TOPICS IN EXERCISE SCIENCE AND KINESIOLOGY

Expedited Article

Is Body Composition or Body Mass Index Associated with the Step Count Accuracy of a Wearable Technology Device?

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ABSTRACT

Topics in Exercise Science and Kinesiology Volume 3: Issue 1, Article 5, 2022. A simple way to gauge daily physical activity levels is to use a wearable technology device to count the number of steps taken during the day. However, it is unknown whether these devices return accurate step counts for persons with different body fat percentages or body mass index scores. The purpose was to determine if there is a correlation between either body fat percentages and/or body mass index values and the percent error calculated between a manual step count and values recorded by a wearable technology device. Forty volunteers participated. *The Samsung Gear 2, FitBit Surge, Polar A360, Garmin Vivosmart HR+, and the Leaf Health Tracker* were evaluated when walking and jogging in free motion and treadmill conditions. All devices were worn simultaneously in randomized configurations. The mean of two manual steps counters was used as the criterion measure. Walking and jogging free motion and treadmill protocols of 5-minute intervals were completed. Correlation was determined by Spearman's rank correlation coefficient. Significance was set at <0.05. There were no significant correlations for body mass index vs percent error. For body fat, significant positive correlations were observed for the *Samsung Gear 2* free motion walk: (r=0.321, p=0.043), *Garmin Vivosmart HR+* free motion walk: (r=0.488, p=<0.001), and the *Leaf Health Tracker* treadmill walk: (r=0.368, p=0.020) and treadmill jog: (r=0.350, p=0.027). Body fat may have a limited association with a device's step count percent error. Lower body mechanics along with device placement may be more of a factor in step counting accuracy.

KEY WORDS: Wearable technology device, correlation, body composition, body mass index

INTRODUCTION

Body composition (BC) and body mass index (BMI) are physiological measurements that are used to classify persons into a general health risk category (underweight, normal, overweight, obese) based on each one's range of value (CDC, 2018; Jeukendrup & Gleeson, 2019). Both methods use an individual's body mass as the primary aspect to accomplish this classification. Research has established that persons who either lack or carry excessive body mass (usually attributed to levels of body fats) experience greater rates of physical and mental maladies that can potentially reduce a person's quality of life and/or shorten their life span (WHO, 02/16/2018). Low body mass has been linked to osteoporosis (Lim & Park, 2016), a suppressed immune response (Ritz & Gardner, 2006), increased rates of depression (de Wit, van Straten, van Herten, Penninx, & Cuijpers, 2009) and slow, curbed body growth (Reese, 2008). High body mass has been linked to an increased risk of cardiovascular disease (Lahey & Khan, 2018), rising cases of type-2 diabetes (Karr, Jackowski, Buckley, Fairman, & Sclar, 2019), an increased prevalence of hypertension (Santiago & Moreira, 2019), and osteoarthritis (Wang & He, 2018). While both use body mass as a primary aspect to classify health status or to help predict the possibility of developing a detrimental condition, the way body mass is utilized for each evaluation is different.

BC is defined the percentage of body mass that is composed of fat rather than other components such as muscle, tissue, or bone (WHO, 02/16/2018). This value can be obtained using laboratory-based systems such as hydrostatic weighing, air displacement, bioelectrical impedance, or dual x-ray absorptiometry or through field-based techniques that utilize a tape measure or skinfold calipers (Kuriyan, 2018). Regardless of the method, BC values have varied accuracy as they represent estimations derived from alternatively measured physiological or physical factors and the associated body fat percentages that are expected to be simultaneously present (Lohman & Miliken, 2019). Because male and females have different levels of body fat (usually females > males) (Schorr et al., 2018) and proportions of body fat normally increase with age due to reduced physical activity levels (St-Onge & Gallagher, 2010), both age and biological sex (not gender: WHO, 2022) play a role in BC health risk classification. The higher the BC value, the greater the risk of developing one or more detrimental health factors.

