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**Research article**

# Validation of the MyWellness Key in walking and running speeds

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**Abstract**
This study was performed to assess the validity of the MyWellness Key (MWK) accelerometer during a treadmill-based protocol. The identification of different exercise intensities is imperative to objectively measure time spent at a specified exercise intensity. Thirty subjects, 15 men and 15 women (age = 24.5 ± 2.6 years; body mass index = 22.5 ± 2.5 kg·m$^{-1}$), participated in a 4-phase treadmill protocol (5 minutes each one) using three different walking velocities (3, 4.5, and 6 km·h$^{-1}$) and run (8 km·h$^{-1}$) while outfitted with a MWK uniaxial accelerometer. Oxygen consumption was measured by indirect calorimetry ($IC_{VO2}$). Results: The relationship between $VO_2$ predicted from MWK ($MWK_{VO2}$) and oxygen consumption ($VO_2$ ($IC_{VO2}$)), yielded a high and significant correlation ($r = 0.944$; $p < 0.001$) with standard error of estimate (SEE) = 2.42 mL·kg$^{-1}$·min$^{-1}$. The average differences between the two methods ($MWK_{VO2}$ - $IC_{VO2}$) were -0.79 (-8.8% at 3 km·h$^{-1}$), -0.02 (-0.2% at 4.5 km·h$^{-1}$), 0.51 (3.3% at 6 km·h$^{-1}$) and -0.74 (-2.7% at 8 km·h$^{-1}$) ml·kg$^{-1}$·min$^{-1}$. Only the 3 km·h$^{-1}$ speed showed a difference when compared to the criterion measure ($p < 0.001$). Bland and Altman analysis revealed less than a 1 MET difference in the mean at each point estimate and relatively tight distribution with the standard errors, especially with the 2 moderate walking speeds. Conclusions: We found a high correlation between oxygen utilization and the MWK with low standard errors estimates. This indicates that this accelerometer can be used to identify exercise intensities that are related to walking and running.

**Key words:** Accelerometry, Indirect Calorimetry, Measurement, Physical Activity

## Introduction

Accelerometers are recognized as a valid and objective tool for assessing free-living physical activity (Chen and Bassett, 2005). They are particularly useful in the research setting since they can be used to measure the intensity, frequency, duration, and total volume of physical activity (Schutz et al., 2001). Since self-report measures are known to typically over-estimate the volume of physical activity (Walsh et al., 2004), devices such pedometers and accelerometers are useful to objectively evaluate the effectiveness of behavioral interventions designed to promote physical activity (Welk et al., 2000). In the past two decades, numerous studies have assessed the validity and reliability of different monitors (Abel et al., 2008; Balogun et al., 1989; Bassett et al., 2000; Brage et al., 2003; King et al., 2004; Kumahara et al., 2004; Pambianco et al., 1990; Swartz et al., 2000), which were used to validate measurements of physical activity from pediatric (Janz, 1994; Maliszewski et al., 1991; Ott et al., 2000) through elderly populations (Hooker et al., 2011).

Recent technological advances have made these devices less expensive and easier to use in field settings by decreasing dimensions and improving the capabilities to analyze data within specific software. The raw outputs of accelerometers are known as counts, which are described in the review by Chen and Bassett (2005). Some studies have focused on interpreting the counts by providing cut points that correspond to light-, moderate-, and vigorous-intensity physical activity (Bornstein et al., 2011; Freedson et al., 2005; Hendelman et al., 2000), normally expressed as MET multiples. This seems to be the popular way in which to interpret the counts into the various intensities of physical activity before more advanced methods become available.

However, accelerometers are not without a number of limitations represented by the fact that some activities cannot be detected (e.g. arm exercises, walking with a load or up/downhill) and the validity of the measurement relies on the accelerometer positioning (e.g. pocket, wrist, various waistband positions). Indeed, it seems that accelerometers cannot accurately predict the energy cost of uphill or downhill walking (Terrier et al., 2001). Optimum data-processing algorithms are needed for different populations, and sensor placement has been found to be an important component to obtain valid data (Chen and Bassett, 2005). Moreover, further limitations may include the cost of the devices and staff time to process and analyze data (Murphy, 2009). Researchers and consumers alike must recognize these limitations, but also must realize that accelerometers are an easy way to get objective data from our most common modalities of movement: walking.

