Accepted Manuscript

Regular Article

Simplified Estimation of Oxygen Consumption During Treadmill Walking Based on Ankle Accelerometry and Velocity

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Number of tables and figures: Five tables and three figures

Running title: Arm Swing and Oxygen Consumption During Walking

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Abstract

We aimed to develop regression models for estimating oxygen consumption (VO_2, $ml \cdot kg^{-1} \cdot min^{-1}$) during treadmill walking based on accelerations of the upper and lower limbs and walking velocity, quantitatively assess the contribution of each sensor location, and validate the accuracy and practicality of a simplified model.

Eighteen healthy adults with regular exercise habits (nine men, nine women) participated in treadmill walking trials at varying speeds (3–6 $km \cdot h^{-1}$; up to 5.5 $km \cdot h^{-1}$ for women). Vector magnitude (VM) from triaxial accelerometers attached to both wrists and both ankles was recorded simultaneously with VO_2 measurements from a portable breath-by-breath gas analyzer. Multiple regression models were constructed using FootVM (ankle VM), HandVM (wrist VM), and walking velocity as predictors.

FootVM alone showed a moderate correlation with VO_2 ($R^2 = 0.464$), but adding walking velocity substantially improved the model's accuracy (Model 2: $R^2 = 0.810$, standard error of estimate = 1.25 $ml \cdot kg^{-1} \cdot min^{-1}$). Incorporating HandVM yielded only a minimal, non-significant model fit improvement ($R^2 = 0.815$, $\Delta AIC = +18.4$, $\beta std = -0.06$), with no meaningful statistical contribution. Bland–Altman analysis indicated 95% limits of agreement for estimation error within ±2.46 $ml \cdot kg^{-1} \cdot min^{-1}$, corresponding to < 1 MET (3.5 ml·kg^{-1}·min^{-1}). These findings support the rational selection of a simplified model using only FootVM and walking velocity, which achieved a balance between high accuracy and practicality. The ability to estimate VO_2 precisely using only ankle-mounted accelerometers highlights its potential for use in clinical and home-based physical activity assessment.

Keywords: accelerometer, oxygen consumption, gait, wearable sensor, model simplification

タイトル

足関節加速度と歩行速度に基づくトレッドミル歩行中の酸素消費量の簡易推定

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抄録

本研究では、トレッドミル歩行中の酸素摂取量（VO_2、$\mathrm{ml \cdot kg^{-1} \cdot min^{-1}}$）を、上下肢の加速度および歩行速度に基づいて推定する回帰モデルを開発し、各センサー位置の寄与を定量的に評価するとともに、簡素化モデルの精度と実用性を検証することを目的とした。

定期的に運動習慣のある健常成人 18 名（男性 9 名、女性 9 名）が参加し、3～6 km/h（女性は最大 5.5 km/h）の異なる速度でトレッドミル歩行試験を実施した。両手関節および両足関節に装着した 3 軸加速度計から得られるベクトルマグニチュード（VM）と、携帯型呼気ガス分析装置による VO_2測定を同時に記録した。FootVM（両足関節の VM 合計値）、HandVM（両手関節の VM 合計値）、歩行速度を説明変数として、複数の回帰モデルを構築した。

FootVM 単独では VO_2と中等度の相関（$R^2 = 0.464$）を示したが、歩行速度を加えることでモデルの精度は大幅に向上した（モデル 2：$R^2 = 0.810$、推定標準誤差 $= 1.25$ $\mathrm{ml \cdot kg^{-1} \cdot min^{-1}}$）。HandVM を追加してもモデル適合度の改善はごくわずかで統計的にも有意ではなかった（$R^2 = 0.815$、$\Delta AIC = +18.4$、β 標準化係数 $= -0.06$）。Bland–Altman 解析では、推定誤差の 95%限界が± 2.46 $\mathrm{ml \cdot kg^{-1} \cdot min^{-1}}$の範囲にあり、1 MET（3.5 $\mathrm{ml \cdot kg^{-1} \cdot min^{-1}}$）未満であった。