While BMI also uses body mass to help determine one's health classification, it does not directly estimate body fat percentage (Bradbury, Guo, Caims, Armstrong, & Key, 2017). Instead it uses the whole body mass to calculate a ratio score based on a person's mass and height (Brazier, 2018) using the following equation: BMI = mass (kg)/ height (m)^2 (Liguori, Dweyer, & Fitts, 2014). The higher the BMI value, the more mass that is carried by the corresponding height. Just like BC, the lower or higher the BMI value, the greater the risk of developing an ailment previously mentioned (Jakicic, Rogers, & Donnelly, 2018). Currently, BMI has no official subcategorizations accounting for age or biological sex. However, recent research has begun to evaluate adjusted health risk category parameters that take into account ethnicity (Misra & Dhurandhar, 2019) and age/biological sex (Bachmann, 2019). The advantage of using BMI rather than BC is that BMI does not require special equipment or training to utilize. Even though it is easy to determine, the current use of BMI can be deceiving. BMI uses overall body mass for its calculations. Thus, it does not account for what portion of that body mass is muscle, body fat, or body tissue. Because muscle and bone are denser than fat (Scrollseek, 2010), BMI can overestimate body fat in athletes with high bone density and muscle mass or underestimate it in older people who have low bone density and muscle mass.

For those in a higher health risk category because of elevated BC and/or BMI values, the implementation of a daily physical activity regime is highly encouraged. One of the more popular methods to accomplish this is by counting the steps taken in one day. Walking 10,000 steps a day has been shown to provide general health benefits (Tudor-Locke, Johnson, & Katzmarzyk, 2009) with 15,000 steps a day benefitting more serious metabolic conditions (Tigbe, Granat, Sattar, & Lean, 2017). The use of a wearable technology device to count daily steps has become extremely popular (Thompson, 2016). Even though it has been shown that wearable technology devices are successfully used to promote physical activity (Cheatham, Stull, Fantigrassi, & Motel, 2018; Espinoza, Chen, Orozco, Deavenport-Saman, & Yin, 2017; Kirk, Amiri, Pirbaglou, & Ritvo, 2018), the ability of many of these devices to accurately count steps has not been adequately defined. This is especially true for those that have differing BC and BMI values and are relying on these devices to facilitate a healthier lifestyle.

Previous research has provided conflicting evidence of the effect of a person's BMI on a pedometer's step counting accuracy. One study indicated that BMI had no significant main effect on a pedometer's accuracy while walking on a treadmill during three different speeds (Feito, Bassett, Thompson, & Tyo, 2012). In contrast, another study which had participants walk briskly for 400m, slow walk for 10m, and then ascend and descend a flight of stairs produced results that the absolute error of the pedometer was positively correlated with BMI (Shepherd, Toloza, McClung, & Schmalzried, 1999). The same conflicting evidence is also evident in BC's effect on a pedometer's step counting accuracy. One study that utilized 2 minute bouts of walking on a treadmill at three separate speeds gave no indication that BC affected pedometer accuracy (Duncan, Schofield, Duncan, & Hinckson, 2007). Contrary to this, another study had participants walk on a treadmill for 3 minute stages at five various speeds with some of the tested devices being less accurate as the BC increased (Crouter, Schneider, & Bassett Jr., 2005). While pedometers have been utilized for many decades, the use of currently available wearable device technology has only been utilized since approximately 2009 (Thompson, 2015, 2016). As such there are no known studies that have evaluated the effect of either BC or BMI on the measurement accuracy for these devices.

The purpose of this study was to determine if either BC and BMI has a significant correlation to the percentage errors calculated between a criterion measure (the mean of two manual counters) and the number of steps recorded by various wearable technology devices. This was carried out four conditions: free motion walking, free motion jogging, treadmill walking, and treadmill jogging. We hypothesized that there would be a significant positive relationship between BC or BMI values and the calculated percent error for each device for each condition in that when BC or BMI increased. the percent error of the device would also increase.

METHODS

Participants

Forty healthy (identified as low risk according to the ACSM pre-participation screening questionnaire) participants aged 25.09±7.17 years (twenty males and twenty females) volunteered for this investigation (descriptive characteristics are provided in **Table 1**.). Participants filled out an informed consent form that was approved by the UNLV Biomedical Institutional Review Board (#885569-3). This work was carried out fully in accordance to the ethical standards outlined in the *International Journal of Exercise Science* (Navalta, Stone, & Lyons, 2019)

Table 1. Participants characteristics. Means ± SD presented.