A new piezoelectric uniaxial accelerometer named '*MyWellness Key*' (MWK) (Technogym, Gambettola, IT) was recently introduced in the market. New advances related with this device are the capability of interfacing with Technogym aerobic and resistance training equipment, recording up to 30 days of physical activity, the possibility of downloading collected data on a dedicated web-portal, and the option of visualizing directly on the device screen a given number of parameters: calories, minutes spent at light, moderate and vigorous intensities, and the total volume of physical activity. Moreover, MWK expresses the volume of accumulated physical activity with a simple user-friendly unit (MOVE), which derives from a conversion of counts through a proprietary algorithm.

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Concurrent validity of the MWK versus subjective and other objective physical activity measures was previously investigated elsewhere (Herrmann et al., 2011). Therefore, the aim of this study is to perform a criterion validity assessment of the MWK versus indirect calorimetry during walking and light running.

## Methods

### Participants

Thirty adults, 15 men (24.9 ± 3.0 yr.) and 15 women (24.2 ± 2.2 yr.) were recruited among University students. The research protocol was performed in the Sports Medicine Division at the University of Padova, Italy. Eligibility criteria included the following: age between 18 and 35 years old, body mass index (BMI) between 18.5 to 29.9 kg•m$^{-2}$, and no other health problems and or any physical limitations that could affect the study results. Information on the purpose and procedures of the study were given to each subject, and written consent was obtained before participation. The study complied with the current laws of Italy for research on human participants and was examined and approved by the local review board.

### Measurement instruments

Each participant was outfitted with a MWK device attached at the midline of the right anterior hip, as suggested by the manufacturer. The MWK expresses the volume of accumulated physical activity with a simple user-friendly unit named ‘*move*’. Acceleration (which is measured between a magnitude of 0.06g to 12g) is sampled at a frequency of 16 Hz, converted into ‘*counts*’, and finally transformed into ‘*move*’ by a specific proprietary algorithm. A detailed description of the MyWellness Key can be found elsewhere (Herrmann et al., 2011). The MWK was set to collect data at 16 Hz using epoch output for every second. Weight was measured using a BWB-800 AS scale (Tanita, Arlington Heights, IL), and height with a HR-200 stadiometer (Tanita, Arlington Heights, IL). Bioimpedance was performed by Bia/STA 101 (Akern, Firenze, IT); measurements were obtained in a resting condition: whole body impedance was measured by pre-gelled electrodes (Red Dot, 3M, Neuss, GER) on right limbs following the standard tetrapolar method described elsewhere (Sun et al., 2003). Body composition analyses were made by manufacturer software (Bodygram, Version 1.2, Akern, Firenze, IT). Oxygen uptake was determined using a gas analysis system (CSD/Net System 2001, Medical Graphics Corporation, St. Paul, MN). The gas analysis system was calibrated before each test using precisely determined reference gases and a 3-liter syringe (Model 5530, Hans Rudolf, Kansas City, MO). Breath by breath oxygen consumption was collected in units of mL·kg$^{-1}$·min$^{-1}$ by the gas analysis equipment and used as the criterion measure for exercise intensity ($IC_{VO2}$). Data included in the statistical analysis were the average amount of oxygen consumption during the final 2 minutes of each exercise phase.

### Procedure

Each subject was required to wear the mask for the gas analysis and an elastic belt at the waist to place the MWK. Participants were then instructed to walk on a treadmill (T-2100, GE Healthcare, Freiburg, GER) at 0% incline. The protocol included 4 exercise phases and started after 10 minutes of warm-up at the average speed of 3.9 km•h$^{-1}$. Each phase lasted 5 minutes, which consisted of speeds of 3, 4.5, 6, and 8 km·h$^{-1}$. The start time of the treadmill was synchronized with the start of the gas analyzer and the MWK.

### Data reduction and statistical analysis

### Accelerometry

MWK was set in ‘*epoch mode*’ through dedicated software provided by Technogym (Gambettola, IT). At the end of each test, data were exported from the device into software for the conversion from “*counts*” to $VO_2$ ($MWK_{VO2}$) expressed in ml·kg$^{-1}$·min$^{-1}$, using an equation (firmware equation version 719) provided by the manufacturer. Data considered for the statistical analysis was the average estimated $VO_2$ detected from the MWK in the last 2 minutes of each exercise phase.

