Validation of the Fitbit® Surge™ and Charge HR™ Fitness Trackers

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INTRODUCTION

This study was designed and executed to test the accuracy of the heart rate monitoring technology—PurePulse™—in fitness trackers manufactured by Fitbit, Inc. ("Fitbit") (together, the "devices" or the "PurePulse Trackers") over a wide range of activities and exercises. We tested both the Fitbit Charge HR™ ("Charge HR") and the Fitbit Surge™ ("Surge") by comparing hundreds of thousands of heart rate readings to a time-synced electrocardiogram ("ECG"). Based on our analysis of those readings, we conclude that the Fitbit PurePulse Trackers do not provide a valid measure of the users' heart rate and cannot be used to provide a meaningful estimate of a user's heart rate, particularly during moderate to high intensity exercise.

EXECUTIVE SUMMARY AND INTERPRETATION

1. The Charge HR exhibited an aggregate mean bias of -6.1 beats per minute (bpm) and a mean absolute differential of 12.2 bpm. During higher exercise intensities, the mean bias was -12.5 bpm and the mean absolute difference increased to 15.5 bpm. In other words, during moderate to high intensity exercise, the Charge HR recorded a heart rate that differed from the ECG by an average of 15.5 bpm.

2. The Surge exhibited a mean bias of -11.6 bpm and a mean absolute differential of 15.6 bpm. During higher exercise intensities, the mean bias was -20.8 bpm and the mean absolute differential increased to 22.8 bpm. In other words, during moderate to high intensity exercise, the Surge recorded a heart rate that differed from the ECG by an average of 22.8 bpm.

3. Together, the PurePulse Trackers exhibited an aggregate mean bias of -8.9 bpm and a mean absolute differential of 13.9 bpm when compared against ECG. During higher exercise intensities (as described above), the mean bias was -16.8 and the mean absolute difference increased to 19.2 bpm. In other words, during moderate to high intensity exercise, the PurePulse Trackers recorded a heart rate that differed from the ECG by an average of 19.2 bpm.

4. In addition to being inaccurate, the PurePulse Trackers are also inconsistent. Statistical analysis indicated a correlation strength of $r = 0.85$ between the time-synced Surge and Charge HR heart rates in aggregate. There was a mean differential of 10.0 bpm between the PurePulse Trackers. However, when comparing the trackers using data above the combined mean value of 124 bpm (i.e. heart rate range associated with lower intensity exercise), the correlation between the PurePulse Trackers weakened substantially to $r = 0.46$ demonstrating greater inconsistencies between the two trackers. The mean differential increased to 12.5 bpm. The correlation during rest and low intensity conditions (<125 bpm) also showed inconsistent heart rate measurements between the two device with only a moderate strength correlation ($r = 0.76$) and a mean difference of 7.23 bpm.

5. The PurePulse Trackers do not accurately measure a user's heart rate, particularly during moderate to high intensity exercise, and cannot be used to provide a meaningful estimate of a user's heart rate.

A. SPECIFIC AIMS

A.1. Specific Aim: In 43 healthy subjects, we tested the accuracy by which the Fitbit Surge and Charge HR wearable fitness trackers and the integrated PurePulse™ technology computes heart rate across a number of structured laboratory-based and less structured free-living exercise tasks.

A.2. Hypothesis: The result of this study is anticipated to determine the validity of the Fitbit Surge and Charge HR wearable fitness trackers for heart rate measurements in reference to the criterion measure electrocardiograph (ECG).

B. BACKGROUND AND SIGNFICANCE

Wearable physical activity monitors have been commercially available for many years[1]. Initially developed to augment personal fitness and weight loss regimens with basic quantitative data, the newest generation of devices provides feedback on many variables related to individuals' nutrition, exercise and sleep. As the technology and functionality of these devices continues to progress, the potential applications have also expanded to include medical surveillance, pervasive health care and mobile health-wellness monitoring.

The search for a practical and accurate method to assess energy expenditure continues to focus on wearable sensor technologies. It is believed that classification of physical activity by either improved analysis through accelerometer metrics or incorporating additional physiologic variables (e.g. body temperature, skin galvanic response, heart rate, etc.) may allow activity-specific prediction algorithms to more accurately reflect real-life energy expenditure. This has fueled the adoption of more recent commercially-available monitors using multiple-sensing technologies that have been shown to outperform existing monitors that use solely basic accelerometer data to infer movement and subsequent energy expenditure[2].

The Fitbit Surge and Charge HR wearable fitness trackers are an example of a current generation device that integrates reflective photoplethysmography to compute heart rate. Fitbit's PurePulse™ feature is its proprietary heart rate monitoring system. We understand, but have not independently verified, that the heart rate monitoring technology in the PurePulse Trackers is identical.

As wearables become more prevalent, the accuracy of the physiological data they provide increases in importance. With the recent development of new types of sensors there has been a steady focus on improving overall device performance, i.e., reliability and validity of measurements. Notwithstanding, there is a scarcity of rigorous, scientifically-based validation studies on physiological measurement accuracy when compared to a gold-standard. These devices are no exception, hence this study's proposed purpose is to compare heart rate (HR) measures and validate them against a criterion measure (ECG).

C. RELEVANT & PREVIOUS VALIDATION STUDIES[1]

C.1. Validation of wearable multi-sensor biofeedback technology for heart rate and energy expenditure tracking. Jo E, Dolezal BA, Lewis K, Directo D. (in preparation for publication).

Our laboratory conducted a validation study on two multi-sensor activity trackers used to monitor heart rate (via optical sensors) and energy expenditure (via multi-sensor technology). Subjects performed a series of exercise tasks while heart rate data was simultaneously acquired from the Basis Peak, Fitbit Charge HR, and ECG (criterion measure). The Basis Peak demonstrated strong correlation (r=0.92) with ECG and a mean bias of -2.53 bpm when examining data in aggregate. The Basis Peak maintained relatively excellent accuracy across all exercise tasks, and met the validation criteria for consumer-use heart rate monitors.

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[1] Per Federal Rule of Civil Procedure 26(a)(2), the CVs and list of relevant publications of Drs. Jo and Dolezal are attached as Exhibits A and B. Neither Dr. Jo nor Dr. Dolezal has previously testified as an expert. The fees paid for this study include $21,750 to Dr. Jo, $12,000 to Dr. Dolezal, and $2,000 to a laboratory assistant. Costs and supplies, including participation fees for the study subjects, totaled $8,100.

C.2. Validity of two commercial grade bioelectrical impedance analyzers for measurement of body fat percentage. Dolezal BA, Lau M, Abrazado M, Storer TW, Cooper CB. Journal of Exercise Physiology online 2013; 16(4): 74-83

Our laboratory has validated an octapolar, multi-frequency bioelectrical impedance analyzer (BIA) against the gold standard of dual x-ray absorptiometry (DXA) in the assessment of body composition (% body fat). Correlations with DXA were extremely strong (r=0.98) and the data suggest this BIA instrument offers superior accuracy compared with other methods of BIA in assessing percent body fat.

C.3. Validation of a Heart Rate Derived from a Physiological Status Monitor-Embedded Compression Shirt against Criterion ECG. Dolezal BA, Boland DM, Carney J, Abrazado M, Smith DL, Cooper CB. Journal of Occupational and Environmental Hygiene 2014; 11:12, 833-39

Our laboratory has validated a Physiological Status Monitor (PSM)-embedded compression shirt against a criterion standard laboratory ECG in the measurement of heart rate when worn concurrently with structural firefighting personal protective equipment during four simulated firefighting activities. These findings demonstrated that the PSM-embedded compression shirt provides a valid measure of HR during simulated firefighting activities when compared with a standard 12-lead ECG.

D. METHODS

D.1. Study Design: This investigation was a prospective study of 43 healthy adults (22 males and 21 females) within the Los Angeles and Orange County communities. Participants visited the Cal Poly Pomona (CPP) Human Performance Research Laboratory for a single visit. An initial assessment included anthropometric measures (height and body weight) after which subjects were fitted with a Fitbit Charge HR on one wrist and the Fitbit Surge on the opposite wrist. Half of the subject pool wore the Charge HR on the dominant wrist and the Surge on the non-dominant wrist. The other half of the subject pool wore the Charge HR on the non-dominant wrist and the Surge on the dominant wrist. This counterbalancing strategy was implemented to avoid any potential confounding factors associated with the wrist on which the devices were placed. The mobile application settings for each watch were adjusted appropriately for each subject and the wrist the device was worn. Each device was fitted according to manufacturer instructions and with full battery charge prior to testing. A previously validated and calibrated heart rate measurement system (Zephyr Technology, BioHarness) accompanied with electrocardiograph (ECG) was used to provide criterion measures of HR using ECG R-R intervals[8,9]. The BioHarness has been previously validated with high agreement to 12-lead and 3-lead ECG[8,9]. The two Fitbit devices were time synchronized with the criterion ECG measurement. Time-synced data acquisition methods for each device is described below in section D.3.3.

The subjects were assigned to perform the tasks below in the listed order for 5 minutes while heart rate data from each device (ECG, Charge HR, and Surge) were concurrently acquired. The total time of testing was 65 minutes for each subject. The exercise tasks were reflective of activities presented in Fitbit advertisements.

Free-living Setting (outdoors)

1. **Standing Rest**
2. **Self-paced jog:** Participants will jog on a predetermined course consisting of flat and hilly surfaces.
3. **Standing Rest**
4. **Jump roping:** Participants will jump rope at a self-selected cadence.

Laboratory Setting

1. **Seated Rest**
2. **Treadmill Jogging:** Participants will jog at a self-selected pace a motorized treadmill (4.5 to 5.9 mph).

3. **Seated Rest**
4. **Treadmill Running:** Participants will run at a self-selected pace a motorized treadmill (> 6.0 mph).
5. **Seated Rest**
6. **Stair Climbing:** Participants will walk, jog, or run up a flight of stairs and return repeatedly for 1 minute intervals up to 5 minutes total.
7. **Seated Rest**
8. **Plyometrics:** Participants will perform 5 minutes of various plyometric (fast movement) exercises with each exercise performed in 1 minute intervals.
9. **Seated Rest**

D.2. Subjects: A randomized sample of 43 subjects (21 males and 22 females) was utilized for this study. The mean age, body weight, and height of the subject pool was 23.23 ± 3.46 years, 168.43 ± 9.76 cm (height), and 70.05 ± 14.33 kg (weight), respectively. Recruitment of subjects was performed by posting flyers on the CPP campus as well as by mass email solicitations. Interested individuals were provided with a full overview of the study procedures as well as the study consent form. Informed consent was obtained after discussing the study procedures in detail, including the voluntary nature of participation and notification that the subject can withdraw at any time. Upon the subject's agreement to participate, a signed copy was given to the subject. The study was approved by the CPP Institutional Review Board. Individuals who reported or exhibited any significant medical diagnoses, including cardiovascular or pulmonary disease that may limit ability to exercise or increase the cardiovascular risk of exercising or confound the interpretation of results were excluded from participation.

D.3. Experimental Procedures

D.3.1. Screening: All subjects completed a pre-participation medical questionnaire (PAR-Q) and a habitual physical activity questionnaire.