これらの結果から、FootVM と歩行速度のみを用いた簡素なモデルの合理的選択が支持さ

れ、高精度と実用性のバランスを実現していることが示された。足関節装着型加速度計のみで VO_2を高精度に推定できることは、臨床や在宅における身体活動評価への応用可能性を示唆している。

Introduction

Estimating oxygen consumption (VO_2) and energy expenditure during walking is crucial in fields such as rehabilitation, sports medicine, and the assessment of daily physical activity[1]. In recent years, the development of wearable devices has led to growing interest in non-invasive and simple estimation methods using accelerometers[2]. Among these, vector magnitude (VM) derived from triaxial acceleration has been widely used as an indicator of physical activity intensity[3,4].

Previous studies have primarily focused on estimating energy expenditure using accelerometers worn on the waist or thigh[4-6]. However, VM characteristics vary significantly depending on sensor placement. Wrist-worn sensors, in particular, are susceptible to variation in arm swing and inter-individual differences, potentially capturing movements not directly related to propulsion during walking, and thereby reducing prediction accuracy[7,8]. To address these limitations, some studies have proposed models incorporating multiple sensor placements or additional physiological indices such as heart rate[9,10]. However, these approaches often require multiple devices and complex data processing, limiting their practicality for clinical and daily use.

Therefore, a more practical approach may lie in identifying sensor placements that offer both predictive accuracy and simplicity. The ankle, which more directly reflects locomotor activity, has been suggested as a promising site for measuring walking-related acceleration. Yet, few studies have systematically compared the contributions of upper and lower limb accelerometry to VO_2 estimation.

This study aimed to develop regression models for estimating oxygen consumption during walking using accelerometer-derived VM data from both the upper and lower limbs, along with walking velocity, and to identify a simplified model that balances accuracy and ease of implementation.

Materials and Methods

Participants

Eighteen healthy adults with regular exercise habits (nine men and nine women, aged 20–50 years) were recruited. Written informed consent was obtained from all participants. The study was approved by the Ethics Committee of Kyoto Tanabe Memorial Hospital (Approval No.: RBMR-220414) and conducted in accordance with the principles of the Declaration of Helsinki.

Protocol

Each participant performed treadmill walking at four different speeds: 3, 4, 5, and 6 $km \cdot h^{-1}$ (up to 5.5 $km \cdot h^{-1}$ for women). Each walking trial lasted 3 min, with data from the final min used for analysis.

Devices

Physical activity was measured using triaxial accelerometers (ActiGraph GT3X, ActiGraph LLC, USA), attached with Velcro straps to both wrists and both ankles (four sites). VO_2 was measured in real time using a portable breath-by-breath gas analyzer (Aeromonitor AE-310S, Minato Medical Science, Japan). The average VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) over the final min of each walking condition was calculated.

Signal Processing

Raw acceleration data (30 Hz) were processed using ActiLife software (ver. 6.13.4, ActiGraph LLC). VM was calculated after applying a normal filter (0.25–2.5 Hz) using the following formula[11] :

$$VM = \sqrt{(X^2 + Y^2 + Z^2)}$$

The resulting counts are dimensionless values derived from ActiGraph's proprietary algorithm and are widely used as indicators of physical activity intensity[4)]. In this study, the sum of VM from the right and left ankles was defined as FootVM, and the sum from both wrists as HandVM, expressed in counts$\cdot 10^{-1}$ s.

Model Construction

We aimed to develop a simple and accurate regression model to estimate VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) based on accelerometer data. First, a comprehensive full model (Model 3) was developed using both upper and lower limb accelerometry data plus walking velocity, and the contribution and predictive performance of each variable were assessed.

The following four regression models were constructed and compared for predictive accuracy:

1. Model 0: $VO_2 \sim$ velocity (univariable model using velocity only)
2. Model 1: $VO_2 \sim$ FootVM (univariable model using FootVM only)
3. Model 2: $VO_2 \sim$ FootVM + velocity (two-variable model)
4. Model 3: $VO_2 \sim$ FootVM + velocity + HandVM (three-variable full model)

Here, velocity was treated as a continuous variable representing the treadmill walking speed ($km \cdot h^{-1}$) under each condition.