	Age (yrs)	Height (cm)	Mass (kg)	BC (%)	BMI
All participants N=40)	25.09±7.17	169.64±11.18	77.19±19.2	26.04±7.62	26.43±5.19

BC = Body Composition; BMI = Body Mass Index

Devices

The five wearable technology devices investigated consisted of four that are worn on the wrist: *Samsung Gear 2, FitBit Surge, Polar A360, Garmin Vivosmart HR*+, and one worn on the waist: *Leaf Health Tracker*. Immediately prior to testing, the participants age, biological sex, height, weight, and where the device was being worn were programmed into the device. The device was synchronized, and the appropriate "activity" mode, if available, was selected. The mean of two manual step counts using a hand-held tally counter (Horsky, New York, NY) was used as the criterion measurement. All devices use proprietary algorithms to determine what constitutes a step for counting purposes.

The Samsung Gear 2 (Samsung Electro-Mechanics, Seoul, South Korea) is a wrist-worn smartwatch. Sensors include an accelerometer, gyroscope, and heart rate monitor.

The Fitbit Surge (Fitbit Inc, San Francisco, CA) is a fitness super wrist-watch that utilizes GPS tracking to determine distance and pace. Sensors and components include 3-axis accelerometers, digital compass, optical heart rate monitor, altimeter, ambient light sensor, and vibration motor.

The Polar A360 (Polar Electro, Kempele, Finland) is a wrist-worn fitness tracker that has a proprietary optical heart rate module. No other specifications are given.

The Garmin Vivosmart HR+ (Garmin Ltd, Canton of Schaffhausen, Switzerland) is smart activity tracker with wrist-based heart rate as well as GPS. Sensors include a barometric altimeter and accelerometer.

The Leaf Health Tracker (Bellabeat, San Fransisco, CA): Sensors include a 3-axis accelerometer and vibration motor.

Protocol

Data for this study was completed concurrently during a collection period that has been recently published (Montes & Navalta, 2019). The protocol has been described here for the convenience of the reader. In the week prior to testing, participants provided anthropometric data. Age in years and biological sex was self-reported, height (cm) was measured with a Health-o-meter wall mounted height rod (Pelstar LLC/Health-o-meter, McCook, IL), mass (kg), Body Composition (BC) and Body Mass Index (BMI) was provided by a hand-and-foot bioelectric impedance analyzer (seca mBCA 514 Medical Body Composition Analyzer, Seca North America, Chino, CA).

On the first day of testing, participants were fitted with the *Samsung Gear 2, FitBit Surge, Polar A360, Garmin Vivosmart HR+ and Leaf Health Tracker*. They then proceeded to a long indoor hallway with cones spaced 200 feet apart. Participants sat for 5 minutes and then completed the first 5-minute self-paced free motion walk back and forth between the cones while step count was recorded by the two manual counters. After a 5-minute seated rest period, participants completed the first 5-minute self-paced free motion jog with step count again recorded by two manual counters. Participants then rested in a seated position for 10 minutes. They then performed a second self-paced 5-minute free motion walk and jog in the same manner as the first with step count recorded in the same manner. The two manual counters for all free-motion walks and jogs were positioned near the center of the testing area but were separated so they could not view each other's thumb motion nor hear the "clicking" from with the tally counter. This prevented any synchronized counting between the two. The manual counters were instructed not to follow or move with the participants to prevent influencing their walking/jogging speed. The distance traveled for both free motion walks and jogs was measured and the speed in miles per hour was calculated and rounded to the nearest 0.1.