D.3.2. Electrocardiograph (ECG): We used a previously-validated and calibrated heart rate measurement system (Zephyr Technology, BioHarness) accompanied with a single channel electrocardiograph (ECG) sensor and circuitry to provide criterion measures of HR using ECG R-R interval calculations at a sampling rate of 250 Hz[8,9]. The BioHarness is a wearable multi-sensor system that acquires, logs, visualizes, and transmits biometrics (e.g. ECG and HR) via Bluetooth-enabled devices and mobile computer application (app). Following all measurements, data stored on the app was uploaded to a secure server and subsequently downloaded for second-by-second HR data analysis. The BioHarness has been previously validated with high agreement to 12-lead and 3-lead ECG[8-9]. The rationale for using the BioHarness ECG sensor as opposed to a traditional 12-lead ECG is as follows: (1) a 12-lead ECG utilizes 10 electrodes placed on the upper torso mostly around the left (anatomical perspective) chest. Therefore, female subjects especially, may experience discomfort as partial disrobing would be required for electrode placement. The BioHarness system integrates ECG into a less cumbersome chest strap device that is placed underneath the pectoral region and does not require disrobing, and (2) with the dynamic nature of movements associated with the exercise tasks, the use of a wired 12-lead ECG would be highly impractical and unfeasible. R-R interval and HR data will be acquired wirelessly using native Android-based software.

D.3.3. Fitbit Charge HR and Surge: For each subject, we positioned the Charge HR and Surge of appropriate size on separate wrists and in accordance to manufacturer instructions. Half of the subject pool wore the Charge HR on the dominant wrist and the Surge on the non-dominant wrist. The other half of the subject pool wore the Charge HR on the non-dominant wrist and the Surge on the dominant wrist. We implemented this counterbalancing strategy to avoid any potential confounding factors associated with the wrist on which the devices are placed. The mobile application settings for each watch were adjusted appropriately for each subject. Each device was confirmed to have full battery charge prior to testing. During testing, the "track exercise" function for the Fitbit devices was used. This function allows for time-synced GPS and HR data acquisition. Upon completion of the testing protocol, the exercise metrics during the "tracked" exercise was uploaded to the Fitbit servers. Subsequently, the GPS (.tcx) file linked to the "tracked" exercise was downloaded from the Fitbit online dashboard and imported into a Microsoft

Excel spreadsheet. The spreadsheet displayed time-synced, second-by-second GPS and HR data. The GPS data was discarded while the HR data was subsequently used for analysis.

D.3.4. Time Syncing and Data Processing: All time stamps corresponding to each HR measurement from each device were linked to Coordinated Universal Time (UTC). The start and end times for each testing session were recorded and used to identify the time/data points for analysis. For some subjects, the Fitbit data sets failed to register a variable number of time points. This may be due to incidences during which the Fitbit device failed to capture a sufficient signal for HR determination. Because the precise reason for these absent heart rate readings cannot be conclusively determined, these data points were not included in the primary analysis. As a secondary method of data acquisition, we recorded heart rate data manually using the value presented on the watch interface. At each minute of testing, the subject was prompted to read the heart rate value indicated on the Charge HR watch interface and researchers hand recorded the data. Simultaneously, researchers recorded the heart rate value presented on the external monitors linked to the ECG as well as on the Surge. This secondary method serves as an alternate approach and may provide value for practical inference since consumers utilize similar procedures to obtain their own heart rate values.

D.3.5. Statistical Analyses: Three levels of statistical analysis were implemented to substantiate the level of validity of the Fitbit devices in reference to ECG:

> A) First, we used a Pearson Product-Moment Correlation analysis to determine the strength of relationship between ECG and each of the Fitbit devices (i.e. ECG vs. Charge HR and ECG vs. Surge) and whether the relationship was statistically significant. A significant correlation was determined if the p-value was less than 0.05 while the strength of correlation was determined by the correlation coefficient (r).
>
> > ******In simplified terms, a correlation analysis would provide information on how well or poorly the heart rate values from the Fitbit relate to the values acquired by ECG for each given time point of measurement. A perfect correlation (represented by an r-value of 1) indicates that the heart rate values from the Fitbit and ECG were the same for each measurement time point. This would indicate that the Fitbit is completely accurate in reference to the ECG. When the heart rate values from the Fitbit and ECG do not match well for each time point, the strength of the correlation weakens (represented by a r-value further away from 1 and closer to 0). The term "significance" is a statistical term that simply indicates that the observed correlation was not simply due to chance. In this case, the data reveals that the Fitbit devices are inaccurate.*
> >
> > *By itself, however, this metric can conceal significant discrepancies in heart rate readings. For example, if an ECG records bpm of 150, 160, and 170 at three discrete moments in time, and a Fitbit device records bpm of 100, 110, and 120, respectively, for those same moments, the devices would demonstrate a perfect correlation,(r= 1.0) even though the actual readings were far apart. Thus, even if the correlation is strong, other means must be referenced as well to determine the devices' validity.*
>
> B) Second, we used a paired sample T-Test to statistically compare the mean/average heart rate between ECG and each of the Fitbit devices. A $p<0.05$ will indicate a significant difference between the mean HR acquired by ECG vs. either Fitbit device.
>
> > **This statistical test is intended to compare the average heart rate from the ECG to the average heart rate value from the Fitbit devices. If the two mean values differed significantly (i.e. statistical significance represented by a p-value less than 0.05), it may be implied from a statistical perspective that the two devices produce discrepant heart rate values.*
> >
> > *By itself, this analytical tool can also undervalue the inaccuracy of the devices. For example, if an ECG shows bpm of 150, 150, 150, and 150, and the Fitbit device shows bpm of 125, 125, 175, and 175 for the same points in time, the*

device would register a mean bias of 0 over this time period, notwithstanding the significant inaccuracy of each reading. Thus, where, as here, the Fitbit devices have a tendency to both under record, and over record, the mean bias may underestimate the extent of the inaccuracy.

C) Third, we used the Bland-Altman method to further assess the agreement between the Fitbit devices and ECG and whether the differences vary in a systematic or ambiguous way over the range of measurements. The mean bias between Fitbit and ECG (=Fitbit HR – ECG HR) and the 95% limits of agreement (LoA; LoA = mean difference ± 1.96 standard deviation of the difference) was identified. Bland-Altman plots demonstrate the Fitbit vs. ECG (Fitbit HR minus ECG HR) heart rate difference scores against the mean of the heart rate measurements from both Fitbit and ECG.

**This analysis provides insight on how well or poorly the Fitbit agrees with ECG in terms of heart rate. More specifically, the mean bias is calculated by subtracting ECG HR from the time-corresponding Fitbit HR and then averaging those computed values. The mean bias score will indicate how much the Fitbit underestimates or overestimates (bias) heart rate in reference to ECG. The 95% limits of agreement incorporate an upper and lower value. This range encompasses 95% of the individual difference scores (= Fitbit HR – ECG HR) within the sample. This can provide information as to the range by which the Fitbit deviates from ECG. Moreover, the range may reflect the tendencies of the Fitbit in terms of heart rate measurement. For example, if the upper limit of agreement is +10 and the lower limit of agreement is -45, then it can be reasonably argued that the Fitbit tends to underestimate since -45 is further away from 0 (0= no difference between devices) than +10. Also, a bias may be considered systematic if the limits of agreement were closer together. In such case, the Fitbit may be used interchangeably with ECG since 95% of the individual difference scores are within a relatively small range. If the limits of agreement were wide, then the bias is more ambiguous or sporadic. In this case, the Fitbit may not be considered interchangeable with ECG since the bias is not systematic.*

D) Fourth, we calculated the absolute difference between the Fitbit devices and the ECG.

**This measurement describes the difference in bpm between the Fitbit devices and the ECG, irrespective of whether the devices recorded a bpm over or under the actual heart rate, as measured by an ECG. For example, if an ECG records a heart rate of 125, Fitbit device readings of 100 and 150 would both render an absolute difference of 25 bpm.*

All four levels of analysis were implemented on aggregate HR data, HR data above the mean ECG HR, and HR data below the mean ECG HR. For ECG vs. Charge HR analysis, a total of 127,215 pairs of data were utilized while for the ECG vs. Surge analysis, a total of 132,263 pairs of data were utilized. The discrepancy in data set size was due to incidences in which either Fitbit device failed to register a HR for a given time point as described above. All results are reflected as mean value ± standard deviation. Previous validation studies[8,9,11,12] have provided validity criteria for heart rate measurement as: 1) a standard error of the estimate (SEE) less than 5 beats/min, 2) a correlation between ECG-derived heart rate and the heart rate measured by the test device of r=0.90 or greater, and 3) a mean bias less than 3 beats/min. These criteria were used to determine validity of the Fitbit devices in this study.

E. RESULTS

E.1. ECG vs. Fitbit Charge HR

E.1.1. Aggregate Data: When examining all time-synced ECG and Charge HR heart rate data in aggregate (n= 127,215 pairs), there was a significant ($p<0.001$) and moderately strong positive correlation between ECG and Charge HR ($r=0.85$) (Table 1, Figure 1). The mean HR from the Charge HR (126.78 ± 29.94 bpm) significantly ($p<0.001$) differed from the mean ECG HR (132.87 ± 33.12 bpm) (discrepancy of 9.46 ± 10.62% or 12.19 ± 10.62 bpm) (Table 1). The Charge HR exhibited a mean bias of -6.09 ± 17.71 bpm (95% LoA 28.63, -40.81) in reference to ECG criterion measure (Table 1, Figure 2).

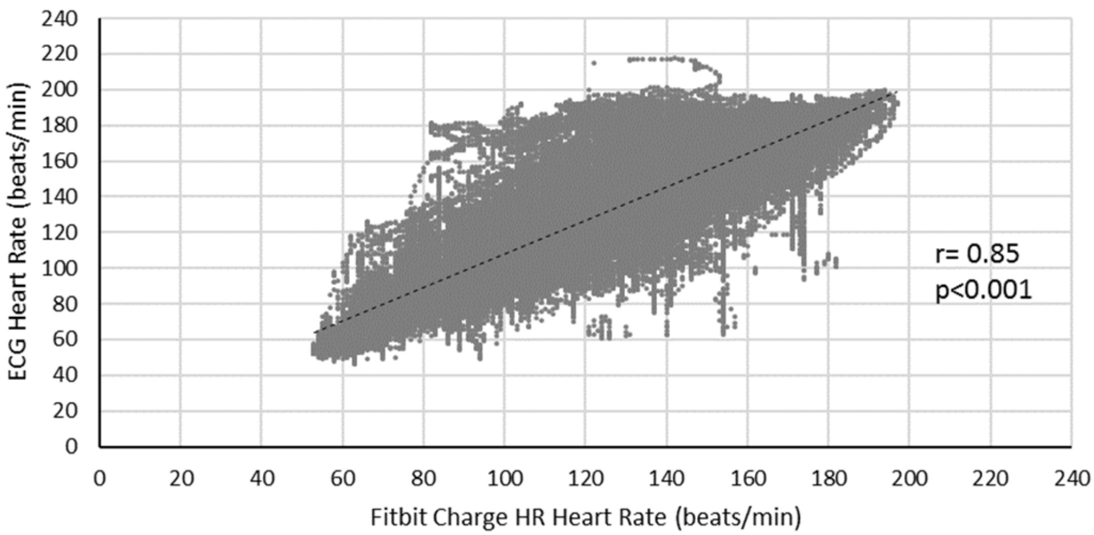

Figure 1. Relationship between time-synced ECG and Fitbit Charge heart rate.