Statistical Analysis

Descriptive statistics (mean ± standard deviation) for participant characteristics (age, height, body mass) were calculated separately for each sex. Between-group comparisons were performed using independent two-sample *t*-tests.

Model performance was evaluated using the coefficient of determination (R^2), standard error of estimate (SEE), Akaike Information Criterion (AIC), and standardized regression coefficients (βstd). A model improvement was considered meaningful when $\Delta AIC \leq -2$. To assess multicollinearity among explanatory variables, the variance inflation factor (VIF) was calculated, with VIF < 5 considered acceptable.

To assess generalizability, subject-stratified five-fold cross-validation was performed, and the mean SEE was calculated. Agreement between predicted and measured VO_2 values was also evaluated using Bland–Altman analysis. All statistical analyses were conducted using R (ver. 4.4.0) and EZR (ver. 1.52, Saitama Medical Center, Jichi Medical University)[12]. A significance level of $p < 0.05$ was adopted.

Results

Participant Characteristics

Overall, 18 healthy adults (nine men, nine women; mean age 34.7 ± 8.3 years) participated in the study. The mean height was 173.8 ± 2.5 cm for men and 158.8 ± 6.1 cm for women. Significant sex differences were observed in both height and body mass (both $p < 0.05$; Table 1).

Changes in Oxygen Consumption and Ankle Vector Magnitude by Speed

Both VO_2 and FootVM increased progressively with walking speed conditions (very slow, slow, middle, high), indicating a speed-dependent response load (Table 2). VO_2 rose from 9.51 ± 0.84 $ml \cdot kg^{-1} \cdot min^{-1}$ in the very slow-speed group to 16.29 ± 1.78 $ml \cdot kg^{-1} \cdot min^{-1}$ in the high-speed group. Similarly, FootVM increased from 8,344.76 ± 1,137.64 counts·10^{-1} s to 16,843.69 ± 2,945.44 counts·10^{-1} s.

Model Development and Comparison

FootVM was significantly and positively correlated with VO_2 ($r = 0.681$, $p < 0.001$; Figure 1). To comprehensively capture physical movement, a three-variable model (Model 3) including FootVM, walking velocity, and HandVM was first constructed. Model performance (Table 3) was as follows:

- **Model 0** (velocity only): $R^2 = 0.786$, SEE = 1.34
- **Model 1** (FootVM only): $R^2 = 0.464$, SEE = 2.10
- **Model 2** (FootVM + velocity): $R^2 = 0.810$, SEE = 1.25, improved AIC (ΔAIC = −124.9)
- **Model 3** (FootVM + velocity + HandVM): $R^2 = 0.815$, SEE = 1.24. However, βstd for HandVM was −0.06 ($p \geq 0.05$), indicating minimal contribution. The AIC worsened compared with that of Model 2 (+18.4).

These findings suggest that upper limb acceleration (HandVM) does not significantly enhance the prediction of VO_2, and that Model 2 (FootVM + velocity) offers the most practical and accurate estimation.

In Model 2, the VIFs for FootVM and velocity were both 1.56, indicating no multicollinearity concerns. An extended model including an interaction term between FootVM and velocity was also tested, but the addition of the interaction ($\beta = 0.00013$, p

< 0.001) did not improve model performance, and the AIC increased by +13.2.

The final selected model, Model 2, was as follows (Table 4):

$$\mathbf{VO_2\ (ml \cdot kg^{-1} \cdot min^{-1}) = 1.563 + 0.00010 \times FootVM\ (counts \cdot 10^{-1}\ s) + 2.15 \times velocity\ (km \cdot h^{-1})}$$

This model achieved an R^2 of 0.810 and SEE of 1.25 $ml \cdot kg^{-1} \cdot min^{-1}$, meeting the practical accuracy criterion of within ±1 metabolic equivalent of task (MET; 3.5 $ml \cdot kg^{-1} \cdot min^{-1}$).

