ORIGINAL RESEARCH

THE ACCURACY OF VARIOUS ACTIVITY TRACKERS IN ESTIMATING STEPS TAKEN AND ENERGY EXPENDITURE

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ABSTRACT

Purpose: Activity monitors are designed for helping to monitor the quantity and intensity of exercise training. While there is a reasonable experience with step counters, there are a rapidly expanding number of devices available on the marketplace, many purporting to be able to accurately measure energy expenditure (EE). This study was designed to test the accuracy of step count and energy expenditure in several commercially available activity monitors.

Methods: Healthy, physically-active volunteers (N=20) performed treadmill walking, treadmill running, elliptical (arm + leg) exercise and an agility drill that included some basketball actions while wearing step counters/activity monitors (Jawbone UP, Nike Fuelband, Fitbit Ultra, NL-2000i, Adidas MiCoach, Body Media FIT Core). Criterion step counts were measured by direct visual observation and EE was measured by a portable metabolic system.

Results: During normal ambulation and elliptical exercise, most of the measured step counts were reasonably accurate (+10% of the criterion measure). During the agility drills, the errors in step counts were systematically less than the criterion measure. Although some of the devices were reasonably accurate for measuring EE during normal ambulation, the errors in measuring EE were, in general, unacceptably large and became larger with non-standard ambulation. However, measured across the entire range of activities, both step counts and EE were broadly accurate if not precise.

Conclusions: The results suggest that step count accuracy during normal ambulation can be measured accurately by a number of devices. However, during non-standard ambulation (particularly for measurement of EE), these contemporary activity monitoring devices require improved algorithms.

Keywords: step counting, energy expenditure, monitoring training

ISSN 2201-5655

INTRODUCTION

It is well-established that living an active lifestyle contributes to good health. The American College of Sports Medicine (ACSM) and the American Heart Association (AHA) have published guidelines [1] for physical activity. These guidelines, updated in 2007, suggest that healthy individuals should get a minimum of 30 minutes of physical activity per day, five days a week, or 20 minutes of vigorous activity per day, three days a week. The recommendations also defined moderate and vigorous levels of physical activity. Moderate activity is defined as within a metabolic equivalent (MET) range of 3.0-6.0. Vigorous activity is defined as greater than 6.0 METS. [1]

In response to the association between sedentary living and cardiovascular disease, evident since the early epidemiologic studies of cardiovascular disease, assessing and monitoring physical activity has been important over the past half century as part of broad strategies to help the public meet guidelines regarding the quantity and quality of exercise training. Monitoring exercise training has become much easier with the help of devices such as pedometers, accelerometers, and other fitness tracking technology. In 1965, Y. Hatano, a Japanese pedometer manufacturer, originated the idea that people should accumulate 10,000 steps per day. It is unknown exactly where the 10,000 step per day recommendation came from, but thanks to its' simplicity, it has become a widely-recommended goal. Tudor-Locke and Bassett [2-4] created categories of steps per day to define activity levels. They suggested that <5000 steps per day could be classified as sedentary, 5000-7499 steps per day without sports or exercise as low active, 7500-9999 steps per day as somewhat active, ≥10 000 steps as active, and >12 500 steps per day as highly active. [2]

Another aspect of evaluating physical activity is the estimation of energy expenditure. Indirect calorimetry can provide data in both laboratory and field settings, but is not practical in a free living situation. It has previously been recommended that a pedometer should not be used to measure energy expenditure due to a lack of accuracy. [5-7] Activity trackers incorporating accelerometers, Global Positioning Systems (GPS), inclinometers, and other technology have been developed to allow the generation of data representing exercise training intensity. Manufacturers of these devices claim that they are able to track activities other than just walking and running, such as stair climbing and/ or playing sports (e.g. basketball).

The accuracy of measuring energy expenditure (EE) has been shown to vary from study to study. Balogun et al. [8] found an overestimation (10-40%) of EE by accelerometers during level treadmill walking. Crouter et al. [6] found that three different accelerometers overestimated (5-40%) EE during both walking and during sedentary activities. These devices were also shown to underestimate (50-70%) steps and EE during slow (<80 $m \cdot min^{-1}$) walking and other forms of activity, such as basketball, racquetball, and fast running. GPS-based monitors have also been shown to be inaccurate, generally overestimating (10-20%) EE for walking and running. [9] Global Positioning System monitors appear to be less accurate for slow walking, but may provide more accurate results during fast walking and running. [9] King et al. [10] studied the Sensewear Armband (SP2) by BodyMedia. The SP2 uses non-invasive sensors to measure different physical parameters, such as heat flux, as well as an accelerometer. The SP2 was tested for the accuracy of measuring EE in normal activities of daily living and was shown to overestimate (20-40%) EE during sit-stand variations and walking. [10]

There are new activity trackers regularly coming onto the market. However, there appears to be very little published research on the validity of these devices. Thus, the purpose of this study was to evaluate the accuracy of five relatively new activity trackers currently on the market to estimate both step count and EE. The five activity trackers used in the present study were the Nike Fuelband, Fitbit Ultra, Jawbone UP, BodyMedia FitCore, and the Adidas MiCoach. Additionally, the NL-2000i was compared as a step counter. The activity trackers were compared to hand counted steps. Second, they were compared to measures of EE derived from indirect calorimetry. Exercise included normal ambulation (walking and running), modified reduced impact ambulation (elliptical exercise) and non-standard ambulation (and agility drill including some basketball specific movements).

METHODS

The subjects were 20 healthy volunteers (10 men and 10 women) between the ages of 18-44 years. All participants were recreationally active (2-5 hours per week of primarily aerobic activity or recreational games). None of the subjects were systematically trained athletes. Each subject completed the Physical Activity Readiness Questionnaire (PAR-Q) to confirm their ability to safely participate in physical activity. The protocol was approved by the university's human subjects committee and all participants provided written informed consent prior to participation.

There were two outcome measures for this study, steps taken and energy expenditure (EE), measured as kcal used, during each 20-minute exercise bout. Along with wearing the activity trackers as designed by the company. Because of slightly different schemes for wearing the activity trackers, the subjects could use all devices simultaneously. The subjects also wore a portable metabolic analyser (Oxycon Mobile, CareFusion GmBH, Haechberg, Germany). Each subject completed four different exercise bouts wearing all devices at the same time. The sessions consisted of treadmill walking and running, an elliptical cross-trainer using both arm and leg exercise, and a gymnasium agility-related exercise bout. The testing was conducted in two different 50-minute sessions. Treadmill walking and running were included as examples of standard ambulatory activities. Elliptical exercise was included as a low-impact exercise form performed with both arms and legs. The sports-related exercise bout was performed to evaluate the accuracy of the activity trackers during more complex ambulatory patterns, which might be relevant to ordinary daily activities. The first session included walking and running on a level treadmill. First, the participant walked at a self-selected speed for 20 minutes, had a 10-minute break then ran for 20 minutes at a self-selected pace. The second session, performed on a different day, was completed on an elliptical cross-trainer and in a gymnasium. There was a 10-minute break between the elliptical cross-trainer and gymnasium portions. The elliptical cross-trainer used was a model that used both the arms and the legs. The participants self-selected their intensity (designed to produce a RPE of 12-13 on the 20 point Borg scale and completed 20 minutes of exercise. After a 10-minute break, participants completed a session of agility-related exercises in a gymnasium. The first sports-related exercise was agility ladder drills. This consisted of seven different moves, completed twice. The ladder drill was followed by 10 basketball free throws. The second exercise was the "T Drill" and was done for 30 seconds. The T drill was followed by another 10 basketball free throws. Last, subjects performed a basketball half-court lay-up drill for one minute. The entire bout of sports-related exercises required 20 minutes to complete The 20-minute duration of each exercise mode was chosen to allow the subjects to reach a metabolic steady state and to reduce the likelihood that the subjects would 'sprint' during a short exercise bout. Energy expenditure and step count were averaged over the entire 20-minute exercise bout.

After completing each 20-minute bout of exercise, EE was recorded from each activity tracker. Steps taken were recorded from the Nike Fuelband, Jawbone UP, Fitbit Ultra, and NL-2000i. The numbers given for "calories burned" were compared to measured values using the portable metabolic analyser. The steps taken for each device were compared to the data collected from direct observation. Direct observation was conducted by hand counting steps for each subject.