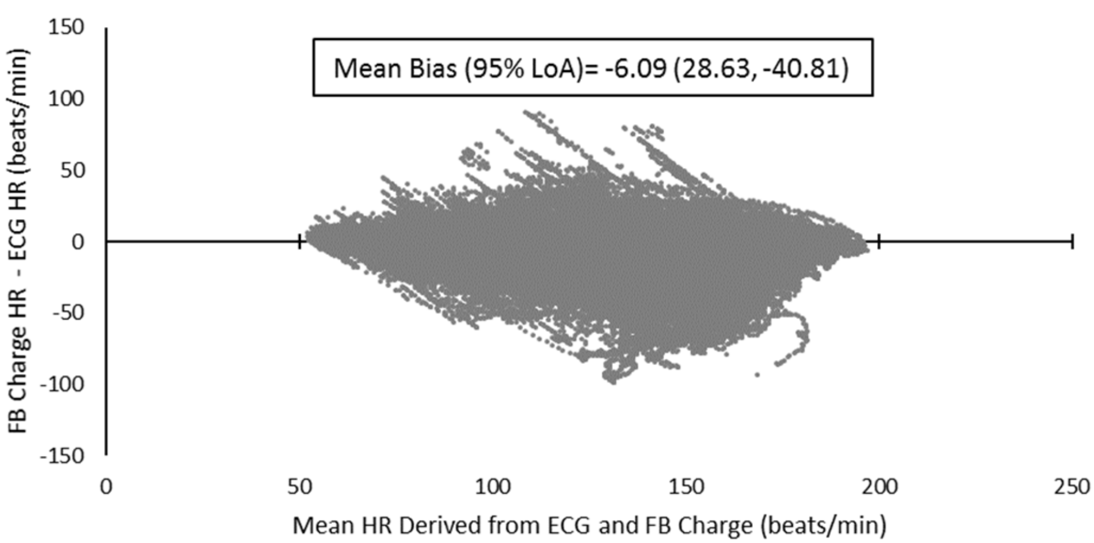

Figure 2. Bland-Altman Plot indicating mean difference in heart rate detection between the Charge HR and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

E.1.2. HR Data above mean ECG HR (>132 bpm): Time synced heart rate data above the mean ECG HR (>132 bpm; n=63,888 pairs) were analyzed. During conditions in which the ECG HR (true HR) exceeded 132 bpm, there was a significant ($p<0.001$) and moderately weak positive correlation between ECG and Charge HR ($r=0.48$) (Table 1, Figure 3). In addition, the mean HR from the Charge HR (148.35 ± 20.10 bpm) significantly ($p<0.001$) differed from the mean ECG HR (160.83 ± 17.03 bpm) (discrepancy of 10.35 ± 11.62% or 15.48 ± 11.62 bpm) (Table 1). The Charge HR exhibited a mean bias of -12.48 ± 19.07 bpm (95% LoA 24.90, -49.86) compared to ECG during higher (>132 bpm) ECG/true heart rate conditions (e.g. high intensity exercise) (Table 1, Figure 4).

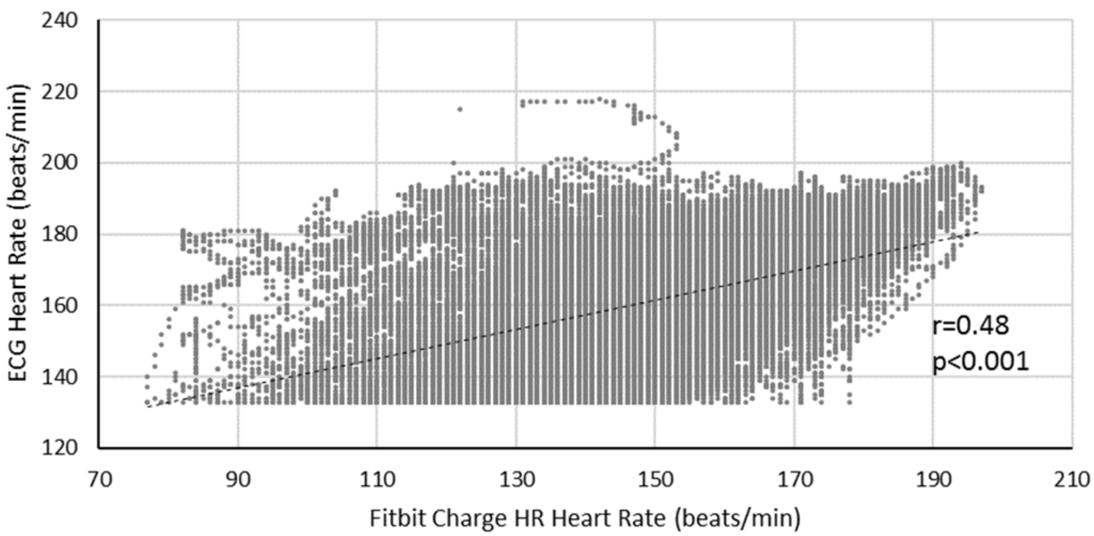

Figure 3. Relationship between time-synced ECG and Fitbit Charge heart rate during high ECG-measured heart rate range (>132 bpm)

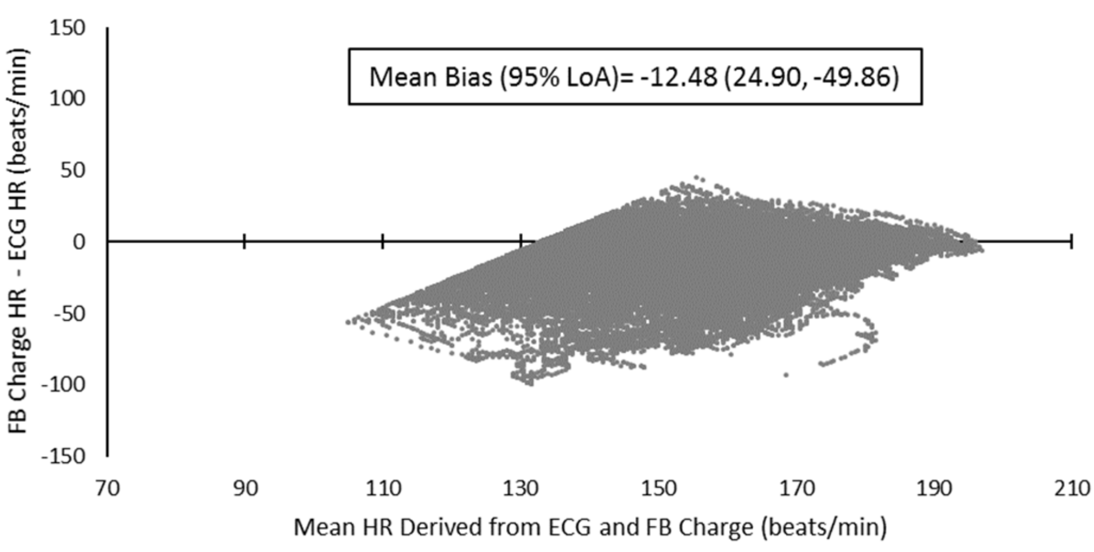

Figure 4. Bland-Altman plot indicating mean difference in heart rate detection between the Charge HR and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

E.1.3. HR Data below mean ECG HR (<133 bpm): Time synced heart rate data below the mean ECG HR (<133 bpm; n=63,327 pairs) were analyzed. During conditions in which the ECG HR (true HR) was below 133 bpm, there was a significant ($p<0.001$) and moderate positive correlation between ECG and Charge HR ($r=0.78$) (Table 1, Figure 5). In addition, the mean HR from the Charge HR (105.02 ± 21.22 bpm) significantly ($p<0.001$) differed from the mean ECG HR (104.67 ± 18.10 bpm) (discrepancy of 8.56 ± 9.42% or 8.86 ± 9.42 bpm) (Table 1). The Charge HR exhibited a mean bias of 0.36 ± 13.44 bpm (95% LoA 18.82, -18.13) compared to ECG during lower (<133 bpm) ECG/true heart rate conditions (e.g. low intensity exercise) (Table 1, Figure 6).

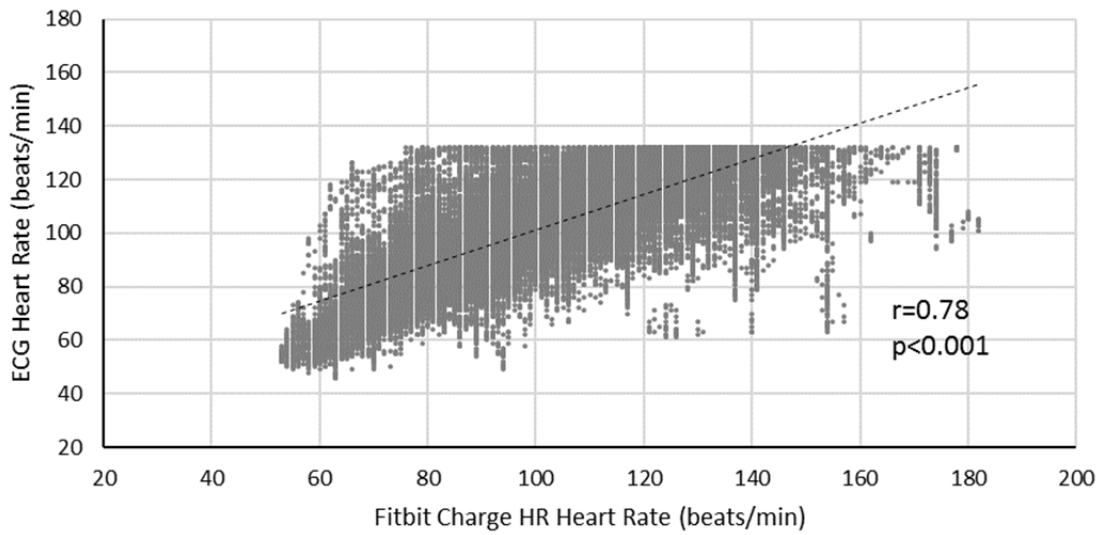

Figure 5. Relationship between time-synced ECG and Fitbit Charge heart rate during low ECG-measured heart rate range (<133 bpm)

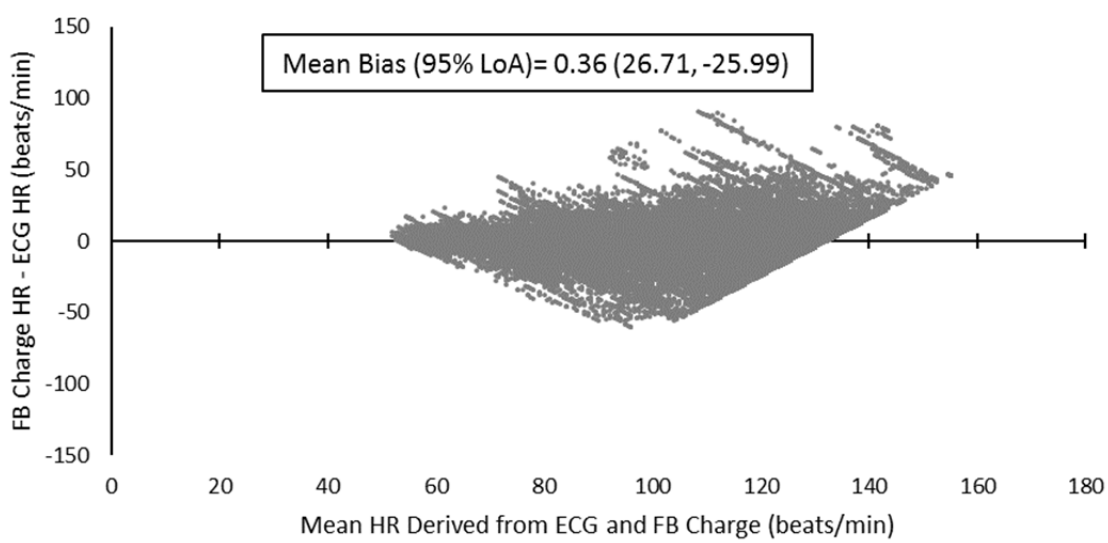

Figure 6. Bland-Altman plot indicating mean difference in heart rate detection between the Fitbit Charge HR (Charge HR) and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