In both Models 2 and 3, βstd for FootVM were negative (−0.877 and −0.764, respectively), likely reflecting multicollinearity, where most of the explained variance was absorbed by velocity. Indeed, the VIF for FootVM in Model 3 was slightly elevated at 5.29.

However, in Model 1 (FootVM only), βstd was +1.964, showing a strong positive contribution, indicating that FootVM remains a valuable independent predictor of VO_2.

Linear Mixed-Effects Model and Cross-Validation

To account for inter-individual variability, a linear mixed-effects model was constructed using FootVM and velocity as fixed effects and participant identity document as a random effect. Both variables remained statistically significant predictors (FootVM: β = 0.00010, $p < 0.001$; velocity: β = 2.15, $p < 0.001$).

In subject-stratified five-fold cross-validation, the mean SEE was 1.32 ± 0.50 $ml \cdot kg^{-1} \cdot min^{-1}$, indicating no signs of overfitting and confirming the model's generalizability.

Bland–Altman Analysis

A Bland–Altman plot was created to compare measured and predicted VO_2 values, showing a mean bias of 0.00 $ml \cdot kg^{-1} \cdot min^{-1}$, with 95% limits of agreement (LoA) ranging from −2.46 to +2.46 $ml \cdot kg^{-1} \cdot min^{-1}$(Figure 2). However, since this analysis was conducted using the same dataset for both model development and evaluation, further validation using independent datasets is warranted.

Comparison Between Predicted and Measured Oxygen Consumption

A scatter plot was created to compare predicted and measured VO_2 values, with data points color-coded by speed category, showing that most points were distributed closely along the identity line (y = x). The overall coefficient of determination was $R^2 = 0.807$, indicating high agreement (Figure 3).

Discussion

In this preliminary study, we developed models to estimate VO_2 during walking using accelerations of the upper and lower limbs along with walking velocity, and statistically evaluated each variable's contribution. A key feature of this study is the structured model development process, beginning with a comprehensive full model including upper limb acceleration (HandVM; Model 3), and then rationally simplifying it to a two-variable model (Model 2) consisting of only lower limb acceleration (FootVM) and walking velocity. This simplification was not arbitrary; rather, it was based on quantitative evidence showing the limited contribution of HandVM to VO_2 estimation.

FootVM alone showed a moderate correlation with VO_2 ($R^2 = 0.464$), but the addition of walking velocity improved the model considerably (Model 2: $R^2 = 0.810$, SEE = 1.25 $ml \cdot kg^{-1} \cdot min^{-1}$). Model 3, which included HandVM, slightly improved the fit ($R^2 = 0.815$, SEE = 1.24); however, βstd for HandVM was −0.06 ($p \geq 0.05$), and the AIC was 18.4 points worse than that of Model 2. These findings suggest that HandVM does not significantly contribute to VO_2 prediction.

Model 2, consisting only of FootVM and velocity, achieved a practical balance between accuracy and simplicity, reducing the burden of both sensor placement and data processing. Prior studies have also pointed out that sensor location affects model accuracy. In particular, wrist acceleration is more prone to variability owing to non-periodic and individual-specific movements, making it less stable for VO_2 estimation [10,13]. The current results support these previous observations.

Model 2 performance was comparable with that of conventional hip-worn models. For example, Freedson et al.[4] reported $R^2 = 0.82$ and SEE = 1.40 kcal·min^{-1}, and Nichols et al.[5] reported $R^2 = 0.68$ and SEE = 2.5 ml·kg^{-1}·min^{-1}. In contrast, our Model 2 achieved $R^2 = 0.81$ and SEE = 1.25 ml·kg^{-1}·min^{-1}, using only FootVM and walking velocity, thus demonstrating equal or superior predictive accuracy with a more minimalistic setup (Table 5). Additionally, ankle-mounted sensors are less prone to displacement than are waist-mounted ones, making them potentially more suitable for use in clinical and home settings[14].