Respiratory gas exchange was measured using open circuit spirometry with a portable metabolic system (Oxycon Mobile, Care Fusion, GmBH, Haechberg, Germany). The analysers were calibrated before each bout using a reference gas (16% O_2, 5% CO_2). The pneumotach was calibrated using a 3-liter syringe. Energy expenditure was calculated using measured VO_2 and the respiratory exchange ratio, averaged over the duration of each exercise bout.

Standard descriptive statistics were used to characterise the subject population. Two-way ANOVA with repeated measures were used to determine differences between activity trackers and gender for both steps and EE. When there was a significant F-ratio, pairwise comparisons were made using Tukey's post-hoc test. Alpha was set at $p<0.05$ to achieve statistical significance. Pearson Product-Moment Correlations were used to compare actual steps and actual EE to values measured by each activity tracker. The analytic strategy was 2-fold. First, each activity tracker was compared for either steps taken or EE during that specific activity versus the criterion measure. Second, the combined results of all comparisons within that activity tracker, intended to give a broader sense of the behavior of each activity tracker across a realistic range of data likely to be collected during routine use, was evaluated.

RESULTS

Descriptive characteristics of the participants in the study are presented in Table 1.

Mean (+SD) step counts recorded by the various activity trackers during treadmill walking, treadmill running, elliptical exercise, and the agility-related test were compared to the actual steps taken during each activity and are presented in Table 2. The pattern of step count measures vs criterion step counts, together with correlation coefficients for each activity tracker and activity, are presented in Figures 1-4. The pattern of step count measures vs criterion steps counts, together with correlation coefficients for combined activities, within each activity tracker and activity, are presented in Figure 5.

Table 1: Descriptive characteristics of the participants in the study (N=20).

	Males (n=10)	Females (n= 10)
Age (years)	21.5±1.35	22.5±1.27
Height (cm)	182.4±6.86	164.8±8.66
Weight (kg)	80.9±8.31	63.0±7.64

Values represent mean ± standard deviation.

During treadmill walking, the only significant difference was for the Nike Fuelband, which underestimated actual steps by 6%. During treadmill running, both the Fitbit Ultra and the NL-2000i significantly underestimated actual steps by 6% and 10%, respectively. For elliptical exercise, the only significant difference was for the NL-2000i, which under predicted actual steps by 6%. During the agility-related test all of the activity trackers underestimated actual steps except for the Jawbone UP. The underestimation was 34% for the Nike Fuelband, 20% for the Fitbit Ultra, and 17% for the NL-2000i, respectively.

For the combined activity step counts, there were smaller relative differences between the criterion step count and that recorded by the activity monitors, with the Nike Fuelband (-5%) and the NL-2000i (-7%) significantly under-predicting vs. criterion steps. The correlations between criterion and measured step counts were all very high (Figure 5).

Measured EE was compared to the EE estimated by the activity trackers during treadmill walking, treadmill running, elliptical exercise, and the sports-specific test. These results are presented in Table 3 and Figures 6-10.

During treadmill walking, the Adidas MiCoach was the only device which was significantly different from the directly measured EE. Energy expenditure was over predicted (+34%) using the Adidas MiCoach. For treadmill running, the Jawbone Up (+20%), the Nike Fuelband (+15%), and the Body Media FIT Core (-13%) were significantly different than measured EE. For elliptical exercise, the Nike Fuelband and the Body Medit FIT Core significantly underestimated measured EE expenditure by 27% and 20%, respectively. For the sports-related exercise bout, actual EE was significantly underestimated by all of the activity trackers. The underestimations were 30% for the Jawbone Up, 14% for the Nike Fuelband, 17% for the Fitbit Ultra, 60% for the Adidas MiCoach, and 18% for the Body Media FIT Core. For the combined activities within each activity monitor, only the Body Media FIT Core significantly underestimated the kcal use (Figure 10).

Table 2: Comparison of steps taken measured using hand counting compared to steps taken from the activity devices.

Device	Treadmill Walking	Treadmill Running	Elliptical	Agility
Actual	2425±177.9	3182±173.9	2631±371.5	805±51.9
Jawbone UP	2403±176.6	3186±171.5	2627±359.0	783±110.1
Nike Fuelband	2273±154.8*	3169±171.2	2580±458.7	533±70.4*
Fitbit Ultra	2425±177.2	2990±313.0*	2630±370.6	645±90.0*
NL-2000i	2425±178.0	2869±247.1*	2477±471.1*	671±106.9*

Values represent means ± standard deviation.

*Significantly different than actual steps (p<.05).

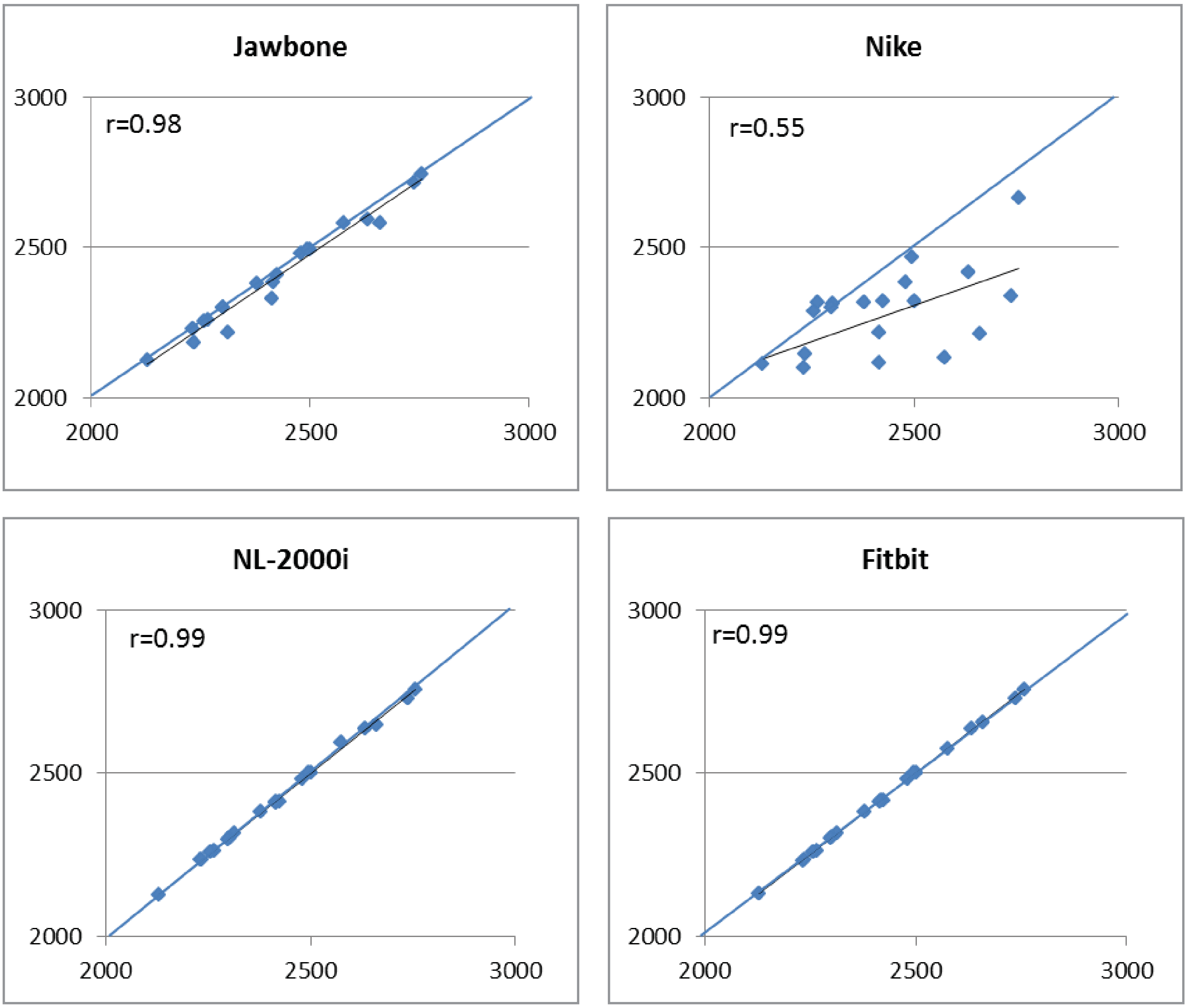


Figure 1: Treadmill Walking - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured steps with the different activity monitors during treadmill walking. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