Parameter	Aggregate Data (n=127,215)	Data above ECG HR >132bpm (n=63,888)	Data below ECG HR <133bpm (n=63,327)
Charge HR Mean HR (bpm ± SD)	126.78 ± 29.94*	148.35 ± 20.10*	105.02 ± 21.22*
ECG Mean HR (bpm ± SD)	132.87 ± 33.12	160.83 ± 17.03	104.67 ± 18.10
Mean Absolute Difference (bpm ± SD)	12.19 ± 10.62	15.48 ± 11.62	8.86 ± 9.42
Mean Percent Difference (% ± SD)	9.46 ± 10.62	10.35 ± 11.62	8.56 ± 9.42
Correlation (r)	0.85^	0.48^	0.78^
Mean Bias (bpm ± SD)	-6.09 ± 17.71 (95% CI -6.19, -5.99)	-12.48 ± 19.07 (95% CI -12.63, -12.33)	0.36 ± 13.44 (95% CI 0.25, 0.46)
95% Limits of Agreement (Upper, Lower)	28.63, -40.81	24.90, -49.86	26.71, -25.99
Standard Error of the Estimate (SEE)	15.92	17.61	13.35

^ Significant (p<0.001) correlation
* Significantly (p<0.001) different than ECG

Table 1. Summary of heart rate comparison data between Charge HR and ECG.

E.2. ECG vs. Fitbit Surge

E.2.1. Aggregate Data: When examining all time-synced ECG and Surge heart rate data in aggregate (n= 132,263 pairs), there was a significant ($p<0.001$) and moderately strong positive correlation between ECG and Surge (r=0.77) (Table 2, Figure 7). The mean HR from the Surge (121.58 ± 27.78 bpm) significantly ($p<0.001$) differed from the mean ECG HR (133.163 ± 32.64 bpm) (discrepancy of 11.98 ± 13.21% or 15.63 ± 13.21 bpm) (Table 2). The Surge exhibited a mean bias of -11.58 ± 21.03 bpm (95% LoA 29.64, -52.80) in reference to ECG criterion measure (Table 2, Figure 8).

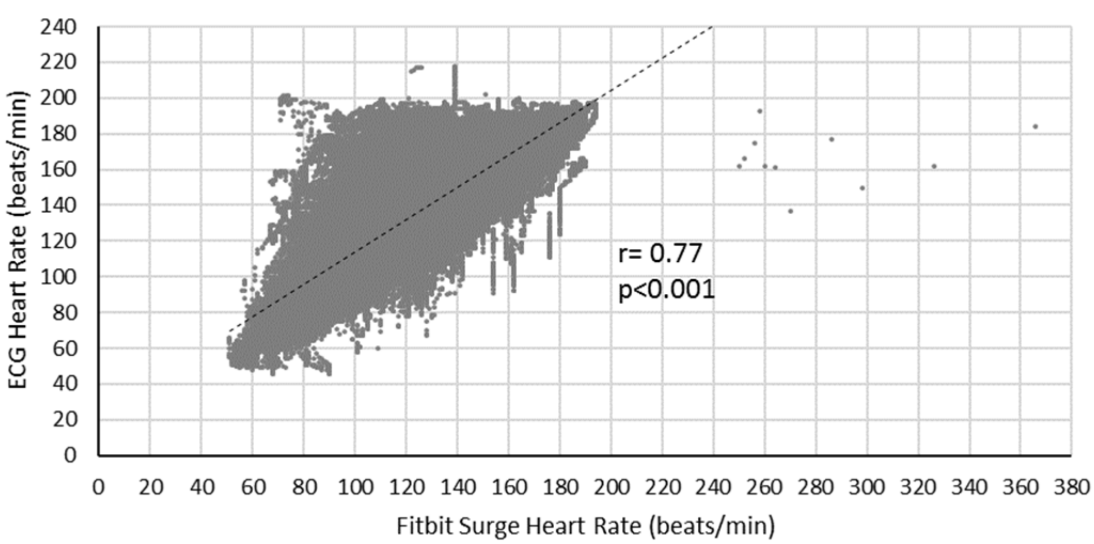

Figure 7. Relationship between time-synced ECG and Fitbit Surge heart rate.

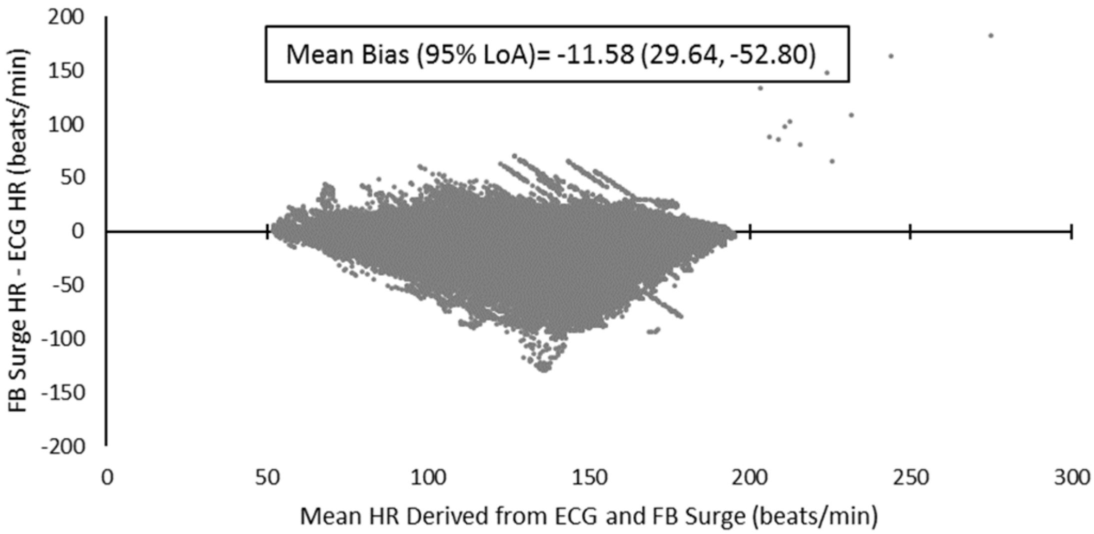

Figure 8. Bland-Altman plot indicating mean difference in heart rate detection between the Fitbit Surge and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

E.2.2. HR Data above mean ECG HR (>132 bpm): Time synced heart rate data above the mean ECG HR (>132 bpm; n=67,668 pairs) were analyzed. During conditions in which the ECG HR (true HR) exceeded 132 bpm, there was a significant ($p<0.001$) and weak positive correlation between ECG and Surge ($r=0.28$) (Table 2, Figure 9). In addition, the mean HR from the Surge (139.50 ± 22.00 bpm) significantly ($p<0.001$) differed from the mean ECG HR (160.308 ± 16.46 bpm) (discrepancy of 15.77 ± 15.53% or 22.75 ± 15.53 bpm) (Table 2). The Surge exhibited a mean bias of -20.81 ± 23.54 bpm (95% LoA 25.33, -66.95) compared to ECG during higher (>132 bpm) ECG/true heart rate conditions (e.g. high intensity exercise) (Table 2, Figure 9).

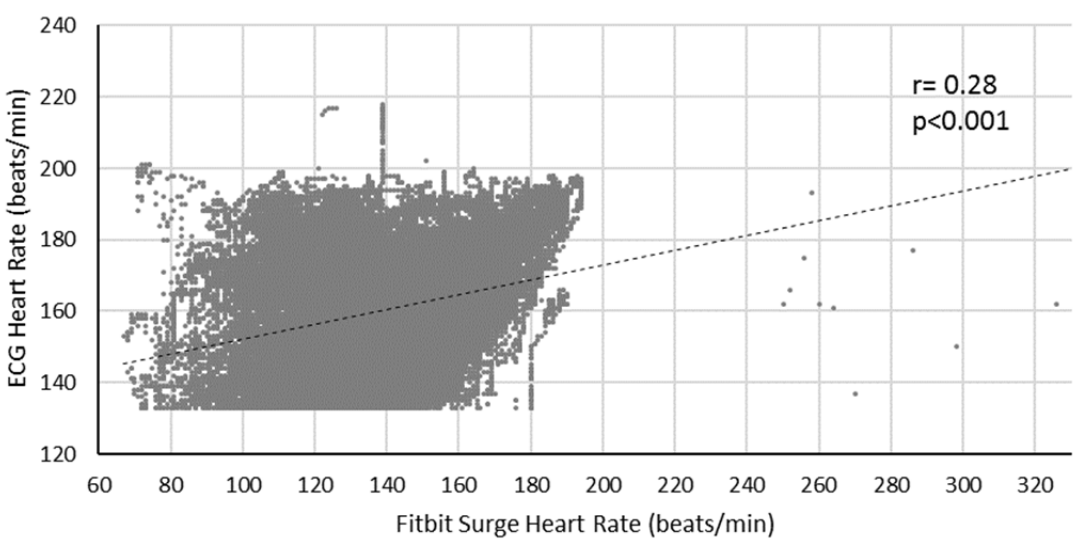

Figure 9. Relationship between time-synced ECG and Fitbit Surge heart rate during high ECG-measured heart rate range (>132 bpm)

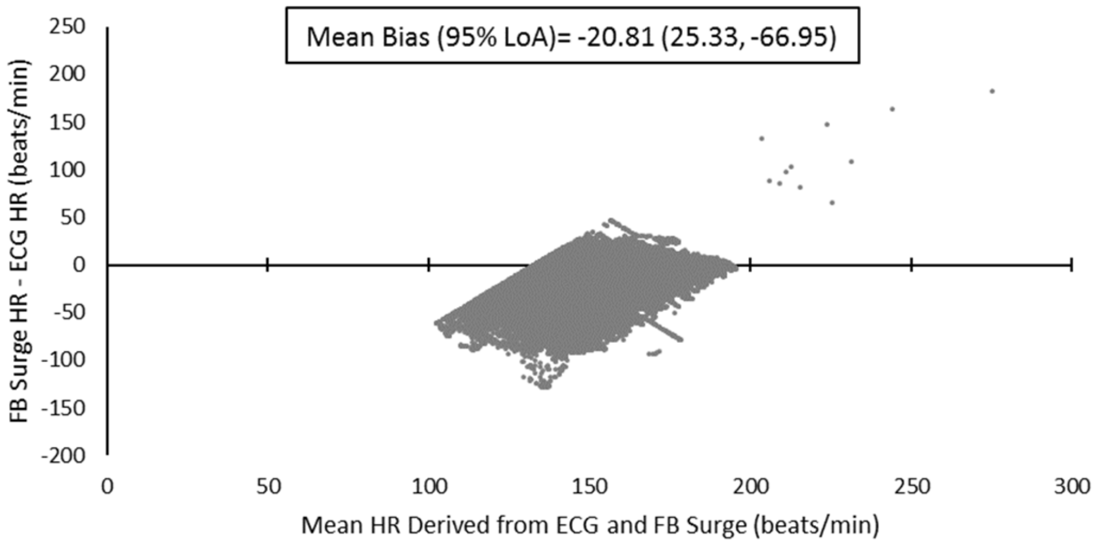

Figure 10. Bland-Altman plot indicating mean difference in heart rate detection between the Surge and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

E.2.3. HR Data below mean ECG HR (<133 bpm): Time synced heart rate data below the mean ECG HR (<133 bpm; n=64,620 pairs) were analyzed. During conditions in which the ECG HR (true HR) was below 133 bpm, there was a significant ($p<0.001$) and moderately strong positive correlation between ECG and Surge ($r=0.80$) (Table 2, Figure 11). In addition, the mean HR from the Surge (102.83 ± 19.61 bpm) significantly ($p<0.001$) differed from the mean ECG HR (104.74 ± 17.83 bpm) (discrepancy of 8.01 ± 8.60% or 8.17± 8.60 bpm) (Table 2). The Surge exhibited a mean bias of -1.91 ± 11.93 bpm (95% LoA 21.47, -25.30) compared to ECG during lower (<133 bpm) ECG/true heart rate conditions (e.g. low intensity exercise) (Table 2, Figure 12).