One to two days later at approximately the same time of day (±1 hour), the participants returned for treadmill-based walking and jogging. They were fitted with all the devices in the same manner and configuration as on day two. All treadmill activities were performed on a Trackmaster treadmill (Full Vision, Inc. Newton, KS). After a 5-minute seated rest period, they completed the first 5-minute treadmill walk at the speed calculated from the first free motion walk with step count recorded by the two manual counters. Following a 5-minute seated rest period, they completed the first 5-minute treadmill jog at the speed calculated from the first free motion jog with step count again recorded by the two manual counters. Participants rested in a seated position for 10 minutes. They then performed a second 5-minute treadmill walk and jog with step count recorded in the same manner as the first treadmill activities. Speeds for the second treadmill walk and jog were calculated from the second free motion walk and jog. Speeds were replicated on the treadmill in order to normalize the distance a participant traveled in the 5-minute testing intervals for both conditions. The grade for all treadmill testing was set to 0%. The two manual counters were positioned at opposite sides of the lab in order to prevent any synchronized "clicking".

Statistical Analysis

IBM SPSS (IBM Statistics version 24.0, Armonk, NY) was used for all statistical analysis. The step count average of the two manual counters (criterion measure) and the wearable technology device step count measurements recorded during the second walk and second jog for the free motion and treadmill activities were used. The percent error was calculated by the formula: absolute value of {(device – criterion) * 100} / criterion. Three outliers of ≥ ±3 standard deviations were removed from the step count analysis (participant #7 and #14, *FitBit Surge*, free motion jog: step count was not recorded properly at the end of both said activities. Participant #37, *Samsung Gear 2*, treadmill walk: device stopped counting and had to be re-synchronized to reset step counting function for next activity). Spearman's rank correlation coefficient (r) was used to determine correlation with the p-value set at <0.05 and the (r) set at ≥ 0.70. Correlation was determined using 1) each participants BC and BMI and 2) the percent error.

RESULTS

There were no significant correlations between BMI and percent error in any environment (**Table 2.**). For BC, significant positive correlations were observed for the *Samsung Gear 2* free motion walk: (r=0.321, *p*=0.043) (**Figure 1., Table 2.**), *Garmin Vivosmart HR*+ free motion walk: (r=0.488, *p*=<0.001) (**Figure 2., Table 2.**), and the *Leaf Health Tracker* treadmill walk: (r=0.368, *p*=0.020) (**Figure 3., Table 2.**) and treadmill jog: (r=0.350, *p*=0.027) (**Figure 4., Table 2.**).

Correlation: Body Composition and Body Mass Index vs Mean Average Percent Error

Table 2. Step count correlation of body composition and body mass index vs percent error (N=40). (#) = data points removed. * = p<0.05. ** = p <0.001

	BC	BMI
Samsung Gear 2	r	r
Free Motion Walk	0.321*	-0.135
Free Motion Jog	0.064	-0.126
Treadmill Walk (1)	0.075	-0.030
Treadmill Jog	-0.110	-0.119
FitBit Surge	r	r
Free Motion Walk	0.227	-0.050
Free Motion Jog (2)	-0.007	-0.109
Treadmill Walk	0.030	-0.078
Treadmill Jog	-0.059	-0.090
Polar A360	r	r
Free Motion Walk	0.122	-0.087
Free Motion Jog	-0.038	-0.187
Treadmill Walk	0.219	-0.016
Treadmill Jog	0.149	-0.233
Garmin Vivosmart HR+	r	r
Free Motion Walk	0.488**	-0.241
Free Motion Jog	0.145	-0.124
Treadmill Walk	-0.046	-0.183
Treadmill Jog	0.245	-0.132
Leaf Health Tracker	r	r
Free Motion Walk	0.173	0.002
Free Motion Jog	-0.078	-0.097
Treadmill Walk	0.368*	-0.014
Treadmill Jog	0.350*	-0.086