### Statistical analysis

Statistical analysis was carried out using SPSS (Version 18.0 for Windows, SPSS Inc., Chicago, IL). Results were expressed as means ± standard deviation (SD). The Kolmogorov-Smirnoff (K-S) test was performed to check if data were normally distributed. Analysis of variance (ANOVA) was used to detect differences between $MWK_{VO2}$ and $IC_{VO2}$ for each speed (2 device type x 4 treadmill speed), using Bonferroni post-hoc comparison while one-way ANOVA was used to compare mean differences among the four speed steps. Significance limits were set at $p < 0.05$. Linear regression analysis was carried out to evaluate the relationship between $MWK_{VO2}$ and $IC_{VO2}$ and standard error of estimate (SEE). Additionally, Pearson Product Correlation Moment was performed between the average of the $IC_{VO2}$ and $MWK_{VO2}$ and the difference scores to determine if the MWK bias was related to the mean oxygen consumption values. Bland and Altman (Bland and Altman, 1986) plots were also created in order to test if MWK and actual $VO_2$ were comparable and therefore observe the difference between the $MWK_{VO2}$ and $IC_{VO2}$ across each exercise phase.

## Results

The characteristics (mean ± SD) of the study participants are described in Table 1. Participants were between the

**Table 1. Descriptive characteristics of the study pParticipants. Data are means (±SD).**

| | Age (years) | Weight (kg) | Height (m) | BMI (kg·m$^{-2}$) | FM (kg) | FM (%) |
|---|---|---|---|---|---|---|
| **Men (n=15)** | 24.9 (3.0) | 75.8 (8.8) | 1.79 (.07) | 23.5 (2.3) | 11.8 (6.6) | 15.1 (5.7) |
| **Female (n=15)** | 24.2 (2.2) | 57.7 (7.9) | 1.64 (.05) | 21.5 (2.4) | 13.6 (5.2) | 22.9 (6.1) |
| **Total (n=30)** | 24.5 (2.6) | 66.8 (12.3) | 1.72 (.01) | 22.5(2.5) | 12.7 (5.4) | 19.0 (7.0) |

BMI : Body mass index, FM : Fat mass

ages of 22 and 32 years, BMI ranged from normal to overweight (21.5 - 28.7 $kg \cdot m^{-2}$), and they were recreationally active. All participants concluded the exercise protocol without any interruptions. K-S analysis indicated that $VO_2$, predicted from MWK device and $VO_2$ measured with gas analysis were normally distributed.

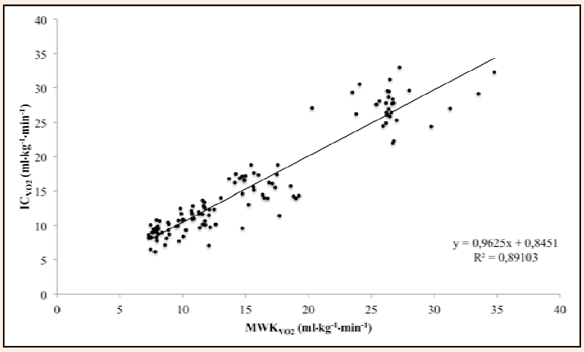


**Figure 1. Relationship between measured oxygen consumption via indirect calorimetry ($IC_{VO2}$) versus predicted oxygen consumption from the MyWellness Key ($MWK_{VO2}$) accelerometer at a range of treadmill speed in 30 male and female subjects.**

The relationship between $MWK_{VO2}$ and $IC_{VO2}$ is presented in Figure 1. The linear regression analysis yielded a statistically significant correlation ($p < 0.001$; $r = 0.944$) between the $VO_2$ predicted from MWK and the $VO_2$ measured by indirect calorimetry with SEE = 2.42 $mL \cdot kg^{-1} \cdot min^{-1}$. The general linear model which predicts the relationship in the analysis can be approximated by the following equation:

$$y = 0.9625\,x + 0.8441 \text{ with } R^2 = 0.891$$

Pearson Product Correlation Moment did not detect significant correlation between the average of the $IC_{VO2}$ and $MWK_{VO2}$ and the difference scores ($p = 0.523$; $r = -0.059$) suggesting that MWK bias was not related to oxygen consumption (Figure 2).