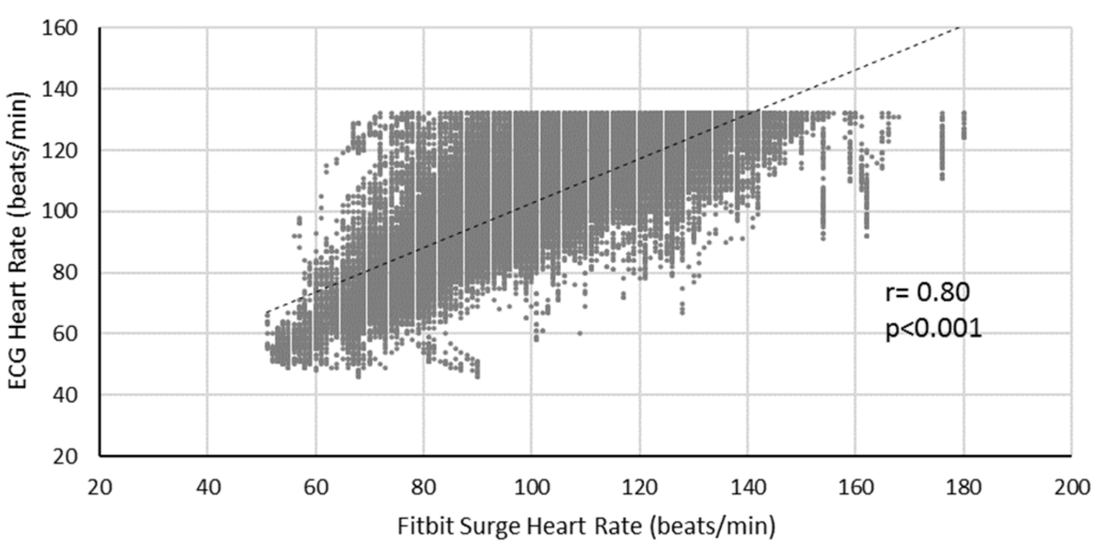

Figure 11. Relationship between time-synced ECG and Fitbit Surge heart rate during low ECG-measured heart rate range (<133 bpm)

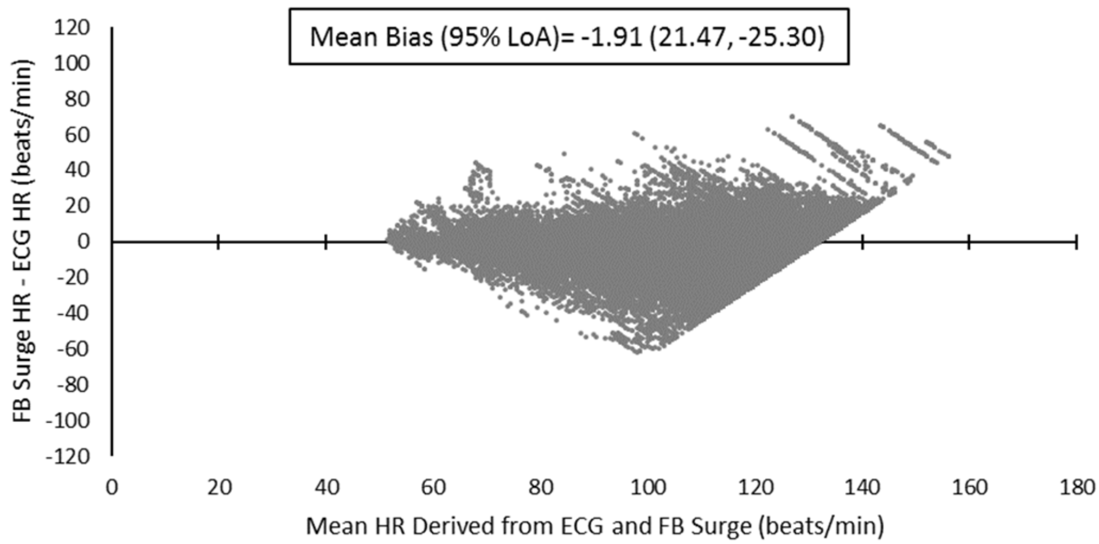

Figure 12. Bland-Altman plot indicating mean difference in heart rate detection between the Fitbit Surge and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

Parameter	Aggregate Data (n=132,263)	Data above ECG HR >132bpm (n=67,668)	Data below ECG HR <133bpm (n=63,327)
Surge Mean HR (bpm ± SD)	121.581 ± 27.78*	139.50 ± 22.00*	102.83 ± 19.61*
ECG Mean HR (bpm ± SD)	133.16 ± 32.64	160.31 ± 16.46	104.74 ± 17.83
Mean Absolute Difference (bpm ± SD)	15.63 ± 13.21	22.75 ± 15.53	8.17 ± 8.60
Mean Percent Difference (% ± SD)	11.98 ± 13.21	15.77 ± 15.53	8.01 ± 8.60
Correlation (r)	0.77^	0.28^	0.80^
Mean Bias (bpm ± SD)	-11.58 ± 21.03 (95% CI -11.70, -11.47)	-20.81 ± 23.54 (95% CI -20.00, -20.63)	-1.91 ± 11.94 (95% CI -2.01, -1.82)
95% Limits of Agreement (Upper, Lower)	29.64, -52.80	25.33, -66.95	21.47, -25.30
Standard Error of the Estimate (SEE)	17.75	21.14	11.74

^ Significant (p<0.001) correlation
* Significantly (p<0.001) different than ECG

Table 2. Summary of heart rate comparison data between Surge and ECG.

E.3. ECG vs. Fitbit Combined (PurePulse Trackers)

E.3.1. Aggregate Data: When examining all time-synced ECG and PurePulse Tracker data in aggregate (n= 259,478 pairs), there was a significant (p<0.001) and moderately strong positive correlation between ECG and PurePulse Trackers (r=0.80) (Table 3, Figure 13). The mean HR from the PurePulse Trackers (124.13 ± 28.97 bpm) significantly (p<0.001) differed from the mean ECG HR (133.02 ± 32.88 bpm) (discrepancy of 10.74 ± 12.08% or 13.94 ± 12.08 bpm) (Table 3). The PursePulse Trackers exhibited a mean bias of -8.89 ± 19.67 bpm (95% LoA 29.66, -47.44) in reference to ECG criterion measure (Table 2, Figure 14).

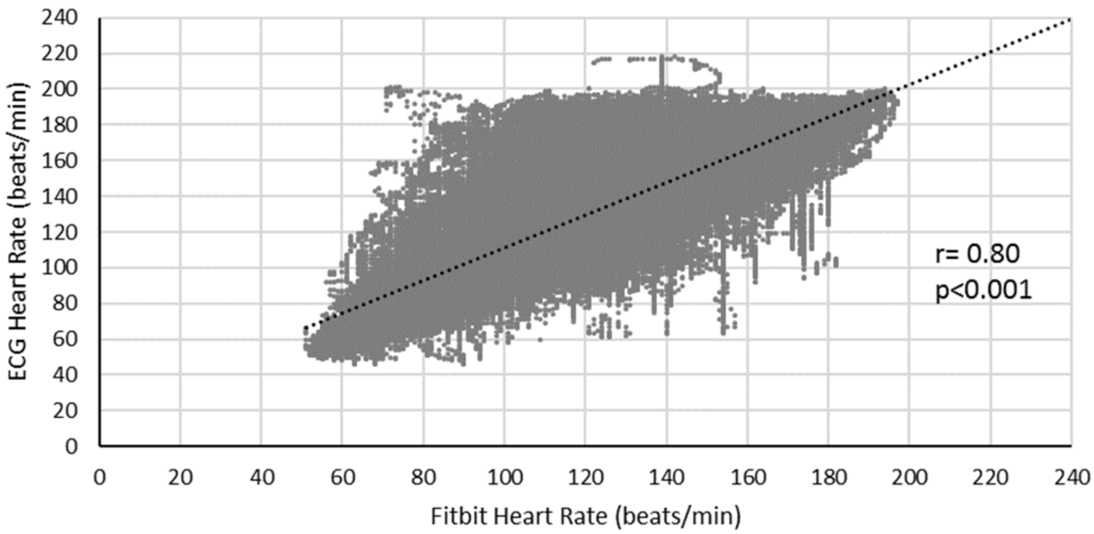

Figure 13. Relationship between time-synced ECG and PurePulse Tracker heart rate.