BC = Body Composition; BMI = Body Mass Index

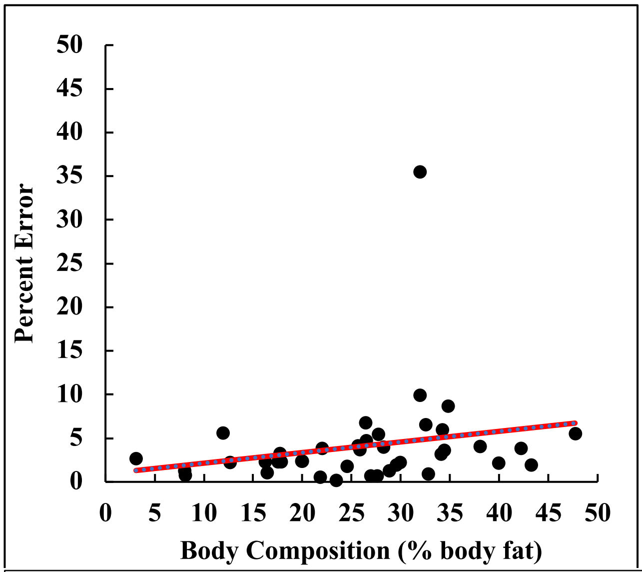

Figure 2. Garmin Vivosmart HR+ free motion walk correlation.

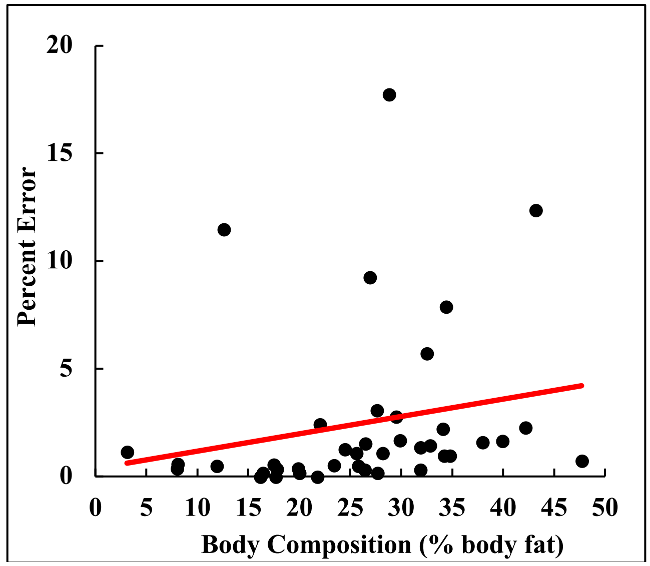

Figure 1. Samsung Gear 2 free motion walk correlation.

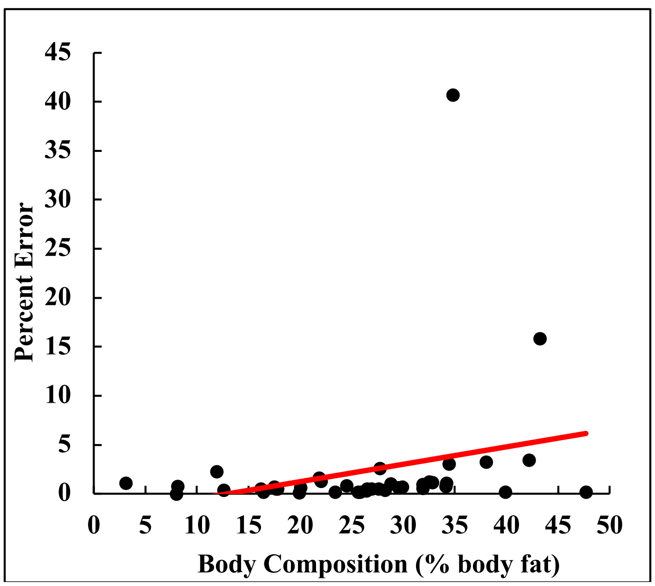

Figure 3. Leaf Health Tacker treadmill walk correlation.

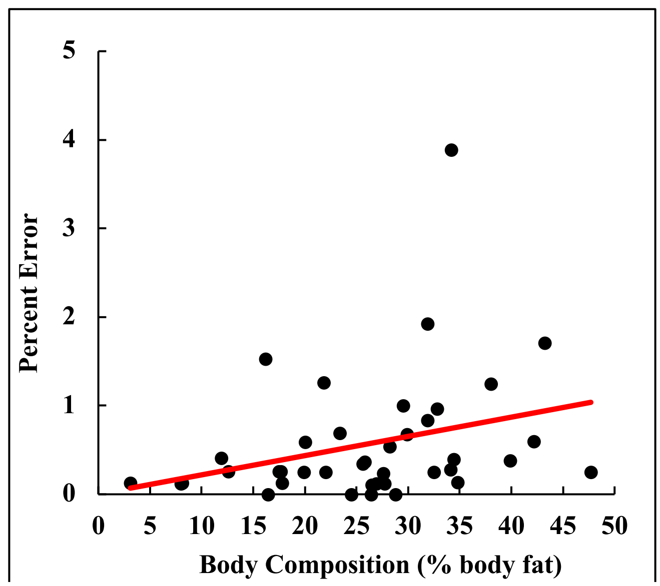

Figure 4. Leaf Health Tacker treadmill jog correlation.