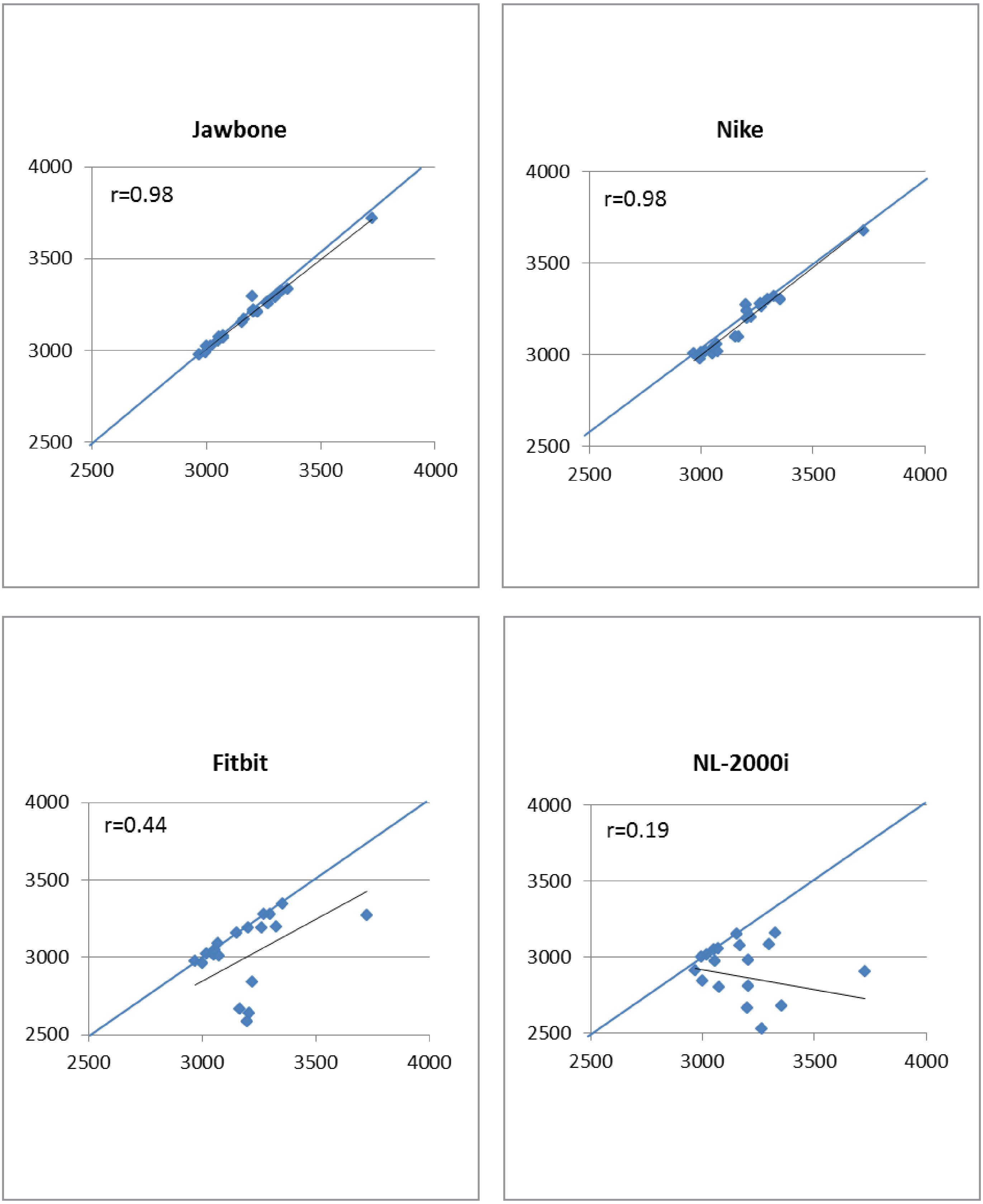


Figure 2: Treadmill Running - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured steps with the different activity monitors during treadmill running. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

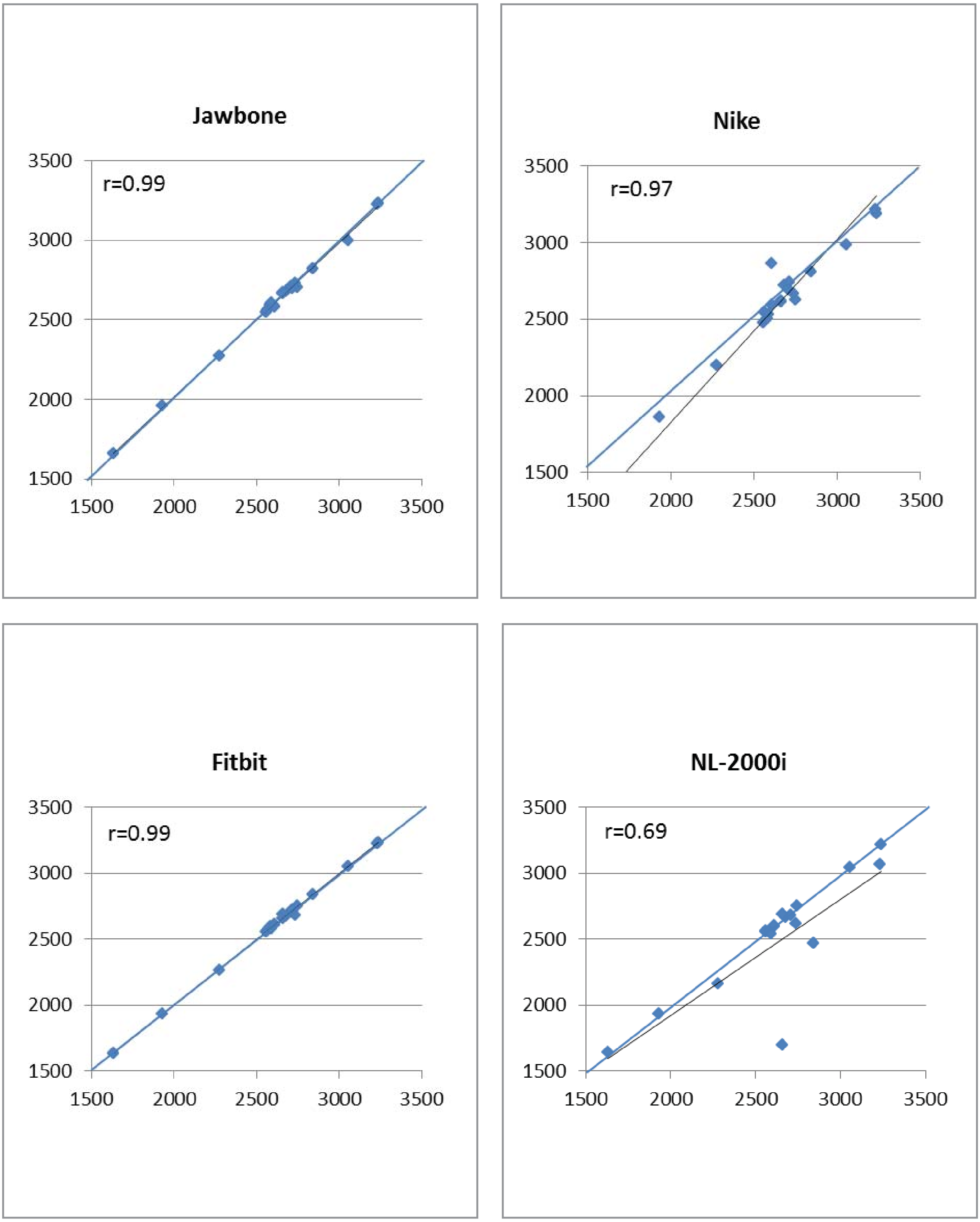


Figure 3: Elliptical Exercise - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured steps with the different activity monitors during elliptical exercise. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