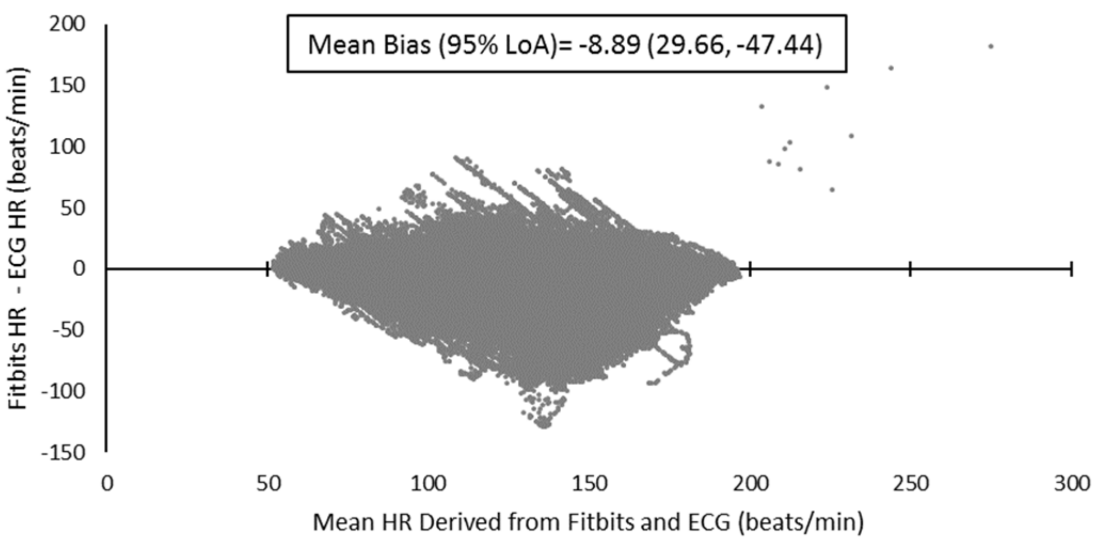

Figure 14. Bland-Altman plot indicating mean difference in heart rate detection between the PurePulse Trackers and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

E.3.2. HR Data above mean ECG HR (>132 bpm): Time synced heart rate data above the mean ECG HR (>132 bpm; n=131,531 pairs) were analyzed. During conditions in which the ECG HR (true HR) exceeded 132 bpm, there was a significant (p<0.001) and weak positive correlation between ECG and PursePulse Trackers (r=0.37) (Table 3, Figure 15). In addition, the mean HR from the PurePulse Trackers (143.80 ± 21.56 bpm) significantly ($p<0.001$) differed from the mean ECG HR (160.57 ± 16.74 bpm) (discrepancy of 13.14 ± 14.04% or 19.22 ± 14.04 bpm) (Table 3). The PurePulse Trackers exhibited a mean bias of -16.77 ± 21.89 bpm (95% LoA 26.13, -59.67) compared to ECG during higher (>132 bpm) ECG/true heart rate conditions (e.g. higher intensity exercise) (Table 3, Figure 16).

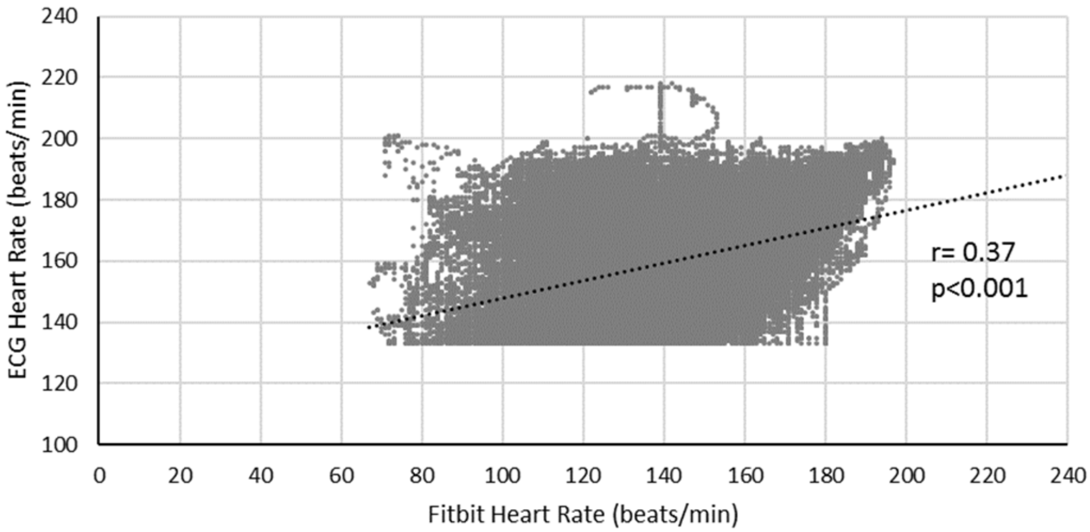

Figure 15. Relationship between time-synced ECG and PurePulse Tracker heart rate during high ECG-measured heart rate range (>132 bpm)

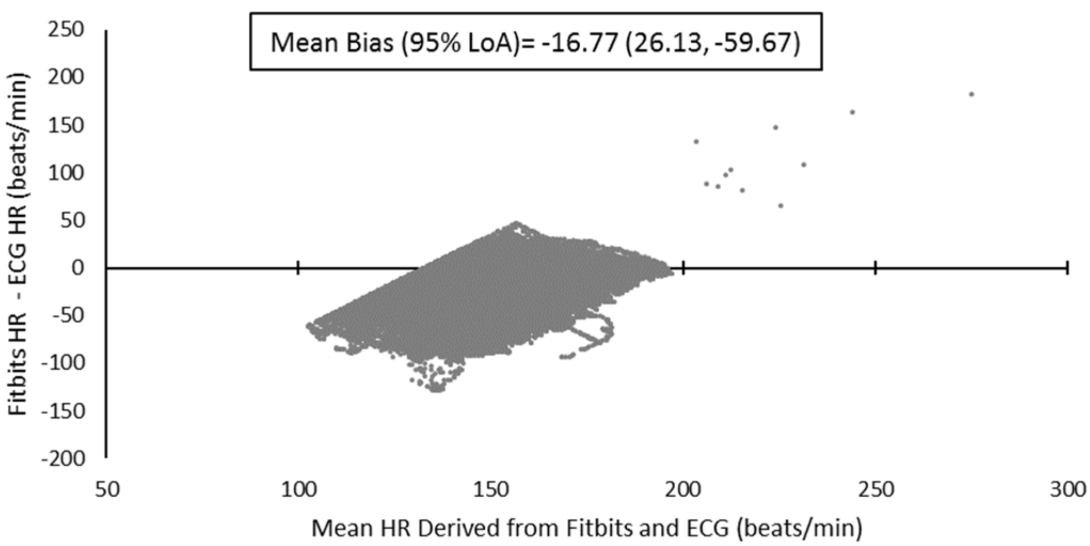

Figure 16. Bland-Altman plot indicating mean difference in heart rate detection between the PurePulse Trackers and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

<u>E.3.3. HR Data below mean ECG HR (<133 bpm):</u> Time synced heart rate data below the mean ECG HR (<133 bpm; n=127,947pairs) were analyzed. During conditions in which the ECG HR (true HR) was below 133 bpm, there was a significant ($p<0.001$) and moderately strong positive correlation between ECG and Surge (r=0.79) (Table 3, Figure 17). In addition, the mean HR from

the PurePulse Trackers (103.91 ± 20.45 bpm) significantly ($p<0.001$) differed from the mean ECG HR (104 ± 17.96 bpm) (discrepancy of 8.28 ± 9.02% or 8.51± 9.02 bpm) (Table 3). The PurePulse Trackers exhibited a mean bias of -0.79 ± 12.75 bpm (95% LoA 24.20, -25.79) compared to ECG during lower (<133 bpm) ECG/true heart rate conditions (e.g. low intensity exercise) (Table 3, Figure 18).

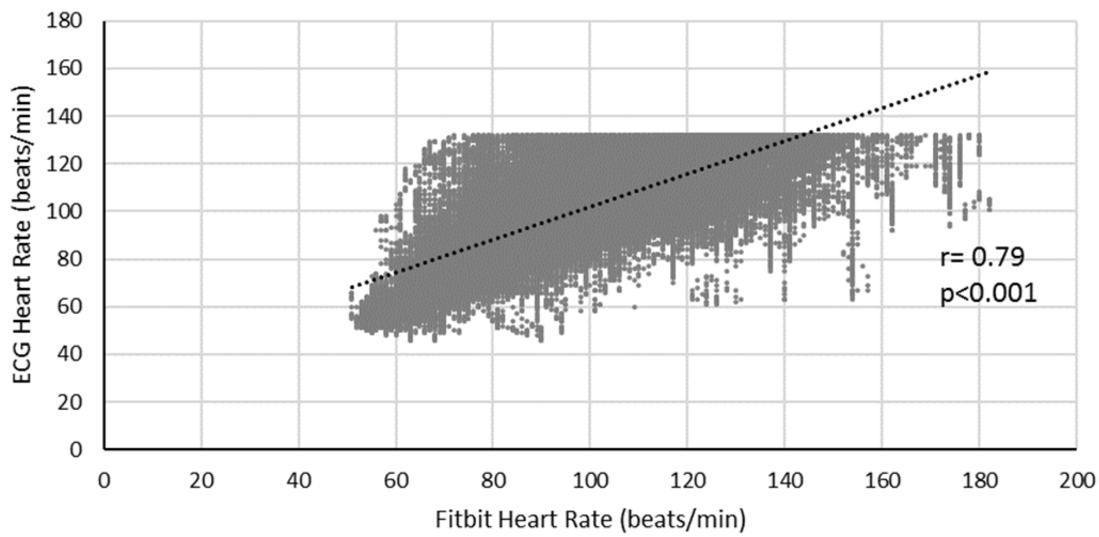

Figure 17. Relationship between time-synced ECG and PurePulse Tracker heart rate during high ECG-measured heart rate range (<133 bpm)

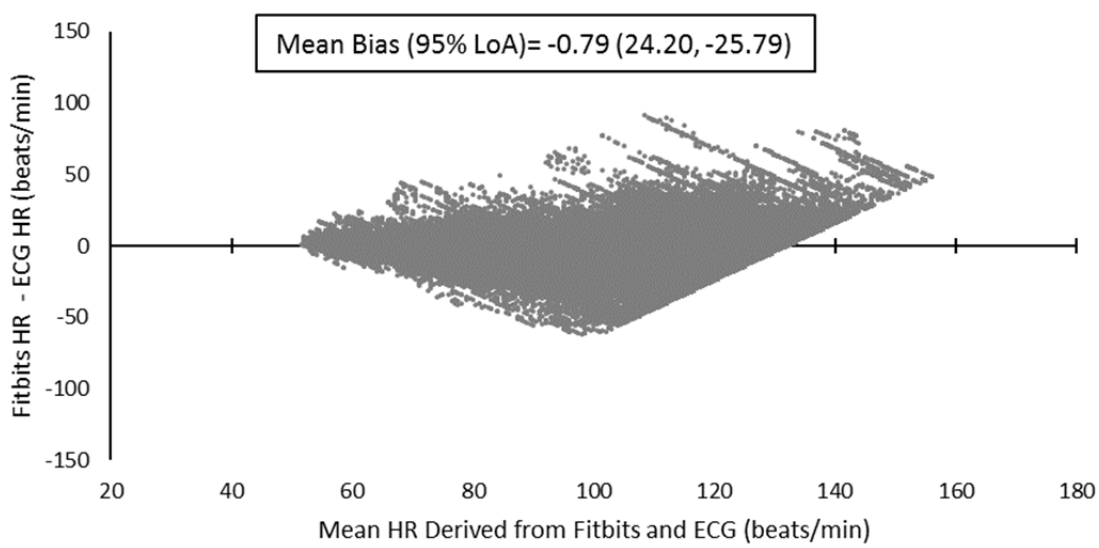

Figure 18. Bland-Altman plot indicating mean difference in heart rate detection between the PurePulse Trackers and ECG criterion measure. Mean bias and limits of agreement (95% LoA) are shown.

Parameter	Aggregate Data (n=259,478)	Data above ECG HR >132bpm (n=131,531)	Data below ECG HR <133bpm (n=127,947)
PurePulse Trackers Mean HR (bpm ± SD)	124.13 ± 28.97*	143.80 ± 21.56*	103.91 ± 20.45*
ECG Mean HR (bpm ± SD)	133.02 ± 32.88	160.57 ± 16.74	104.70 ± 17.96
Mean Absolute Difference (bpm ± SD)	13.94 ± 12.08	19.22 ± 14.04	8.51 ± 9.02
Mean Percent Difference (% ± SD)	10.74 ± 12.08	13.14 ± 14.04	8.28 ± 9.02
Correlation (r)	0.88^	0.37^	0.79^
Mean Bias (bpm ± SD)	-8.89 ± 19.67	-16.77 ± 21.89	-0.79 ± 12.75
95% Limits of Agreement (Upper, Lower)	29.66, -47.44	26.13, -59.67	24.20, -25.79
Standard Error of the Estimate (SEE)	17.19	20.04	12.62

^ Significant (p<0.001) correlation
* Significantly (p<0.001) different than ECG

Table 3. Summary of heart rate comparison data between PurePulse Trackers and ECG.

