-Locke (2018) produced very large standardised differences. There was a very high probability of the true difference being greater than 37 steps·min^{-1} for both the right (99 %) and left (100 %) wrists.

Discussion

The major finding of the current study is that when measured using a modern wearable activity tracker, the walking cadence required to reach the lower bound of moderate-intensity physical activity (40 % VO_2R) is substantially higher than previously reported. The estimated walking cadences of 140 and 138 steps·min^{-1} reported here are approximately 40 % higher than the current ≥100 steps·min^{-1} recommendations for walking cadence required to elicit moderate-intensity (Tudor-Locke et al., 2018). These walking cadences of ~140 steps·min^{-1} translate into approximately 4000 steps over a 30-minute duration. Moreover, the walking cadence required to achieve moderate-intensity physical activity is moderated by fitness status, such that those with lower fitness can walk at a slower cadence to achieve moderate-intensity. These are important findings for adults using a wearable device to monitor their physical activity and for those exercise professionals prescribing both individualized and population-based physical activity based on data from a wearable device such as the Apple Watch.

Our results have important implications for public health messages that use step count to promote physical activity to improve health outcomes associated with a range of chronic diseases. A number of campaigns promote a step count, typically 10,000 for adults, that should be reached as a daily target to improve health (Le-Masurier, Sidman, & Corbin, 2003; Tudor-Locke & Bassett, 2004). Based on the results of the current study it is clear that target step counts alone do not necessarily translate into criterion measures of physical activity intensity prescribed in guidelines (Tudor-Locke et al., 2011). There is no doubt that there would be some benefit from reaching step count targets associated with public health campaigns for many, given that we know that the greatest improvements in mortality are seen in those who move from being inactive to active (Blair et al., 1995; Paffenbarger et al., 1993). However, the data from the present study would suggest that some people working towards these population-based step count targets might not be completing physical activity at a high enough cadence to meet the moderate-intensity guidelines to maximize health outcomes. Although some benefit for the individual is expected even from lower-intensity physical activity (below 40 % HRR) (Carson et al., 2013; Pruitt et al., 2010), our results have important implications for goal setting, individualized prescription and managing expectations of the associated changes to health parameters and fitness levels for both the individual and exercise professional.

The implications from our results are numerous. First, the feedback provided to users of activity trackers needs to include a measure of intensity, rather than step count alone. This feedback should be individualized based on the physiological response and educate the user concerning the walking cadence required to reach (at a minimum) the lower bound of moderate-intensity. Second, public health recommendations need to go beyond daily step count targets to include targets based on walking cadence (intensity). Lastly, the current suggestion that a walking cadence of approximately 100 steps·min^{-1} will allow most people to achieve moderate-intensity physical activity (Tudor-Locke et al., 2018) appears to be a substantial underestimation. Our study, using directly measured VO_2R, clearly shows that even in those with lower fitness (~30 mL·kg^{-1}·min^{-1}), approximately 130 steps·min^{-1} would be required to reach the lower bound of moderate-intensity physical activity. It must be said that the value of 100 steps·min^{-}

^{1} recommended by Tudor-Locke et al. (2018) is clearly a mean and therefore masks the normal distribution of walking cadences between individuals.

Our study is not without limitations. The Apple Watches used in our study were first generation (series 0) devices running watchOS 2.0.1, and therefore might not represent the capability of the most recent Apple Watch released (series 4). That being said, it is not clear how the latest Apple Watch would produce different walking cadence values compared to the series 0 device used here as the step count measured by pre-series 4 Apple Watches has been reported to have high agreement and low (< 2 %) mean absolute percent error compared to manually counted steps (Fokkema, Kooiman, Krijnen, Van Der Schans, & De Groot, 2017; Veerabhadrappa et al., 2018). We also relied on the Apple Watch for our step count values rather than manually counting steps. Although we did this in order to examine the 'real world' relationship between walking cadence as measured by a wearable device and VO_2R, our results need to be interpreted in light of this. However, the studies cited above (Fokkema et al., 2017; Veerabhadrappa et al., 2018) suggest that the relationships we report here should not be affected substantially by using walking cadence as measured by the Apple Watch rather than manually counted steps. Bunn, Jones, Oliviera and Webster (2019) reported that the Apple Watch meets the Consumer Technology Association standard for both walking and running, with a mean absolute percentage error of < 4 % compared with manually counted steps. This study was also carried out under controlled laboratory conditions, and therefore the relationships we report here may differ compared to those under free-living conditions and warrants further investigations. Future research now needs to examine how consumer wearable devices might help and/or guide the user to achieve individualised intensity targets. This might include using a combination of both volume (total steps) and relative intensity (% HRR), such that people are encouraged to move more but also to reach a target step count at a relative intensity high enough for the individual to achieve substantial health benefits.