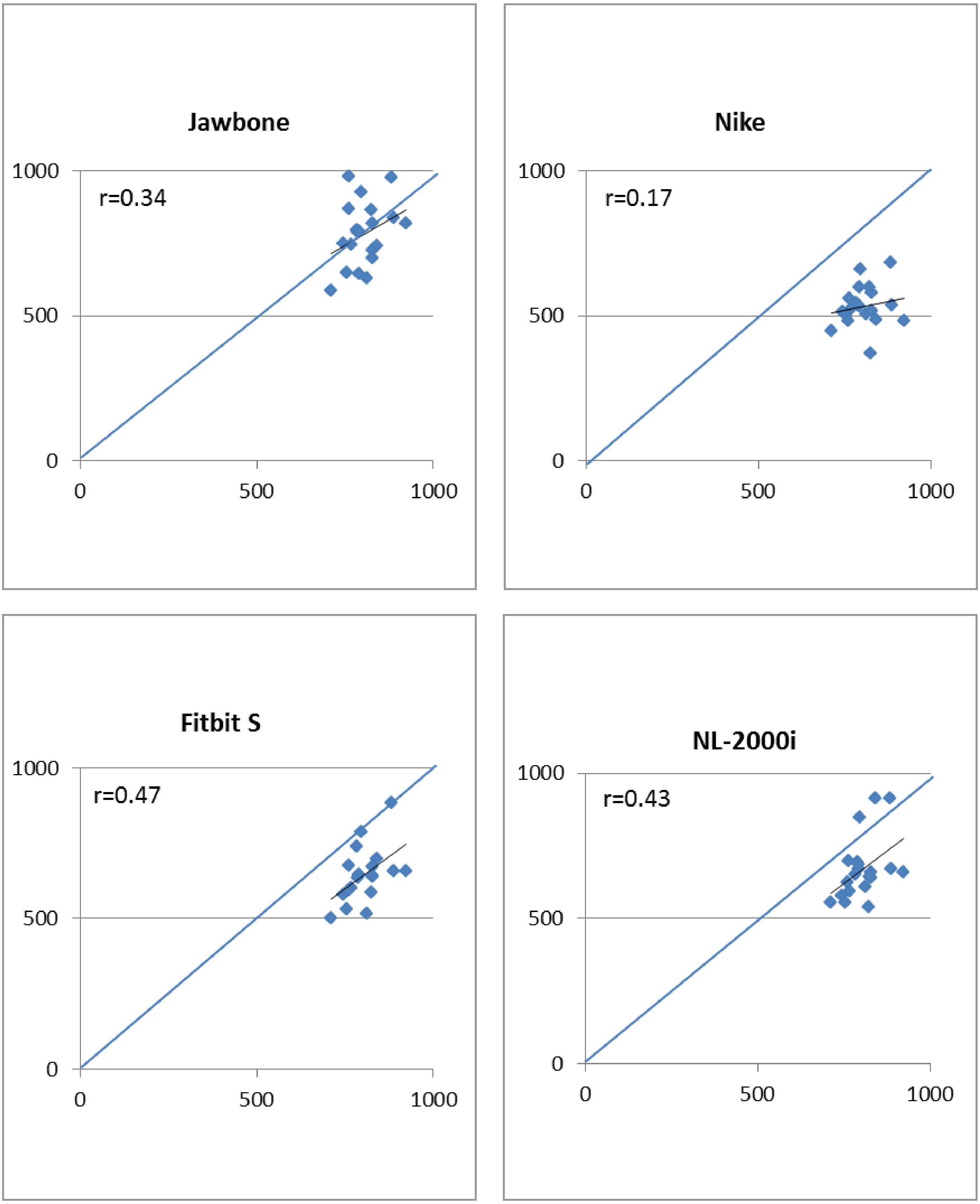


Figure 4: Agility Exercise Bout - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured steps with the different activity monitors during the agility exercise bout. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

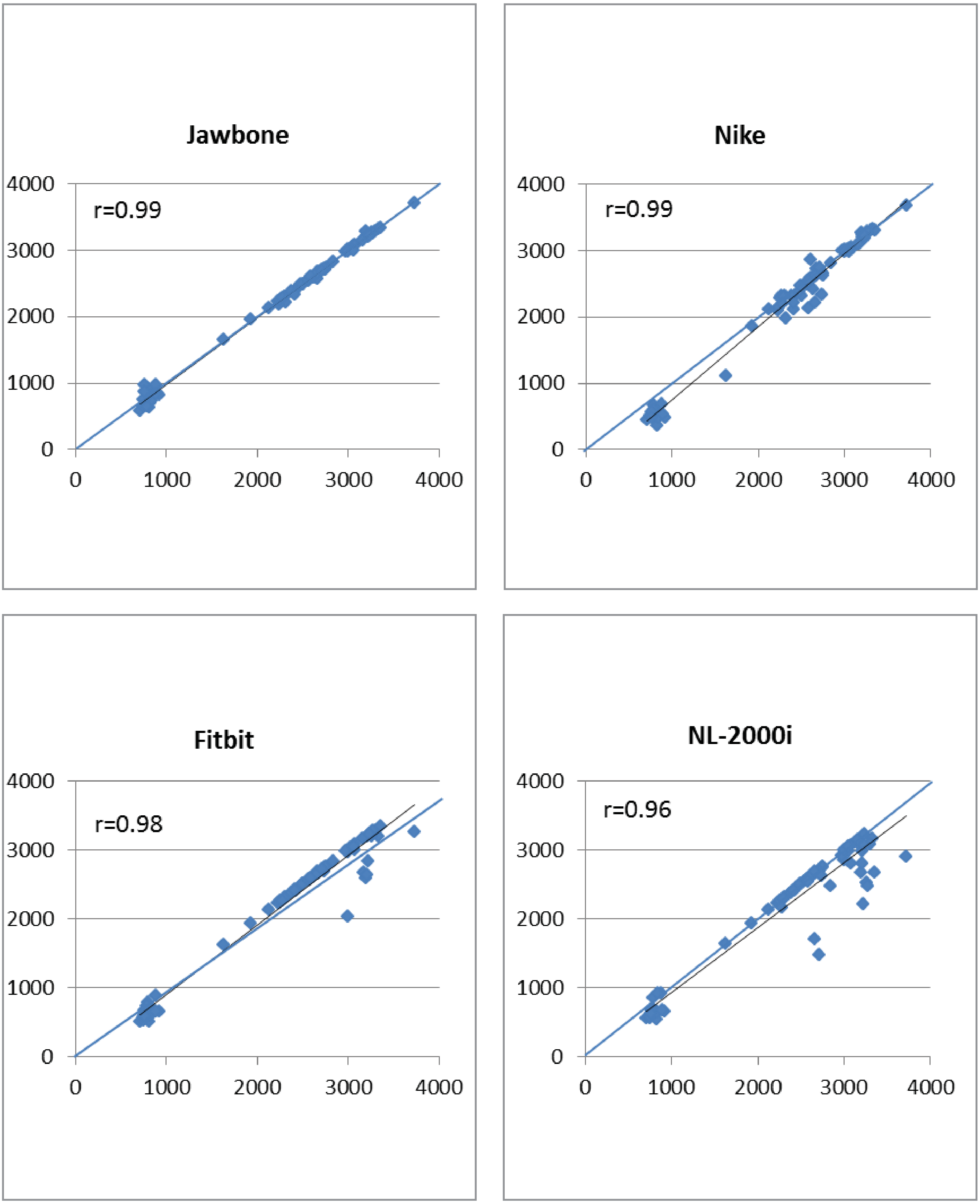


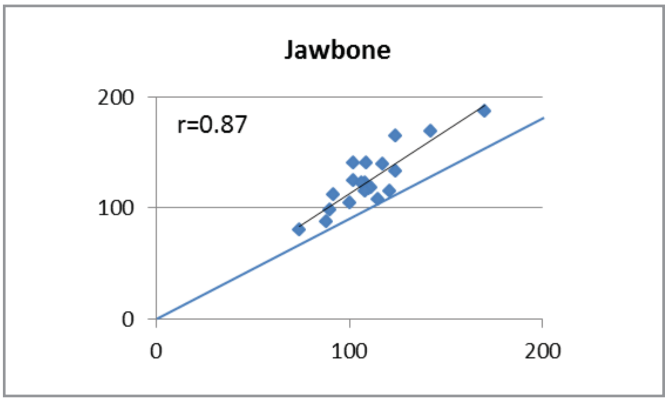
Figure 5: Step Comparison - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured steps with the different activity monitors using the combined data from all activities. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

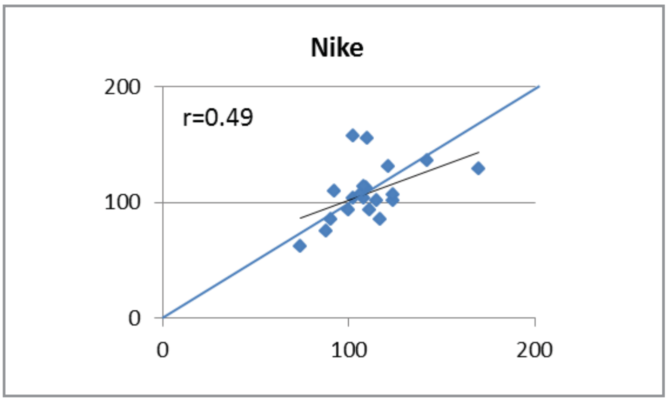
Table 3: Comparison of EE (total kcal) measured using the portable metabolic gas analyser compared to EE obtained from the activity devices.