DISCUSSION

The current study investigated if there was an association between a person's BC and/or BMI to a device's percent error when counting steps. Our hypothesis was that of the twenty possible combinations for each measurement using the five tested devices and four testing conditions (forty total data collections between both BC and BMI) that most of the combinations would have a significant positive relationship in that when BC or BMI increased the percent error of the device would also increase. However, only four of the forty tested combinations (all in the BC category) in our data collection were significantly correlated.

Of the two wrist worn devices to have a significant relationship (Samsung Gear 2, Garmin Vivosmart HR+) both produced a significant relationship during free motion walking. While both were positive associations, the correlations were considered poor for each (r=0.321 and r=0.488 respectively). Previous research has provided evidence that slower walking speeds increase the inaccuracy of current pedometers (Balmain et al., 2019; Melanson et al., 2004; Schneider, Crouter, & Bassett, 2004) and newer wearable technology devices (Montes, Young, Tandy, & Navalta, 2017, 2018; Tanner et al., 2016). Regarding the lower body, persons with higher BC values tend to walk at a slower gait (Berrigan, Simoneau, Tremblay, Hue, & Teasdale, 2006) and have a longer double support phase with reduced time in the leg swing phase when walking (Hills & Parker, 1991; Wearing, Hennig, Byrne, Steele, & Hills, 2006). For the upper body, higher BC has been shown to reduce the range of motion in both shoulder joint extension and adduction (Park, Ramachandran, Weisman, & Jung, 2010) and in elbow flexion and supination (Jeong, Heo, Lee, & Park, 2018). These differences in walking mechanics due to slower walking may have resulted in the positive correlations for the two devices. It is interesting to note that none of the treadmill walks for any of the devices had a significant correlation. While it could be logically assumed that walking at a similar speed for the same time interval in either the free motion or treadmill environment would elicit a similar step count by a step counting device, previous research on this comparison is very limited and not conclusive. Some research indicates that treadmill walking influences smaller step length and quicker cadence when compared to a similar free motion activity (Murray, Spurr, Sepic, Gardner, & Mollinger, 1985) while other research has concluded there is little difference in the motion mechanics between the two (Frishberg, 1983). Because we only observed a significant correlation in two of the four wrist worn devises and only in free motion walking, it would be prudent to conclude that each device's proprietary measurement mechanism and algorithm for detecting, registering, and recording what it constitutes a completed step is a primary factor in its accuracy.

The Leaf Health Tracker was the only device not worn on the wrist. It was worn on the waist on the anterior midline of the thigh. Previous research has shown that device placement on the body can affect its accuracy for step counting with waist worn devices being shown to be more accurate than those that are wrist worn for those in a normal BC range. (Simpson et al., 2015; Tudor-Locke, Barreira, & Schuna, 2015). However, growing evidence suggests that waist worn step count devices are prone to increased measurement error as a person's BC value increases (Crouter et al., 2005). First, it is possible that a large amount of abdominal adipose tissue may dampen vertical accelerations of the trunk, which could contribute to a lower step count (Shepherd et al., 1999; Tudor-Locke, Williams, Reis, & Pluto, 2002). Second, due to the corresponding increase in waist circumference or the waist-to-hip ratio for those with higher BC values, waist worn step counters worn by persons in the overweight or obese health risk category may become slanted with respect to the body's vertical plane. This tilting has been shown to create increased friction in a device's internal counting mechanism, resulting in a failure to register all steps (Duncan et al., 2007).