E.4. Manually Recorded Data

As a secondary method of data acquisition, heart rates were manually recorded from the device/watch interface and mobile monitors linked to the devices, including ECG, each minute of testing. Tables 4-6 below include the results for Charge HR, Surge and combined (i.e. PurePulse Trackers), respectively, with and without null data (i.e. “--“ readings) included in the analysis. Where included, the null readings were interpreted as a heart rate of 0 bpm.

The results for the Charge HR are reflected in the chart below.

Parameter	Aggregate Data w/ Null Data (n=2,795)	Aggregate Data w/o Null Data (n=2,711)	Data above ECG HR >132bpm w/ Null Data	Data above ECG HR >132bpm w/o Null Data	Data below ECG HR <133bpm w/ Null Data	Data below ECG HR <133bpm w/o Null Data
Charge HR Mean HR (bpm ± SD)	123.24 ± 36.75*	127.24 ± 30.11*	145.50 ± 31.35*	149.75 ± 19.37*	100.57 ± 26.58*	103.87 ± 19.66
ECG Mean HR (bpm ± SD)	133.42 ± 33.70	133.32 ± 33.58	162.00 ± 17.32	161.74 ± 17.19	104.33 ± 17.55	104.30 ± 17.61
Mean Absolute Difference (bpm ± SD)	14.01 ± 34.26	10.21 ± 10.02	18.24 ± 33.60	13.79 ± 11.30	9.70 ± 34.91	6.55 ± 8.32
Mean Percent Difference (% ± SD)	13.62 ± 34.26	7.85 ± 10.02	14.54 ± 33.60	9.13 ± 11.30	12.69 ± 34.91	6.54 ± 8.32
Correlation (r)	0.69^	0.88^	0.25^	0.53^	0.61^	0.86^
Mean Bias (bpm ± SD)	-10.18 ± 27.85	-6.27 ± 15.70	-16.49 ± 31.88	-11.99 ± 17.87	-3.76 ± 21.18	-0.42 ± 10.22
95% Limits of Agreement (Upper, Lower)	44.39, -64.76	24.50, -37.03	46.00, -78.98	23.04, -47.01	37.76, -45.28	19.61, -20.46
Standard Error of the Estimate (SEE)	24.37	15.69	16.80	14.61	13.96	9.13

^ Significant ($p<0.001$) correlation
* Significantly ($p<0.05$) different than ECG

Table 4. Summary of heart rate comparison manually recorded data between Fitbit Charge and ECG.

The results for the Surge are reflected in the chart below.

Parameter	Aggregate Data w/ Null Data (n=2,795)	Aggregate Data w/o Null Data (n=2,711)	Data above ECG HR >132bpm w/ Null Data	Data above ECG HR >132bpm w/o Null Data	Data below ECG HR <133bpm w/ Null Data	Data below ECG HR <133bpm w/o Null Data
Surge Mean HR (bpm ± SD)	117.24 ± 36.13*	121.81 ± 28.26*	133.17 ± 33.67*	141.50 ± 22.20*	101.01 ± 22.59*	102.64 ± 18.74
ECG Mean HR (bpm ± SD)	133.42 ± 33.70	132.63 ± 33.71	162.00 ± 17.32	161.90 ± 17.21	104.33 ± 17.55	104.13 ±17.54
Mean Absolute Difference (bpm ± SD)	19.63 ± 38.18	14.40 ± 13.13	30.21 ± 46.26	21.88 ± 16.03	8.86 ± 25.30	7.12 ± 7.68
Mean Percent Difference (% ± SD)	18.09 ± 38.18	10.99 ± 13.13	25.88 ± 46.26	14.99 ± 16.03	10.16 ± 25.30	7.10 ± 7.68
Correlation (r)	0.52^	0.79^	0.13^	0.28^	0.63^	0.84^
Mean Bias (bpm ± SD)	-16.19 ± 34.30	-10.82 ± 20.70	-28.82 ± 41.23	-20.40 ± 24.03	-3.32 ± 17.80	-1.49 ± 10.34
95% Limits of Agreement (Upper, Lower)	51.04, --83.42	29.75, -51.38	51.98, -109.63	26.70, -67.50	31.56, -38.20	18.78, -21.75
Standard Error of the Estimate (SEE)	28.80	20.64	17.19	16.54	13.60	9.53

^ Significant ($p<0.001$) correlation
* Significantly ($p<0.05$) different than ECG

Table 5. Summary of heart rate comparison manually recorded data between Fitbit Surge and ECG.

The results for the PurePulse Trackers combined are reflected in the chart below.

Parameter	Aggregate Data w/ Null Data (n=5,590)	Aggregate Data w/o Null Data (n=5,401)	Data above ECG HR >132bpm w/ Null Data	Data above ECG HR >132bpm w/o Null Data	Data below ECG HR <133bpm w/ Null Data	Data below ECG HR <133bpm w/o Null Data
PurePulse Mean HR (bpm ± SD)	120.24 ± 36.56*	124.45 ± 29.32*	139.34 ± 36.28*	145.69 ± 21.21*	100.79 ± 24.66*	103.25 ± 19.20
ECG Mean HR (bpm ± SD)	133.42 ± 33.69	132.98 ± 33.65	162.00 ± 17.32	161.82 ± 17.20	104.33 ± 17.55	104.21 ± 17.57
Mean Absolute Difference (bpm ± SD)	16.82 ± 36.34	12.29 ± 11.77	24.23 ± 40.81	17.77 ± 14.14	9.28 ± 30.51	6.84 ± 8.01
Mean Percent Difference (% ± SD)	15.86 ± 36.34	9.41 ± 11.77	20.21 ± 40.81	12.01 ± 14.14	11.42 ± 30.51	6.82 ± 8.01
Correlation (r)	0.60^	0.83^	0.18^	0.39^	0.62^	0.85^
Mean Bias (bpm ± SD)	-13.18 ± 31.38	-8.53 ± 18.50	-22.66 ± 37.36	-16.13 ± 21.54	-3.54 ± 19.56	-0.96 ± 10.29
95% Limits of Agreement (Upper, Lower)	48.32, -74.69	27.72, -44.79	50.56, -95.88	26.09, -58.34	34.80, -41.88	19.21, -21.13
Standard Error of the Estimate (SEE)	26.87	18.46	17.05	15.87	13.82	9.34

^ Significant ($p<0.001$) correlation
* Significantly ($p<0.05$) different than ECG

E.5. Charge HR vs. Surge

E.5.1. Aggregate Data: When examining all time-synced Surge and Charge HR heart rate data in aggregate (n= 113,994 pairs), there was a significant ($p<0.001$) and moderately strong positive correlation between the two trackers ($r=0.85$) (Table 4, Figure 19). The mean HR from the Charge HR (126.90 ± 29.60 bpm) significantly ($p<0.001$) differed from Surge (121.62 ± 27.50 bpm) (discrepancy of 7.93 ± 10.09% or 10.00 ± 10.09 bpm) (Table 4).

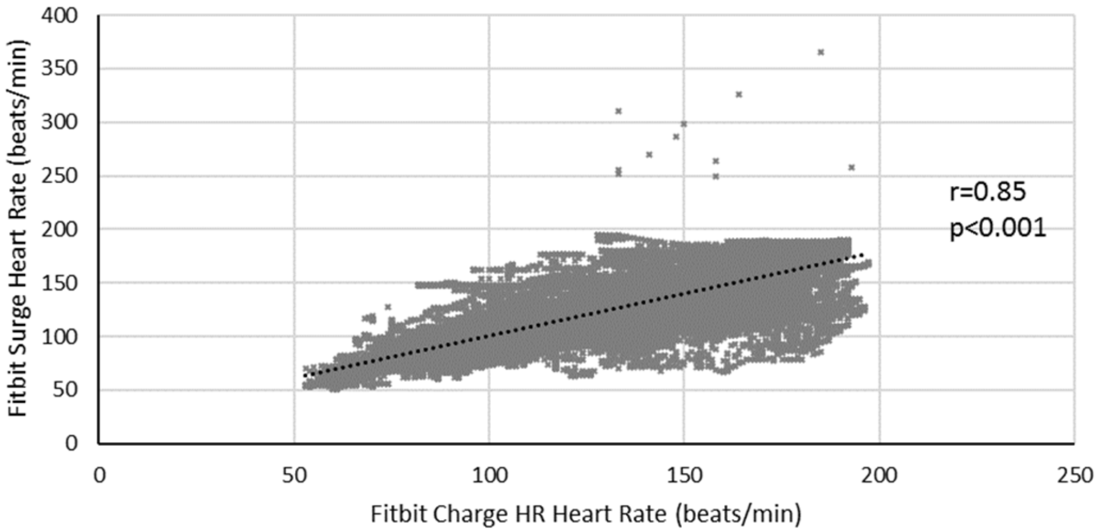

Figure 19. Relationship between time-synced Fitbit Charge HR and Fitbit Surge heart rate.

<u>E.5.2. HR Data above mean combined HR (>124 bpm):</u> When examining all time-synced Surge and Charge HR heart rate data above the combined average of 124 bpm (average of heart rate values across all PurePulse Tracker heart rate data) (n= 60,292 pairs), there was a significant ($p<0.001$) and weak correlation between the two trackers ($r=0.46$) (Table 4, Figure 20). The mean HR from the Charge HR (149.48 ± 17.11 bpm) significantly ($p<0.001$) differed from Surge (141.79 ± 18.27 bpm) (discrepancy of 8.66 ± 10.89% or 12.47 ± 10.89 bpm) (Table 4).

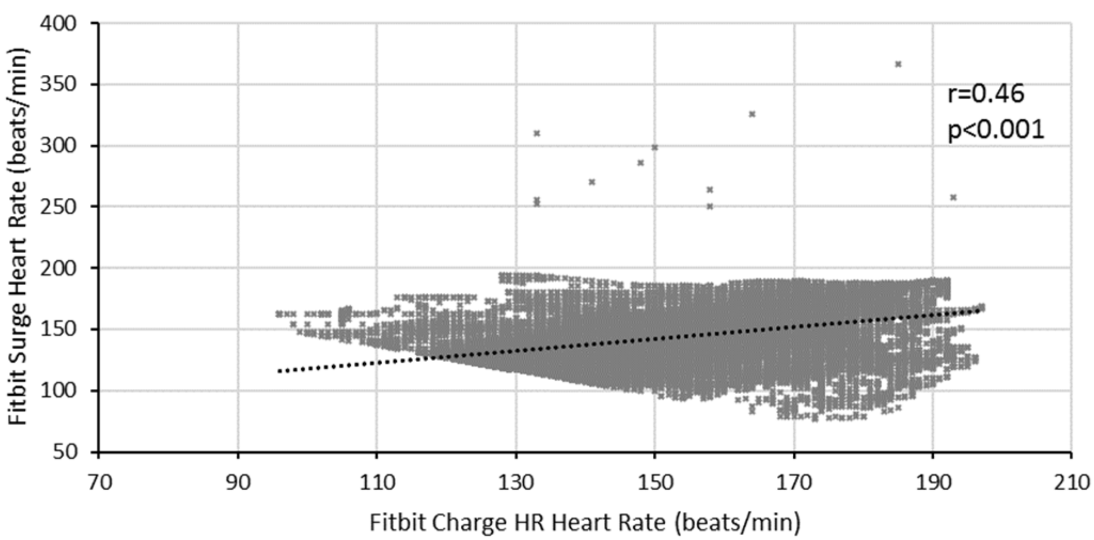

Figure 20. Relationship between time-synced Fitbit Charge HR and Fitbit Surge heart rate when data separated above average combined heart rate (>124 bpm)

<u>E.5.3. HR Data below mean combined HR (<125 bpm):</u> When examining all time-synced Surge and Charge HR heart rate at and below the combined average of 124 bpm (n= 53,702 pairs), there was a significant ($p<0.001$) and moderate correlation between the two trackers ($r=0.76$) (Table 4, Figure 21). The mean HR from the Charge HR (101.55 ± 17.76 bpm) significantly ($p<0.001$) differed from Surge (98.98 ± 16.17 bpm) (discrepancy of 7.11 ± 9.04% or 7.23 ± 9.04 bpm) (Table 4).