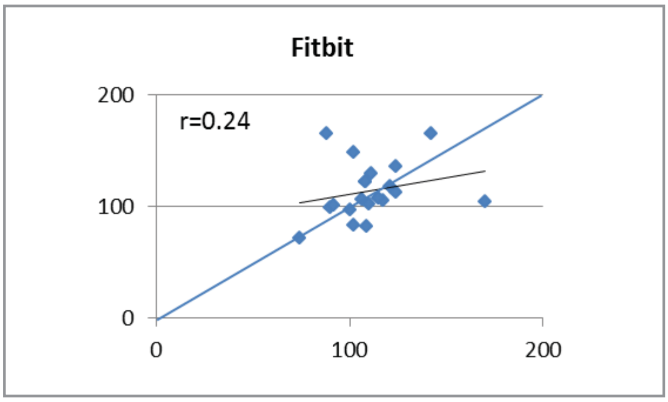
Devices	Treadmill Walking (n=19)	Treadmill Running (n=18)	Elliptical (n=20)	Agility (n=20)
Actual	109±19.6	240±47.3	161±25.6	90±20.7
Jawbone UP	123±25.2	288±63.6*	161±74.1	63±23.5*
Nike Fuelband	107±24.2	275±56.4*	118±38.0*	77±18.0*
Fitbit Ultra	111±22.8	230±50.5	154±34.1	75±19.2*
Adidas MiCoach	146±18.2*	261±52.4	-	36±6.8*
BodyMedia FIT Core	112±16.2	210±37.2*	129±19.5*	74±19.2*

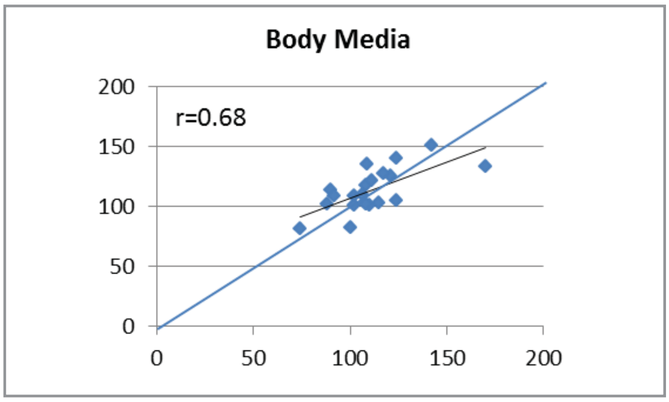
Values represent means ± standard deviation.

*Significantly different than portable metabolic gas analyser Kcals (p<.05).









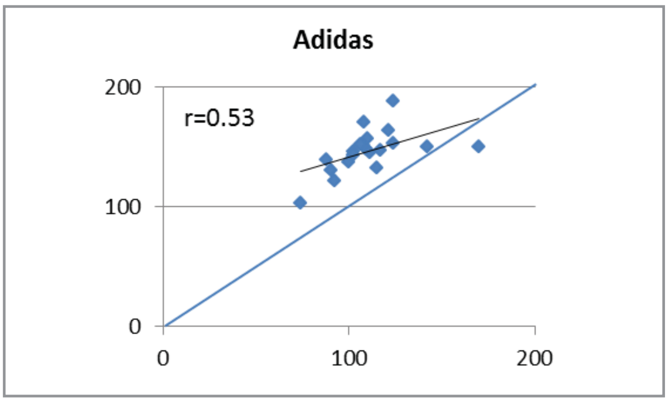
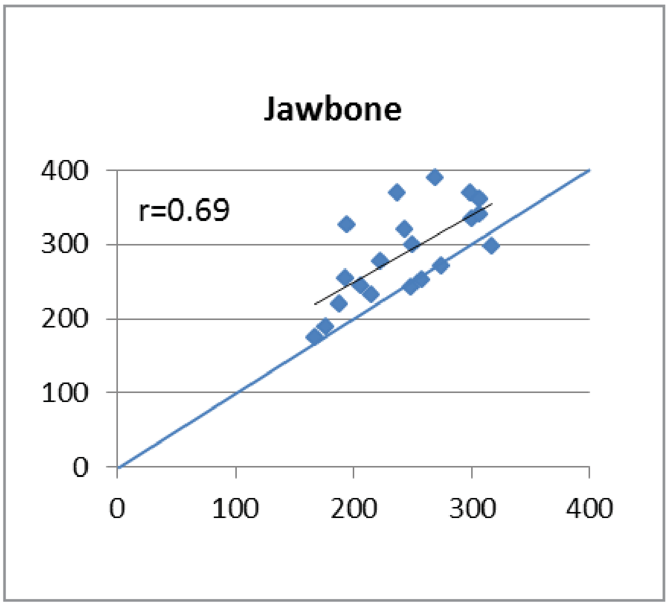
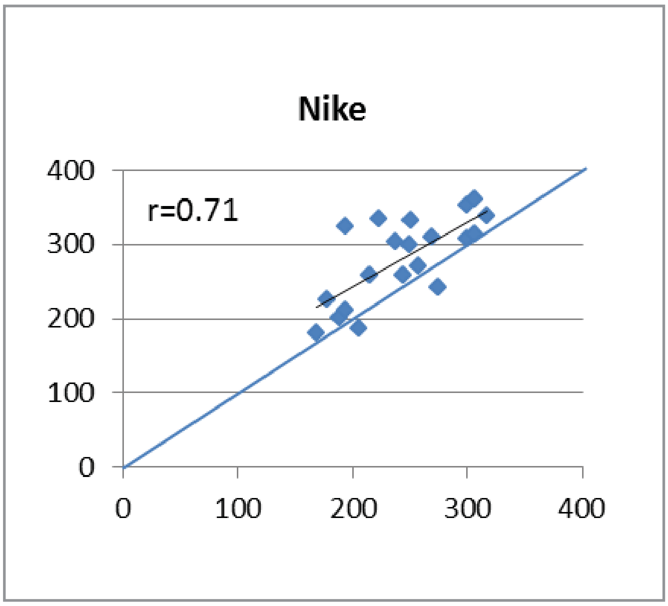
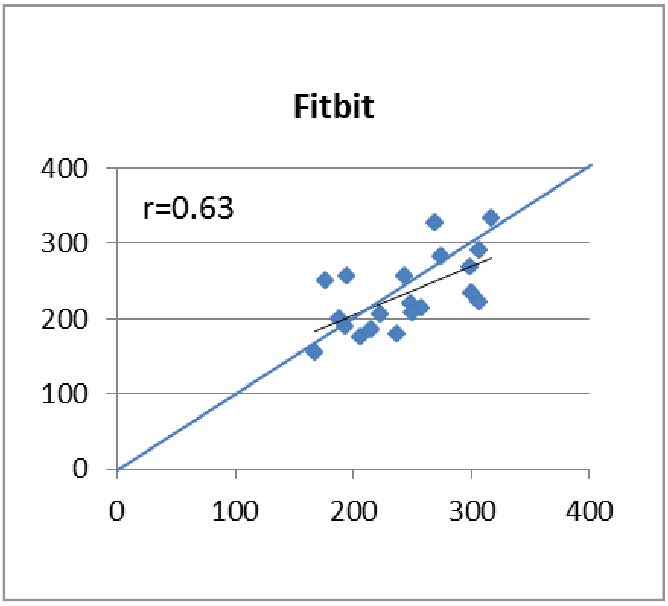
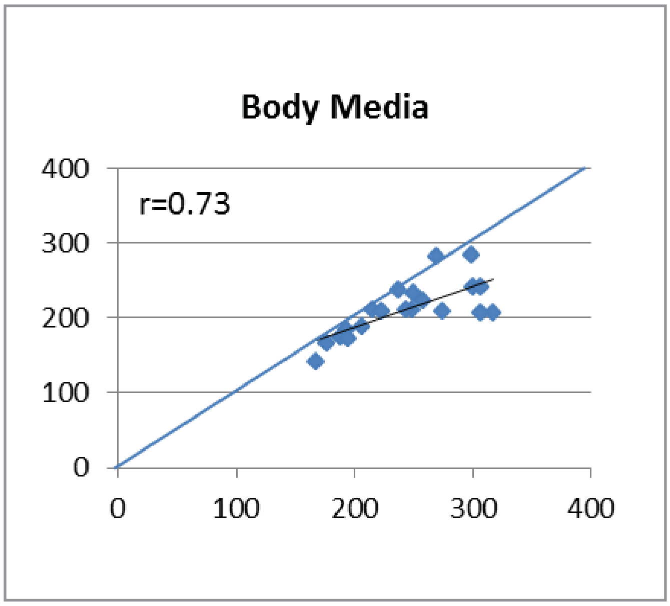