Bland–Altman analysis revealed a mean bias of 0.00 ml·kg^{-1}·min^{-1} and LoA of ±2.46 ml·kg^{-1}·min^{-1}, well within the 1 MET threshold (3.5 ml·kg^{-1}·min^{-1}), indicating the model's practical utility for physical activity monitoring and exercise prescription.

However, since this study was conducted under controlled treadmill conditions, its generalizability to free-living environments remains untested. Barnett et al.[9] reported that treadmill-based models can overestimate VO_2 by +4.99 $ml \cdot kg^{-1} \cdot min^{-1}$ in free-living conditions, highlighting how environmental differences can affect model accuracy. Further validation in diverse settings and populations is therefore essential to enhance the model’s applicability.

Collectively, the final model using FootVM and velocity is a statistically validated, simplified, and highly accurate estimator of VO_2, with promising potential for clinical and real-world applications.

Limitations

This study has some limitations. First, regarding the participant characteristics, the sample was limited to young to middle-aged healthy adults with exercise habits. The model's applicability to older adults or individuals with gait impairments remains unverified. Second, the study was conducted in a controlled environment, and all data were collected on a treadmill. The accuracy of the model in free-living conditions has not been evaluated. Previous studies have shown that models developed in laboratory settings tend to overestimate VO_2 in free-living contexts[9], which remains a challenge for real-world application. Third, the sensor placement: only sensors attached to the wrists and ankles were investigated in this study. Comparison with hip- or trunk-mounted sensors, which are commonly used in prior studies, was not conducted and warrants future investigation. Fourth, the model, which was intentionally kept simple, using only two predictors, FootVM and velocity, does not account for individual biomechanical differences such as height, body mass, or muscle strength, which may also influence VO_2. Lastly, the sample size: while cross-validation using the leave-one-subject-out method confirmed acceptable generalizability, the sample size (n = 18) was relatively small. Future studies should include larger and more diverse populations to evaluate external validity.

Conclusions

In this study, we initially developed a full model incorporating upper limb acceleration and quantitatively evaluated the contribution of each variable. Based on these analyses, we rationally derived a simplified two-variable model (Model 2) consisting of FootVM and walking velocity. This model demonstrated high predictive accuracy for VO_2 (R^2 =

0.810, SEE = 1.25 $ml \cdot kg^{-1} \cdot min^{-1}$), achieving a practical level of precision within the acceptable error range of less than 1 MET.

Notably, the addition of upper limb data did not lead to a significant improvement in prediction accuracy, indicating that the proposed model offers excellent wearability, simplicity, and reproducibility. These characteristics make it highly applicable in real-world settings. Future studies should explore its generalizability and feasibility in free-living environments and among clinical populations.

Acknowledgments

We sincerely appreciate the invaluable support and cooperation of the rehabilitation staff at Kyoto Tanabe Memorial Hospital in conducting this study. We would also like to express our gratitude to Mitsuko Nakata, Ph.D., for her valuable statistical advice. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Contributions

RN conceived and designed the study, conducted the experiments, analyzed the data, interpreted the results, and wrote the manuscript. TI contributed to the study conception and design, provided guidance on data interpretation, and gave critical advice on data analysis and manuscript preparation. KO, HK, RI, and TH contributed to the execution of the study. SO and YM provided critical comments and advice on manuscript preparation. All authors reviewed and approved the final version of the manuscript.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Figure Legends

Figure 1. Relationship between FootVM and oxygen consumption per body mass (ml·kg^{-1}·min^{-1}). Each point represents one trial. A significant positive correlation was observed (r = 0.681, *p* < 0.001). VO_2, oxygen consumption; FootVM, vector magnitude of both ankles.

Figure 2. Bland–Altman plot showing the agreement between measured and predicted VO_2 (ml·kg^{-1}·min^{-1}). The solid line represents the mean difference (bias), and the dotted lines indicate the limits of agreement (mean ± 1.96 standard deviation). VO_2, oxygen consumption.