Conclusion

Our study, using directly measured VO_2R, shows that individuals with moderate levels of fitness require approximately 140 steps·min^{-1} to reach the lower bound of moderate-intensity physical activity (40% VO_2R). Moreover, the walking cadence required to achieve moderate-intensity physical activity is moderated by fitness status, such that those with lower fitness can walk at a slower cadence to achieve moderate-intensity. Consequently, the public health recommendation that walking at ~100 steps·min^{-1} will allow most people to reach moderate-intensity substantially underestimates the required walking cadence required to maximize health outcomes. Therefore, step count should be used in conjunction with a suggested walking cadence (intensity) based on an individual's fitness status to improve the tailoring of this public health message.

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Table and figure legends

Table 1. Demographic data for all participants and also separately for female and male.

Table 2. Mean (*s*) walking cadence measured by Apple Watch on left and right wrists together with the mean (*s*) directly-measured % VO_2R during 5-min stages of treadmill walking.

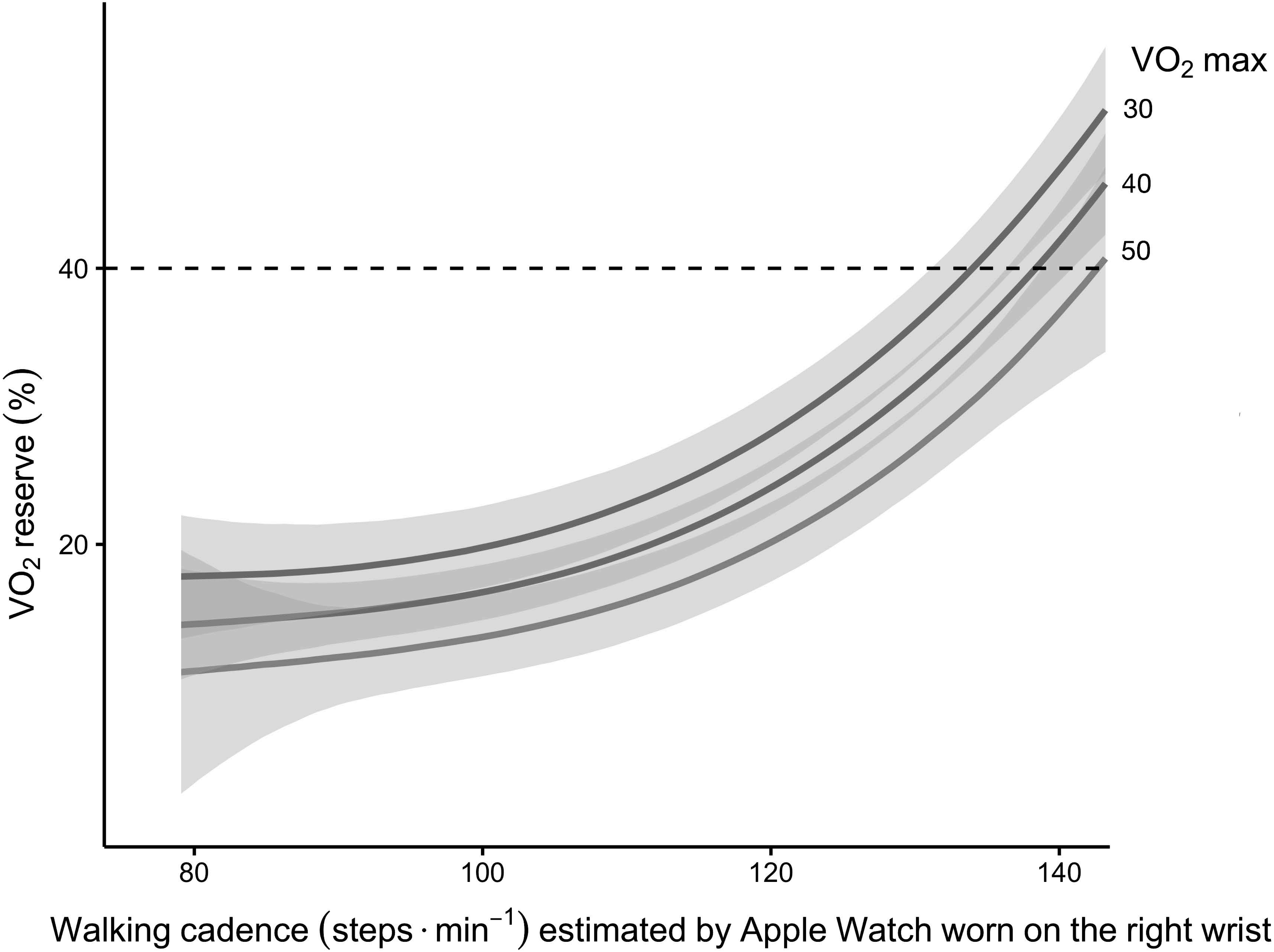
Table 3. Predicted % VO_2R (95% credible interval) for female and male participants for a range of walking cadence values. Data were generated by Apple Watch's worn on the left and right wrists.