Figure 6: Treadmill Running Energy Expenditure - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured energy expenditure (kcal) with the different activity monitors during treadmill walking. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.









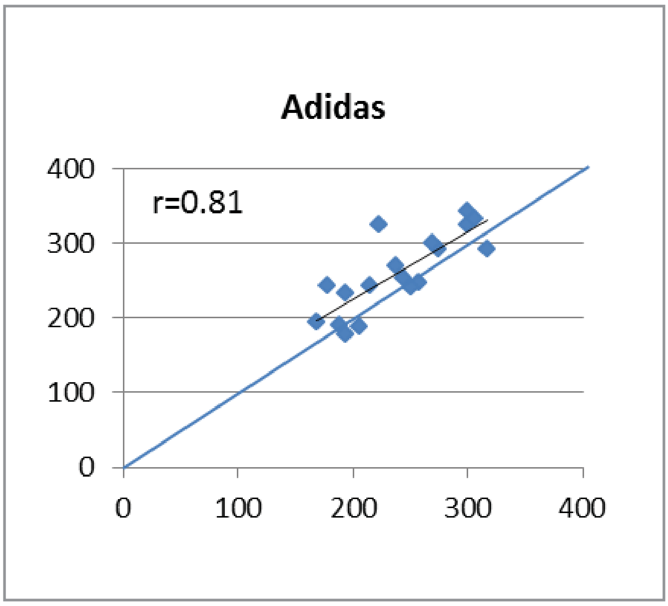


Figure 7: Treadmill Running Energy Expenditure - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured energy expenditure (kcal) with the different activity monitors during treadmill running. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

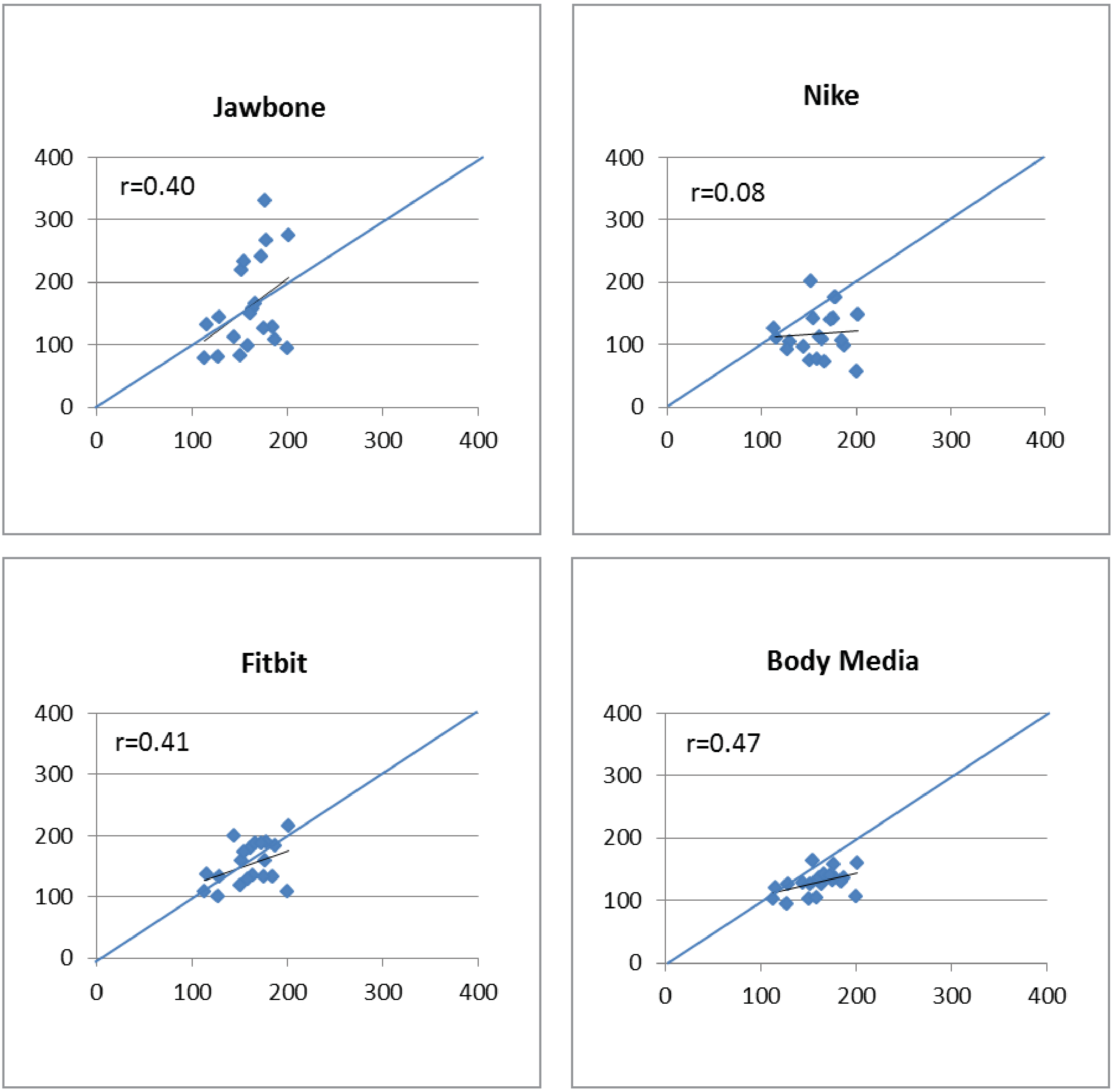
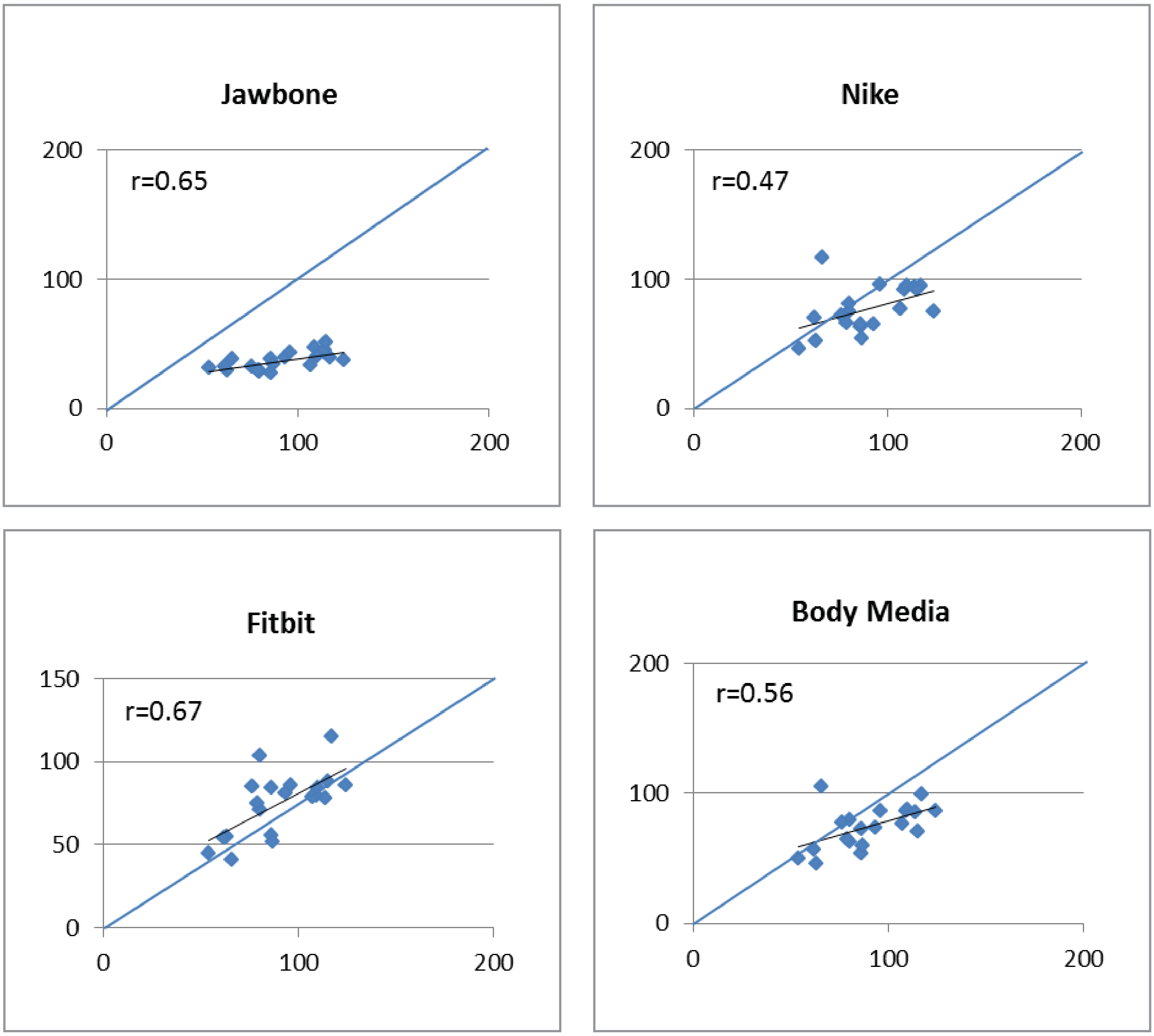