Our results produced relatively few significant positive correlations. More than likely, this was due to the mean BC being 26.04±7.62% and the mean BMI being 26.43±5.19. Because our participants were mostly young, healthy college students (age 25.09±7.17), very few of them could be considered as having excessively high BC or BMI values. This normal, healthy range of BC and BMI values was a study limitation as we were not able to evaluate a population in which elevated BC or BMI values would have made a noticeable overall impact. Therefore, our evaluation is only truly meaningful for this specific population during the four conditions that were tested in. The application of the results of our current investigation to other age ranges or special populations should be done with caution (Bassett, Rowlands, & Trost, 2012). In contrast to the current participants, certain populations such as the obese and the elderly (Melanson et al., 2004) will have different walking speeds, BC, and BMI values specific to that group. The testing of wearable technology devices used by these populations should be completed separately and in the normally accessed environments where use is expected to occur (Wahl, Duking, Droszez, Wahl, & Mester, 2017).

In summary, the purpose of our investigation was to perform an initial evaluation of whether BC or BMI values would correlate to the step count percent error extrapolated from a wearable technology device's recorded step count. Our results showed that for a healthy, young sample population with a normal to slightly elevated BC or BMI value, there appears to be little relationship between these two variables. The waist worn device displayed an association but only when used on a treadmill. It appears that device placement is the primary reason for any positive associations in a normal, healthy population. Future research should narrow the scope of participants to various special populations in which differencing BC/BMI values are more prevalent. This will allow for an updated assessment as to whether elevated BC/BMI values are related to wearable technology step counting accuracy.

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TOPICS IN EXERCISE SCIENCE AND KINESIOLOGY

Is Body Composition or Body Mass Index Associated with the Step Count Accuracy of a Wearable Technology Device?

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PURPOSE

It is estimated that over 2/3 of the American population is categorized as either overweight or obese with the numbers in each category growing annually. The use of wearable technology by these persons has become popular in recent years. While wearable technology has been shown to encourage persons to be more physically active, it is not clear if these devices are accurate for all populations (biological sex, fat composition, age, etc.). Because those who are overweight/obese greatly benefit from being more physically active, it is important that any metric (i.e. wearable technology) used to monitor daily movement is both consistent and accurate. This study was a preliminary look at whether persons with higher body composition (fat content) or a higher body mass index (height/weight ratio) would see a larger percent of error between actual steps taken and what was recorded by the wearable technology utilized to count said steps.

MAIN RESULTS

Our hypothesis was that there would be a significant positive correlation between higher body composition or body mass index values of the wearer and the percent error in the recorded steps. This assumption was not entirely supported as only a few combinations of devices and movements fit this assumption. However, this may be due to the fact that the body composition and body mass index values used in our analysis were not extreme in nature. While participants technically fit the overweight/obese categories criteria, they barely did so. Those with very high values may have results that differ.

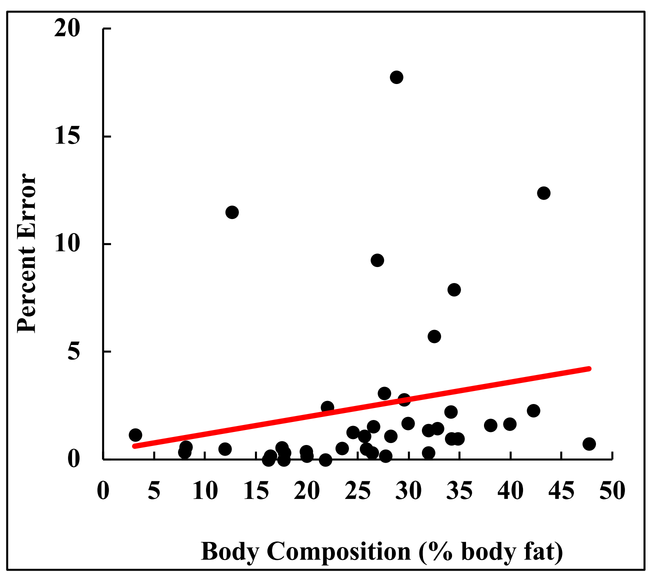

Figure. Correlation (r = 0.488) between percent body fat and step count percent error of Garmin Vivosmart HR+ during free motion walking.