Figure 3. Scatter plot of predicted and observed VO_2 (ml·kg^{-1}·min^{-1}) during treadmill walking. The dashed line represents the line of identity (y = x). Each marker indicates a different walking speed category: + (very slow), ▲ (slow), × (middle), ● (high). VO_2, oxygen consumption.

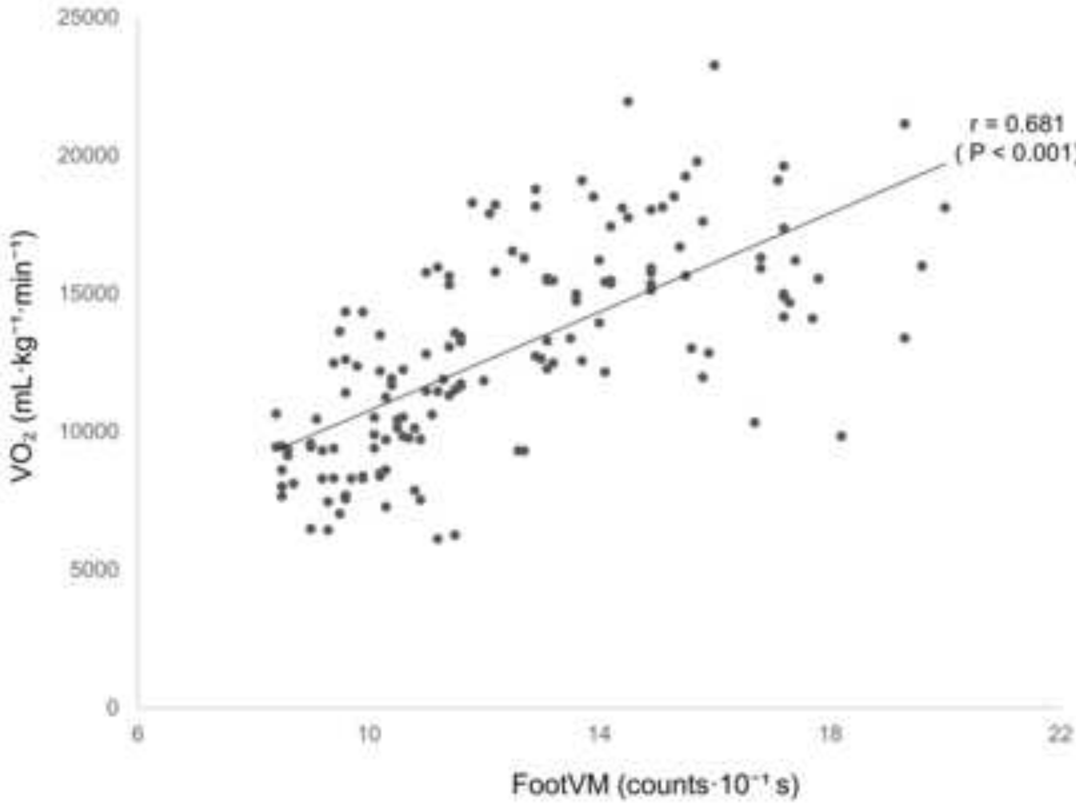
25000
20000
15000
10000
5000
0
6
10
14
18
22
VO2 (mL·kg⁻¹·min⁻¹)
FootVM (counts·10⁻¹ s)
r = 0.681
(P < 0.001)