Figure 8: Elliptical Exercise Energy Expenditure - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured energy expenditure (kcal) with the different activity monitors during elliptical exercise. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure. There is no data for the Adidas MiCoach, as the activity tracker would not detect the motion.



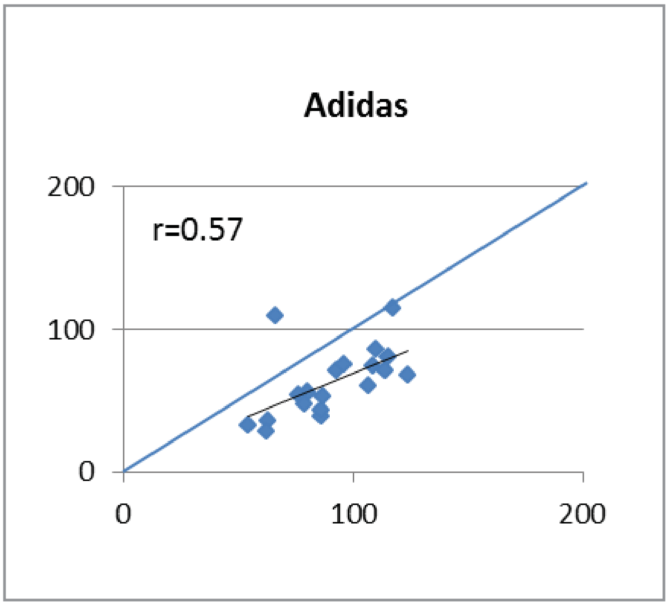
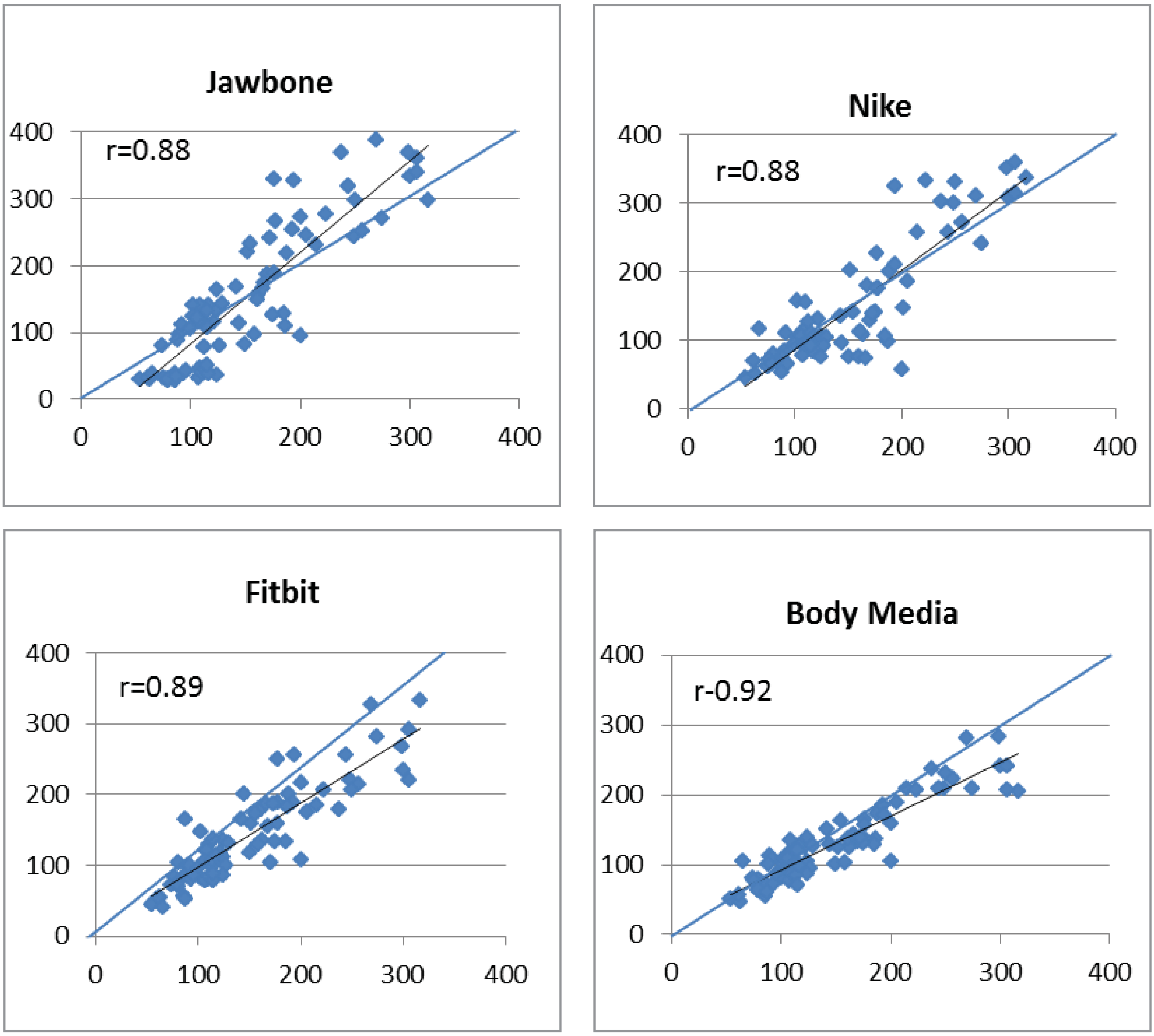


Figure 9: Agility Bout Energy Expenditure - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured energy expenditure (kcal) with the different activity monitors during the agility exercise bout. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.