In the analysis, we found that values for $MWK_{VO2}$ underestimated oxygen consumption by 8.8% at the 3 $km \cdot h^{-1}$ stage ($p < 0.001$). Smaller differences were found at the 4.5 $km \cdot h^{-1}$ stage, where the means were approximately equal (-0.2%; $p = 0.94$). The analysis for the highest speed of walking (6 $km \cdot h^{-1}$) and running (8 $km \cdot h^{-1}$), did not significantly differ between the two measures ($p = 0.33$ and $p = 0.24$, respectively). However, at 6 $km \cdot h^{-1}$, the $MWK_{VO2}$ slightly overestimated the criterion measure by 3.3%, while at 8 $km \cdot h^{-1}$, it underestimated it by 2.7%. Table 2 shows the mean error associated with the $MWK_{VO2}$ and $IC_{VO2}$ during the three walking speeds and the light run. One-way ANOVAs among the means in the four treadmill velocities did not achieve statistical differences [$F$ (3, 116) = 1.946, p = 0.126] as well as in the post-hoc analysis. This implies that the errors between $MWK_{VO2}$ and $IC_{VO2}$ did not significantly change among different speeds and can be considered similar.

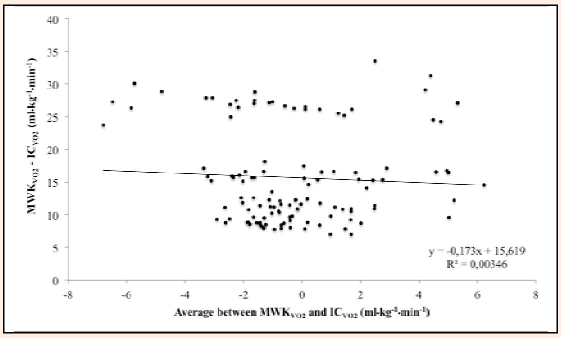


**Figure 2. Relationship between average on the predicted ($MWK_{VO2}$) and actual oxygen uptake ($IC_{VO2}$) versus difference values predicted from MyWellness Key and indirect calorimetry.**

The Bland and Altman analyses were performed to detect the error scores in MWK prediction of oxygen consumption. Separate analyses for each speed were displayed in Figures 3, 4, 5, and 6. The mean errors (average errors between point estimated) indicated deviations of -0.79, -0.02, 0.51, and -0.74 $ml \cdot kg^{-1} \cdot min^{-1}$ for 3, 4.5, 6, and 8 $km \cdot h^{-1}$, respectively from 0. The limits of agreement (difference between methods ± 1.96 x SD), for the deviations were 1.63 to -3.21 $ml \cdot kg^{-1} \cdot min^{-1}$ for 3 $km \cdot h^{-1}$, 3.26 to -3.31 for 4.5 $km \cdot h^{-1}$, 6.02 to -5.01 for 6 $km \cdot h^{-1}$, and 5.92 to -7.41 for 8 $km \cdot h^{-1}$, upper and lower limits of agreement were represented in Figures 2, 3, 4, 5 with dashed lines. The examination of the plots indicates that during walking (3, 4.5, 6 $km \cdot h^{-1}$), a tighter distribution was observed when compared with the light run (8 $km \cdot h^{-1}$). The most accurate $MWK_{VO2}$ prediction was detected at 4.5 $km \cdot h^{-1}$, while the MWK underestimated at lower and higher speeds.

## Discussion

The aim of this study was to observe how the MWK uniaxial accelerometer predicted the oxygen consumption at different walking speeds and during run under laboratory conditions. We can affirm that the MWK reasonably predicted the exercise intensity at these tested conditions.

**Table 2. Difference in oxygen consumption ($VO_2$) as estimated by the MyWellness Key (MVK) accelerometer versus indirect calorimetry by treadmill speed in 30 male and female subjects. Data are means (±SD).**