Figure2

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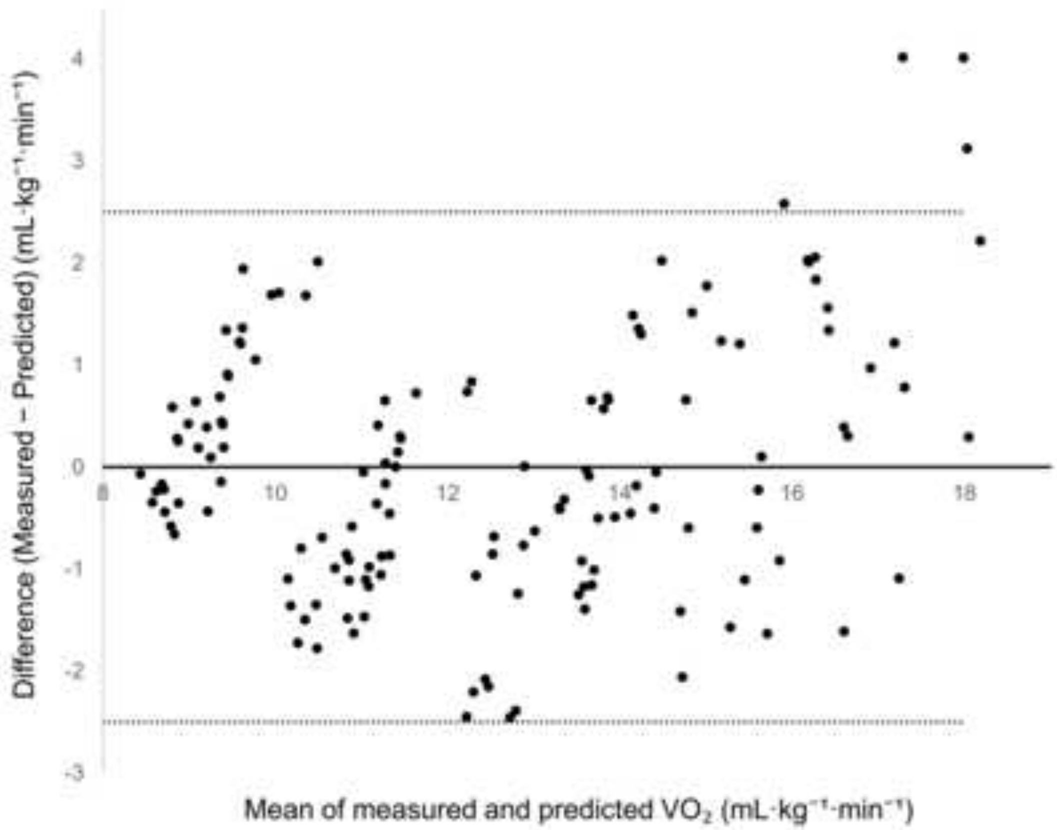

Figure3

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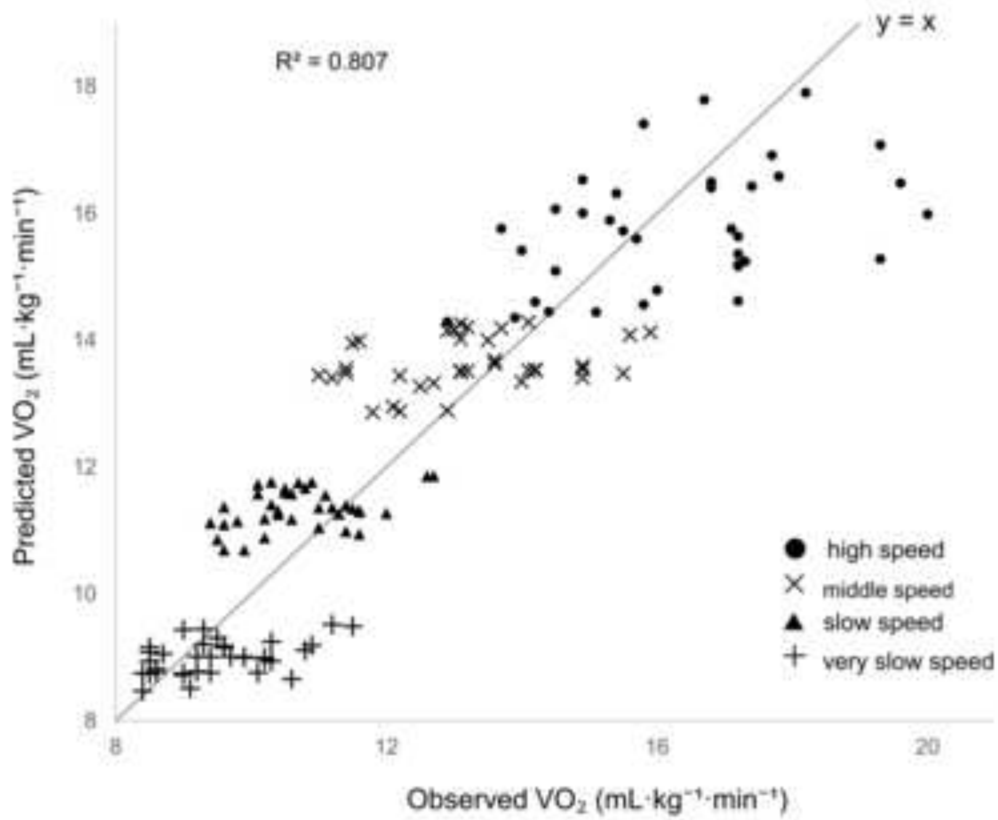