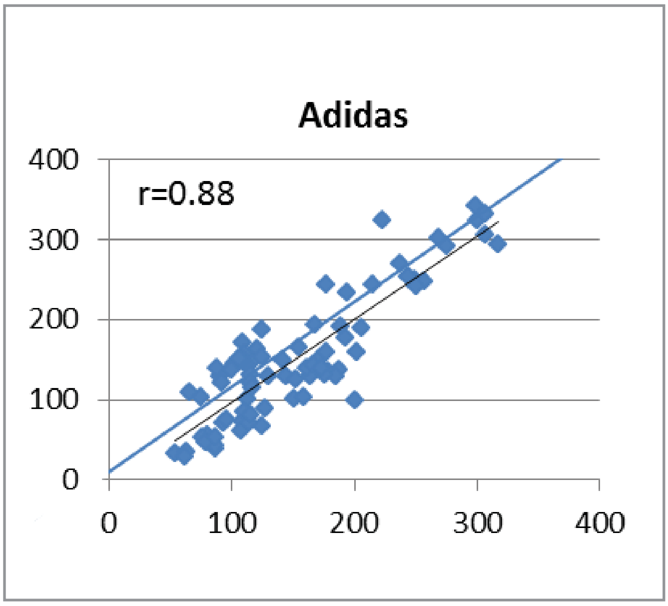


Figure 10: Energy Expenditure Comparison - Scatter plots of the relationship between criterion (x-axis) and activity monitor measured energy expenditure (kcal) with the different activity monitors using the combined data from all activities. The diagonal line represents the line of identity for each graph. The correlation coefficient and individual regression line for each data set is indicated in the figure.

DISCUSSION

The purpose of this study was to assess the ability of various activity trackers to accurately measure the number of steps taken and energy expenditure (EE) in healthy students performing a variety of activities. We found that the accuracy of activity trackers depended both on the type of exercise being done and the activity tracker. For steps taken, the activity trackers were generally reasonably accurate. During walking, no activity tracker was more than 10% off for total steps, and collectively they averaged 4% underestimation. This is within the generally acceptable range of less than 5% [5,11-13] Likewise, during running, the errors were all <10%, averaging 4%. Even during elliptical exercise, the error (always an underestimation) was never larger than 6%, averaging only 2%. However, as the ambulatory pattern became more complex during the agility-related exercise, the error in step counts became larger, ranging from 3-24%, and averaging 18%, Crouter et al. [5] noted that there could be inaccuracies with recording of steps with elderly people or others with a shuffle gait. Steps taken during the ladder, T-drill, and the basketball layup drill included forward, back, and side-to-side motions. The smaller or quicker steps taken may not always register on the activity trackers. The smaller steps also appeared to lead to less arm movement, which would also affect the accuracy of the activity trackers that were worn on the arm or wrist. Shuffling side-to-side may also only register half the steps. Also, the basketball portion included dribbling a basketball. This could have affected steps recorded due to the change of arm movement. Thus, although the activity trackers were acceptably accurate with normal ambulation, they appear to systematically underestimate steps taken when a non-standard ambulatory pattern was used. However, viewed from the larger perspective off all activities combined (Figure 5), the differences between criterion and measured steps taken was not meaningfully different, and errors appeared to be individual and random, rather than systematic.

For estimating EE, the devices were systematically less accurate. The recording of EE is a more complex process and involves incorporating data measured by the device into an algorithm within the devices' software. This likely explains why there was more variation in the recordings. The difference between measured and predicted EE ranged from 13-60%, with some devices over predicting and some under predicting. Viewed from the perspective of all activities combined (Figure 10), there was remarkably good agreement between the criterion and measured EE, although there were frequent individual examples of individual comparisons outside 10%. Thus, while the overall EE measured in the group of subjects was broadly accurate, individual comparisons were notably less precise.

The NL-2000i has been shown to be accurate in assessing steps taken while walking in other studies. Schneider et al.[3] found the NL-2000i to be within +3% of the actual steps taken on a 400 m track. Crouter et al. [5] found the NL-2000i to be within +1% of actual steps on the treadmill. This supports the data from the present study which also found the NL-2000i to be accurate in measuring steps taken during treadmill walking, although the NL-2000i significantly under predicted steps in other ambulatory modes. Steeves et al. [11] assessed the accuracy of three pedometers (Omron HJ-303, Sportline Traq, and Yamax SW200) relative to their ability to measure steps during walking, running, elliptical, front-back-side-side stepping (FBSS), stair climbing/descending, and ballroom dancing. Just as with the agility test in the present data, significant differences were found between all three pedometers, especially for the FBSS stepping and ballroom dancing. Although the NL-2000i was not used in the previous study, the current study's NL-2000i was also unable to accurately measure steps taken during the agility movements.

A number of studies have found that EE expenditure is either underestimated or overestimated, depending upon the activity. For instance, Balogun et al. [8] found the Caltrac accelerometer to overestimate EE. The difference between the Caltrac and directly measured EE ranged from 13.3-52.9%. They suggested that a different regression equation needed to be created to improve the accuracy of the device. Crouter et al. [6] studied three different accelerometers: the Actigraph, Actical, and AMP-331. They found that the Actigraph and Actical both overestimated EE during walking. All three accelerometers underestimated EE during highly vigorous activities (such as basketball and fast running), suggesting that the algorithms created for these devices did not work across a wide range of physical activity levels (light, moderate, and vigorous). This supports the present findings, since some activity devices were shown to be more accurate for one type of activity and not another. It also supports the underestimation of EE during vigorous activities (e.g. agility and basketball activities). All activity devices in the current study underestimated EE during the agility portion by 13-60%.

Previous research on the BodyMedia Sensewear Pro II (SP 2) found that it overestimated EE when subjects walked on a level treadmill. [12] King et al. [10] found that the SP 2 underestimated EE at all treadmill speeds. In the current study, there was no significant difference between measured and predicted EE when using the BodyMedia FIT Core activity tracker. This suggests that BodyMedia may have updated the arm band or used a different algorithm in the FIT Core activity tracker compared to the SP 2.

The Jawbone UP was first released in 2011, but due to technical difficulties was recalled. The new Jawbone UP band performed fairly well in the current study. It was accurate with steps taken across all activities and was fairly accurate with EE. The EE was only significantly different than measured during treadmill running (+20%) and the agility portion (-14%) of study. There were also no technical difficulties while operating the new Jawbone UP, thus the technical issues with the first generation of this device appear to have been solved.

Several factors could have affected the results of the current study. One factor could be where the activity trackers were worn on the body. Instructions were provided for each device on where to wear the activity trackers. We were able to accommodate the correct body position of each activity trackers, although there is not data available demonstrating whether wearing multiple activity trackers at the same time changes the ability to properly sense movement. Another factor that could have influenced the results was the biomechanics of the individual participants. Activity trackers worn on the arms may have been affected by the different arm movement of subjects. Thus, subjects who inherently limit their arm movement may have had lower step and EE values. Arm movement was especially low during the agility portion. Reminding subjects to use their arms while walking and performing the agility ladder may lead to more accurate results during these activities. However, given that the point of activity monitors is to allow assessment to step counts and EE during spontaneous activity, having to remind subjects to use their arms, which some people do not seem to do, would seem more likely to introduce errors in step counts and EE measurement than to solve errors.

Finally, future studies may want to incorporate a wider variety of activities. The current study exercised at one self-selected pace per piece of equipment, with each modality being conducted at a steady state. The treadmill walking speeds ranged from 3.0-4.2 mph, which is a fairly limited range of walking speed. The treadmill running speeds ranged from 5.0-8.5 mph, which eliminates really fast running speeds in individuals fit enough to run at higher speeds. Additionally, Fruin and Rankin [12] found differences in measured energy expenditure when comparing 0% to 5% grade. Thus, future studies may profitably explore multiple inclines into the research design.

PRACTICAL APPLICATIONS

In summary, when choosing an activity device, it is important to think about the information you want to track. During normal ambulation, all of the tested activity monitors were reasonably accurate for measuring step count. During non-normal ambulatory patterns, the accuracy of all of the activity monitors begins to decrease. In particular, slide steps (such as in the agility exercise or basketball) may be hard for activity monitors to detect. However, from the perspective of the entire range of activities tested, the step counts were mostly within 5%, which is reasonable accuracy. EE is generally less accurately measured, in some cases the inaccuracy is rather large. As with step counts, errors in the measurement of EE were larger during non-normal ambulatory patterns. Considered across the range of activities used, it seems safe to suggest that the algorithms used to measure EE are not robust enough to yield individually accurate estimates of EE across a wide range of ambulatory patterns and intensities, although average responses are broadly accurate.

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