| Speed ($km \cdot h^{-1}$) | $IC_{VO2}$ ($ml \cdot kg^{-1} \cdot min^{-1}$) | $MWK_{VO2}$ ($ml \cdot kg^{-1} \cdot min^{-1}$) | Mean Error (±SD)* ($ml \cdot kg^{-1} \cdot min^{-1}$) | Upper and Lower IC ($ml \cdot kg^{-1} \cdot min^{-1}$) | Absolute error ($ml \cdot kg^{-1} \cdot min^{-1}$) | p-value |
|---|---|---|---|---|---|---|
| 3.0 | 8.95 (1.15) | 8.16 (.67) | -.79 (1.23) | \|-1.25, -.33\| | \|-2.90, 2.03\| | < .001 |
| 4.5 | 11.19 (1.47) | 11.16 (.85) | -.02 (1.67) | \|-.65, .58\| | \|-2.64, 5.03\| | = .94 |
| 6.0 | 15.53 (2.04) | 16.04 (1.65) | .51 (2.81) | \|-.54, 1.56\| | \|-3.37, 6.24\| | = .33 |
| 8.0 | 27.51 (2.59) | 26.77 (2.73) | -.74 (3.40) | \|-2.01, .53\| | \|-6.80, 5.33\| | = .24 |

$MWK_{VO2}$ = oxygen consumption predicted by the MyWellness Key accelerometer, $IC_{VO2}$ = oxygen consumption measured by indirect calorimetry, * Mean Error (± SD) = $MWK_{VO2}$ minus $IC_{VO2}$ ± standard error, IC = interval of confidence

We observed a high correlation of r = 0.944 ($p < 0.001$) between the $MWK_{VO2}$ prediction and indirect calorimetry. The average error between the point estimates of the criterion and the MWK were less than a 1 MET. This indicates that the MWK is suitable for measuring intensities in the selected range, and could be considered an instrument used for research purposes to objectively measure exercises involving walking and running.

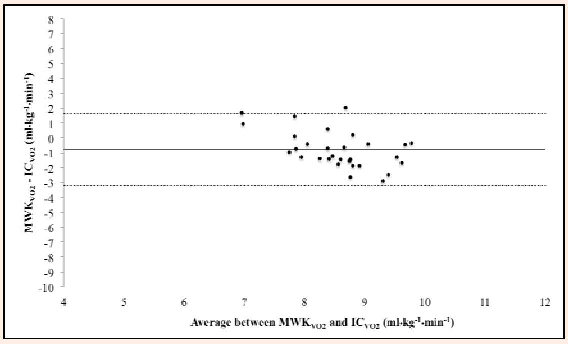


**Figure 3. Bland and Altman plot during walk at speed of 3 km·h$^{-1}$ showing differences in oxygen consumption ($VO_2$) between values predicted from MyWellness Key ($MWK_{VO2}$) and actual oxygen uptake by indirect calorimetry ($IC_{VO2}$) versus the average of predicted and actual values of $VO_2$. The solid line represents the bias (mean of the difference) and the dashed lines are at ±95% limits of agreement.**

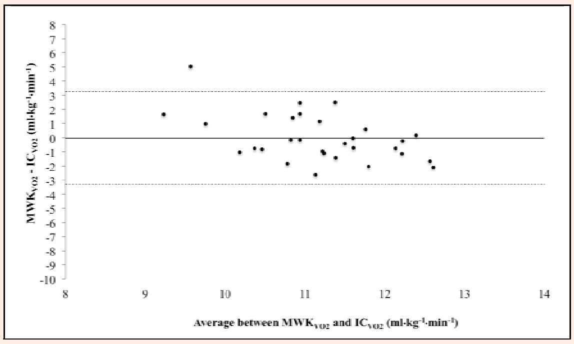


**Figure 4. Bland and Altman plot during walk at speed of 4.5 km·h$^{-1}$ showing differences in oxygen consumption ($VO_2$) between values predicted from MyWellness Key ($MWK_{VO2}$) and actual oxygen uptake by indirect calorimetry ($IC_{VO2}$) versus the average of predicted and actual values of $VO_2$. The solid line represents bias (mean of the difference) and the dashed lines are at ±95% limits of agreement.**