Table 1. Participant characteristics

	All (n = 18)	**Males (n = 9)**	**Females (n = 9)**	**P-value (Male vs Female)**
Age (years)	34.7 ± 8.3	33.6 ± 7.7	35.8 ± 8.7	0.51
Height (cm)	166.3 ± 8.8	173.8 ± 2.5	158.8 ± 6.1	< 0.05
Weight (kg)	61.3 ± 10.5	66.7 ± 9.8	55.9 ± 8.0	< 0.05

P-value: Two-sample t-test

Table 2. Changes in VO_2 per body mass and FootVM at each speed

Speed	**VO_2 (ml·kg^{-1}·min^{-1})**	**FootVM (counts·10^{-1} s)**
Very slow	9.51 ± 0.84	8344.76 ± 1137.64
Slow	10.72 ± 0.83	11558.88 ± 1369.06
Middle	13.22 ± 1.30	14975.10 ± 1752.17
High	16.29 ± 1.78	16843.69 ± 2945.44

FootVM: Vector magnitude of acceleration counts summed over 10 seconds, measured at both ankles; VO_2: Oxygen consumption.

Table 3. Comparison of regression models

Model	**Explanatory Variables**	**R^2**	**SEE ($ml \cdot kg^{-1} \cdot min^{-1}$)**	**ΔAIC (vs Model 1)**	**βstd**
Model 0	velocity	0.786	1.34	–72.3	velocity: +2.556
Model 1	FootVM	0.464	2.1	0 (border)	FootVM: +1.964
Model 2	FootVM + velocity	0.81	1.25	–124.9	FootVM: -0.877 velocity: +3.309
Model 3	FootVM + velocity + HandVM	0.815	1.24	18.4	FootVM: -0.764 velocity: +3.330 HandVM: -0.162 (ns)

ns: not significant ($P \geq 0.05$). SEE: Standard Error of Estimate; βstd: Standardized Regression Coefficients; ΔAIC: Improvement in Akaike Information Criterion

Table 4. Regression equation of the final model (Model 2)

Variable	***βstd***	**SEE**	**95% Confidence Interval**	**P-value**
intercept	1.563	0.4	0.76–2.36	<0.001
FootVM	0.0001	0.00002	0.00006–0.00014	<0.001
velocity	2.15	0.12	1.91–2.39	<0.001

SEE: Standard Error of Estimate; βstd: Standardized Regression Coefficients

Table 5. Comparison of model performance across previous studies and the present study

Study	**Device Location**	**Environment**	**R^2**	**SEE**
Freedson et al., 1998	Hip	Treadmill	0.82	1.40 $kcal{\cdot}min^{-1}$
Nichols et al., 2000	Hip	Treadmill	0.68	2.5 $ml{\cdot}kg^{-1}{\cdot}min^{-1}$
This study (Model 2)	Ankle + velocity	Treadmill	0.81	1.25 $ml{\cdot}kg^{-1}{\cdot}min^{-1}$

SEE: Standard Error of Estimate