Figure 1. The curvilinear relationships observed between walking cadence estimated by Apple Watches worn on the left and right wrists and % VO_2R. Grey shaded area is the 95 % credible interval.

Figure 2. The effect of fitness status (VO_2max) on the curvilinear relationship observed between walking cadence estimated by Apple Watch worn on the right wrist and % VO_2R. Grey shaded areas are 95 % credible intervals.

Figure 3. The effect of sex (female/male) on the curvilinear relationship observed between walking cadence estimated by Apple Watch worn on the left and right wrist and % VO_2R. Grey shaded areas are 95 % credible intervals.

VO$_2$ reserve (%)
50
40
30
20
10
80
100
120
140
Left wrist
Right wrist
Walking cadence $(\text{steps} \cdot \text{min}^{-1})$ estimated by Apple Watch



VO$_2$ max
30
40
50
40
20
VO$_2$ reserve (%)
80
100
120
140
Walking cadence (steps · min^{-1}) estimated by Apple Watch worn on the right wrist

50
40
30
20
10
% Vo_2 reserve
Female
Male
100
120
140
left wrist
right wrist
Sex differences in walking cadence $(\text{steps} \cdot \text{min}^{-1})$ estimated by the Apple Watch

Table 1. Demographic data for all participants and also separately for female and male.

N	Sex	Age (years)	Body mass (kg)	Stature (cm)	VO_2rest (mL·kg^{-1}·min^{-1})	VO_2max (mL·kg^{-1}·min^{-1})
20	All	32 (10)	71.4 (14.2)	175 (7)	3.4 (0.6)	45 (10)
10	Female	34 (10)	66.6 (8.2)	170 (5)	3.3 (0.6)	40 (6)
10	Male	31 (11)	76.2 (17.6)	179 (6)	3.5 (0.6)	50 (10)

Table 2. Mean (*s*) walking cadence measured by Apple Watch on left and right wrists together with the mean (*s*) directly-measured % VO_2R during 5-min stages of treadmill walking.

Treadmill Speed ($km \cdot h^{-1}$)	Walking Cadence - Left ($steps \cdot min^{-1}$)	Walking Cadence – Right ($steps \cdot min^{-1}$)	VO_2R (%)
3.0	93 (13)	96 (9)	16 (4)
3.5	99 (13)	104 (6)	18 (4)
4.0	108 (7)	110 (7)	20 (6)
4.5	115 (9)	116 (6)	21 (5)
5.0	121 (6)	121 (6)	25 (6)
5.5	125 (6)	125 (6)	29 (7)
6.0	130 (6)	130 (5)	34 (8)

Table 3. Predicted % VO_2R (95% credible interval) for female and male participants for a range of walking cadence values. Data were generated by Apple Watch's worn on the left and right wrists.

Steps·min^{-1}	%VO_2R (female)		%VO_2R (male)	
	Left	Right	Left	Right
100	19 (8 to 30)	19 (8 to 30)	15 (4 to 26)	15 (4 to 26)
110	23 (12 to 33)	22 (11 to 33)	18 (7 to 28)	18 (7 to 29)
120	27 (16 to 38)	26 (16 to 38)	22 (11 to 33)	22 (11 to 33)
130	34 (23 to 45)	34 (23 to 45)	28 (17 to 39)	29 (18 to 40)
140	44 (33 to 55)	45 (34 to 56)	37 (26 to 49)	41 (29 to 54)