Numerous studies have evaluated the correlation between indirect calorimetry and energy expenditure prediction from accelerometer-based technology. The review of Chen et al. highlighted a correlation coefficient (r) that ranged from 0.52 to 0.92 in manifold activities (Chen and Bassett, 2005). The vast majority of studies were conducted on the Caltrac (Muscle Dynamics Fitness Network, Torrance, CA), the Actigraph (CSA) from Computer Science and Applications, Inc. (Shalimar, FL), the Actical (Minimatter / Respironics, Bend, OR), and the Lifecorder (Suzuken, Nagoya, JPN). With Caltrac some studies showed a good oxygen consumption prediction in walking exercise (Haymes and Byrnes, 1993; Melanson and Freedson, 1995) while others reported low correlation coefficient, highlighting a general overestimation of energy expenditure (Balogun et al., 1989; Pambianco et al., 1990). The CSA was also compared with Caltrac (Melanson and Freedson, 1995) and showed similar ranges in its validity. Other research groups have tried to improve the prediction of CSA, in particular Freedson et al. (1998). They found a relationship between counts·min$^{-1}$ and METs of r = 0.88 in 4.8, 6.4, and 9.7 km·h$^{-1}$ treadmill speeds (Nichols et al., 2000). Lifecorder was considered an effective tool for the prediction of EE during different walking velocities in the two studies (Kumahara et al., 2004). More recently, it has been demonstrated that the Lifecorder tended to underestimate energy expenditure, mainly at lower speeds in subjects with a body mass index from normal to obese (Swartz et al., 2009). The Actical monitor is different from previous devices in which it was designed with an omnidirectional accelerometer and it seemed to predicted accurately intensity in METs in both hip and wrist positions (Klippel and Heil, 2003). Crouter et al. (2006) compared the Actical with the CSA using equations from Swartz and colleagues (2000), and found similar over-estimation in the energy cost during walking. Continuing refinement of cut-points are ongoing with most models of accelerometers to better predict EE (Crouter et al., 2011).

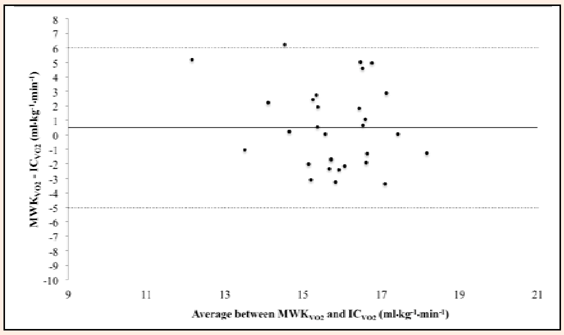


**Figure 5. Bland and Altman plot during walk at speed of 6 km·h$^{-1}$ showing differences in oxygen consumption ($VO_2$) between values predicted from MyWellness Key ($MWK_{VO2}$) and actual oxygen uptake by indirect calorimetry ($IC_{VO2}$) versus the average of predicted and actual values of $VO_2$. The solid line represents the bias (mean of the difference) and the dashed lines** are at **±95% limits of agreement.**

On the whole, comparing our findings with other studies, the oxygen consumption prediction of the MWK is aligned with the CSA (Freedson et al., 1998) and Lifecorder devices (Kumahara et al., 2004; Yokoyama et al., 2002). The MWK most accurately predicted $VO_2$ at the fastest walking speed. On the other hand, at the slowest pace of 3 km·h$^{-1}$, the MWK under-estimated $VO_2$ (-0.79 ml·kg$^{-1}$·min$^{-1}$) approximately the same as the CSA has shown (3.24 km·h$^{-1}$). In Bassett et al. (Bassett et al., 2000), it seemed that Caltrac and Kenz Select 2 monitors, worn on the hip, over-estimated the oxygen consumption during 6 km·h$^{-1}$ walking (5.29 and 2.59 ml·kg$^{-1}$·min$^{-1}$) when compared against indirect calorimetry. Also MWK, at the same speed, tended to over predict exercise intensity, however the mean difference between the $MWK_{VO2}$ and $IC_{VO2}$ was 0.51 ml·kg$^{-1}$·min$^{-1}$. During light run (8 km·h$^{-1}$), the MWK under estimated exercise intensity by 0.74 ml·kg$^{-1}$·min$^{-1}$, with a SEE slightly less than 1 MET (3.40 ml•kg$^{-1}$•min$^{-1}$). Crouter et al. (Crouter et al., 2006) compared the CSA METs estimate of their 2-regression model versus other equations during running at 9.6 km·h$^{-1}$. The 2-regression model of Crouter et al., using the Actigraph, tended to under-predict by 1.05 ml·kg$^{-1}$·min$^{-1}$ while CSA equation provided by Freedson et al. (P. S. Freedson et al., 1998) and Swartz et al. (Swartz et al., 2000) over-predicted by 1.02 and 1.79 ml·kg$^{-1}$·min$^{-1}$. Our results were based on lower running speed and MWK, compared to the criterion measure, may be more accurate at that exact speed.

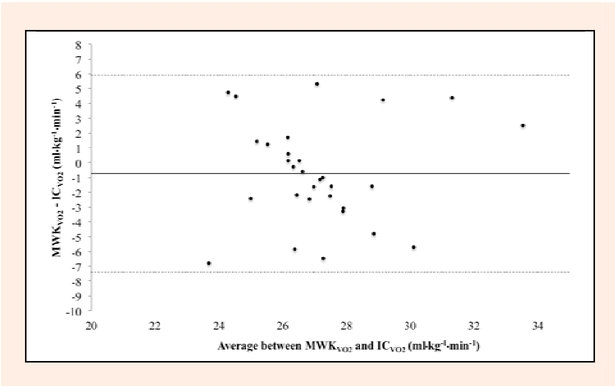


**Figure 6. Bland and Altman plot during run at speed of 8 km·h$^{-1}$ showing differences in oxygen consumption ($VO_2$) between values predicted from MyWellness Key ($MWK_{VO2}$) and actual oxygen uptake by indirect calorimetry ($IC_{VO2}$) versus the average of predicted and actual values of $VO_2$. The solid line is at the bias (mean of the difference) and the dashed lines are at ±95% limits of agreement.**

Even though the MWK underestimated $VO_2$ by 8.8% during the 3 km·h$^{-1}$ test phase, the Bland and Altman plot at 8 km·h$^{-1}$ highlighted substantial limits of agreement. This suggests that the MWK is a good device to predict oxygen consumption in activities of low and moderate intensity. Considering that MWK has been created as device to measure lifestyle physical activity and considering the comparison with other uniaxial accelerometers, the MWK showed general good validity, with excellent prediction ability during walking at moderate to high speeds.

## Study limitations

Since our results were based on a laboratory protocol, which required walking and running on a treadmill, we are unable to comment on the accuracy during field applications or in other populations. It was not the intent of this study to determine the impact of free living activity on prediction of exercise intensity (Terrier et al., 2001). Differences between field applications and laboratory testing of accelerometers have been previously examined. Other devices, such as the Actigraph, have also detected different counts between laboratory settings and field applications, especially for running speeds (Nichols et al., 2000). Other limitations for this study involve the generalizability of our findings. This study was conducted on a relatively young population with a low BMI, where the MWK was placed on the participant by a trained staff member. This correlation may not be applicable for other locations, or with individuals who have excessive weight or waist circumference. Inter-individual differences may explain variances in the data collected from the MWK and other similar devices warrant specific correlations on target populations that are under investigation.

This study involved a convenient sample that presented similar characteristics for age, body composition and lifestyle. However differences in anthropometric measures such as height, weight, or leg length were not considered. Level of training, age, sex, as well as biomechanical factors could modify the moment walk-run transition and the economy of walk and run with energy consumption *per se* (Beaupied et al., 2003; Martin and Morgan, 1992). As stressed by Nichols et al. (2000), stride length and frequency could yield marked differences in data output which would contribute to inter-individual variability. Likely, MWK with a multiple regression equation including anthropometric measures could better predict the actual $VO_2$. Future evaluation could be performed in field setting and utilize new single / multiple regression models to improve the MWK prediction of exercise intensity.

## Conclusion

There are many uniaxial accelerometers on the market that have shown to be capable of a valid measure of physical activity. This study shows that the MyWellness Key can also accurately predict exercise intensity during a treadmill protocol consisting of a range of walking and running activities for young healthy adults. This study provides validity evidence for using the MyWellness Key to assess a range of ambulatory activities in addition to the capabilities to give real-time feedback to the participant in health promotion studies. These are key features for accelerometer selection for future research interventions through which accurate representation of physical activity is paramount.

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## Key points

- First laboratory validation of a new uniaxial accelerometer, the MyWellness Key.
- Results indicate a good exercise intensity prediction during walking at moderate to high speeds.
- Comparing with other laboratory validations, MyWellness Key exercise intensity detection is aligned with other accelerometers.
- MyWellness Key can be used to give valid measurements for a range of ambulatory activity in addition to the capabilities to give real-time feedback to the participant in health promotion studies.

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