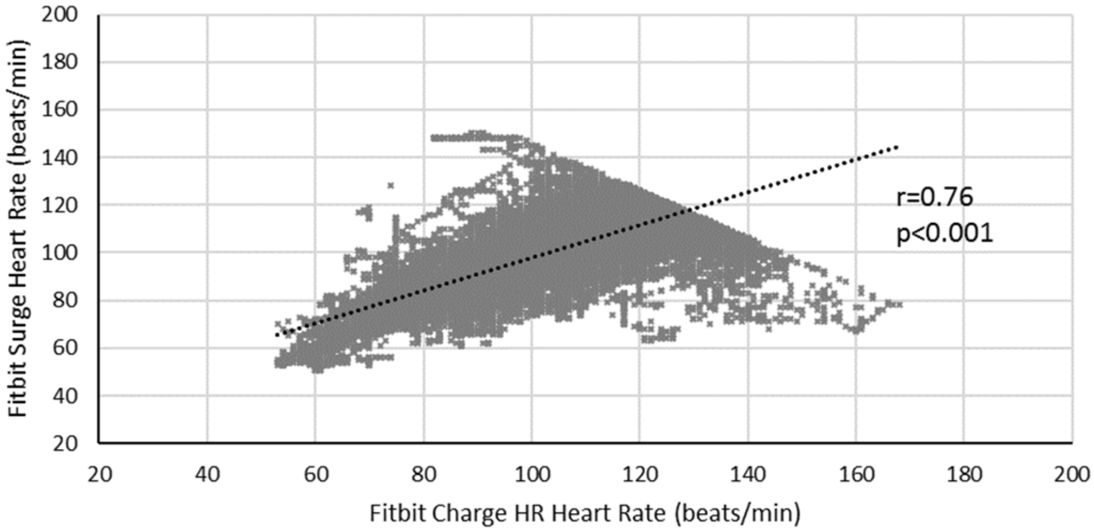

Figure 21. Relationship between time-synced Fitbit Charge HR and Fitbit Surge heart rate when data separated below average combined heart rate (<125 bpm)

Parameter	Aggregate Data (n=113,994)	Data above combined avg. HR >124bpm (n=60,292)	Data below combined avg. HR <125bpm (n=53,702)
Charge HR Mean HR (bpm ± SD)	126.90 ± 29.60*	149.48 ± 17.11*	101.55 ± 17.76*
Surge HR (bpm ± SD)	121.62 ± 27.50	141.79 ± 18.27	98.98 ± 16.17
Mean Absolute Difference (bpm ± SD)	10.00 ± 10.09	12.47 ± 10.89	7.23 ± 9.04
Mean Percent Difference (% ± SD)	7.93 ± 10.09	8.66 ± 10.89	7.11 ± 9.04
Correlation (r)	0.85^	0.46^	0.76^

^ Significant (p<0.001) correlation
* Significantly (p<0.001) different than Surge HR

Table 6. Summary of heart rate comparison data between Charge HR and Surge.

F. INTERPRETATION OF RESULTS

When examining the data in aggregate (n=127,215), the Charge HR failed to meet previously established validity criteria for heart rate monitors (SEE ≤ 5 bpm, r ≥ 0.90, and mean bias < 3 bpm). Although we observed a moderately strong correlation (r=0.85) between the Charge HR and ECG, there was a statistically significant (p<0.001) 9.5% (12.2 bpm) discrepancy between the Charge HR and ECG with the Charge HR exhibiting an average bias of -6.1 bpm (SEE= 15.9). This was a non-systematic bias based on the relatively wide limits of agreement (95% LoA 28.63, -40.81) (i.e. very sporadic difference scores), and therefore, both methods may not be used interchangeably for the measurement of heart rate. The LoA also suggests that the Charge HR trends towards an underestimation of heart rate. This inaccuracy is much more prominent when assessing validation among data pairs above the mean ECG heart rate (~132 bpm) compared to below. During these “high” heart rate conditions (e.g. assumingly moderate to high intensity exercise), the Charge HR demonstrated a weak relationship and extremely poor agreement with ECG (r= 0.48, mean difference= 10.4% or 15.5 bpm, SEE=17.6, mean bias= -12.5 bpm, 95% LoA 24.9, -49.9). However, it must be noted, that during lower ECG-based heart rate conditions (e.g. rest to low intensity exercise), only one out of the three established validity criteria were met (r= 0.78, mean bias= 0.36 bpm, SEE=13.35). Moreover, despite a relatively small mean bias, the wide limits of agreement (95% LoA 26.7, -26.0) indicate that even during rest to relatively light physical activity, the Charge HR may not be utilized interchangeably with ECG for the measurement of heart rate.

The Surge presented with weaker correlation (r=0.77) and less agreement (mean bias= -11.6 bpm, 95% LoA 29.6, -52.8, SEE= 17.8) to ECG than the Charge HR when examining the entire data set (n=132,263). Additionally, the 12.0% (15.6 bpm) discrepancy between Surge and ECG was statistically significant (p<0.001). The Bland-Altman Plot for the aggregate data set reflect not only large underestimation by the Surge, but wide limits of agreement. Thus, the Surge may not be considered interchangeable with ECG for the measurement of heart rate. As with Charge HR, we observed an increased level of inaccuracy with the Surge during physical activities eliciting higher ECG heart rates (i.e. >132bpm). The extremely weak correlation (r= 0.26) together with the large mean bias (= -20.8 bpm), and high SEE (=21.14) strongly suggest the Surge to be highly inaccurate during elevated physical activity. The Surge appeared to perform better during conditions corresponding to lower ECG heart rates based on a marginal average bias (= -1.9 bpm). However, other validity criteria were not met and thus may not be considered valid even during rest to light physical activity.

When examining both PurePulse Trackers in combination, the correlation (r-value), mean bias, and SEE also failed to meet validation criteria for heart rate monitors. As with each tracker analyzed separately, the combined data demonstrate compromised accuracy especially during higher intensities of exercise (>132 bpm).

The manually recorded data, as presented in Tables 4-6, adds further support to the results derived from the analysis of data acquired through the primary method of acquisition. That is, the results of manually recorded data strongly corroborate the results of the data obtained through the primary acquisition method. The manual approach to data collection, although not as sophisticated as the primary method, adds practical value to the overall findings given that consumers acquire heart rate data through similar methods (i.e. reading the value provided in real time through the watch interface). On the basis of these corroborating results, it is with strong scientific reasoning that it can be concluded that the Fitbit Charge HR and Surge fail to provide even reasonably accurate and reliable heart rate measurements.

Furthermore, a comprehensive comparison between both PursePulse Trackers (Section E.5) demonstrates considerable inconsistencies between the devices. This is surprising and concerning. The two Fitbit models purportedly incorporate the same PurePulse™ sensor technology for heart rate detection. And yet there were statistically significant discrepancies and a very imperfect correlation between the two models that were simultaneously recording the same heartbeat. It is reasonably assumed that both devices would yield similar heart rate values per given time point producing a near-perfect to perfect correlation (e.g. r= 1.00). However, the results from our analysis indicated only a moderately-strong correlation (r=0.85) which, in fact, weakened with increasing physical effort (r=0.46). This discrepancy in heart rate detection between the two devices with the same optical sensor technology further substantiates the inaccuracies reflected by the validation data and further confirms the failure of the PurePulse Trackers to accurately and consistently record heart rate data.

G. CONCLUDING STATEMENT

With strong scientific reasoning, the PurePulse™ technology embedded in the Fitbit optical sensors does not accurately record heart rate, and is particularly unreliable during moderate to high intensity exercise. The relatively weak correlations along with high biases and errors (i.e. poor agreement to ECG) reveal the significant limitations of PurePulse™ for biometric monitoring during exercise; although moderately better performance was observed during resting conditions. The devices are also inconsistent, as can be reasonably inferred from the notable discrepancies between Fitbit devices simultaneously measuring the heart rate. Moreover, disruptions to continuous heart rate detection in both Fitbit devices were quite common during testing periods based on manually recorded data. Although the factors underlying the observed inaccuracies extend beyond the scope of this study, it may be speculated that the current algorithms for heart rate estimation lack proper sophistication and sufficient data support to control for the multitude of confounding factors associated with PPG-based heart rate detection. Overall, the results of this investigation demonstrate that the PurePulse™ technology integrated in Fitbit's heart rate monitoring devices is not a valid method for heart rate measurement, and cannot be used to provide a meaningful estimate of a user's heart rate.

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Thesis: *Influence of Rest Duration Following a Potentiating Stimulus on Muscular Power*

California State University, Long Beach
Bachelor of Science in Kinesiology
Spring 2006
College of Health and Human Services
Department of Kinesiology

PROFESSIONAL EXPERIENCE IN ACADEMIA

California State Polytechnic University, Pomona
Department of Kinesiology and Health Promotion

- *Assistant Professor,* Fall 2013- Current
  - KIN303: Physiology of Exercise I
  - KIN303L: Physiology of Exercise I Lab
  - KIN403: Physiology of Exercise II
  - KIN403L: Physiology of Exercise II Lab
  - KIN462: Senior Project
  - KIN591: Graduate Research Design and Statistics
  - KIN683: Advanced Exercise Physiology
  - KIN683L: Advanced Exercise Physiology Lab

- *Director,* Fall 2013-Current
  - Cal Poly Human Performance Research Laboratory

Florida State University
Department of Nutrition, Food, and Exercise Sciences

- *Course Assistant*, Fall 2010-Summer 2013
  - PET3380: Applied Exercise Physiology

- *Teaching Assistant*, Fall 2009-Summer 2013
  - PET 3380: Applied Exercise Physiology Laboratory
  - PET 6931: Applied Exercise Physiology II Laboratory (graduate advanced topic)
  - PET 3323: Functional Anatomy and Physiology II Laboratory (Spring 2013)
  - PET 3102: Introduction to Exercise Science (Summer 2010)

- *Invited Lecturer*, Fall 2009-Summer 2013
  - PET 3380: Applied Exercise Physiology
  - PET 3322: Functional Anatomy and Physiology I

- PET 3102: Introduction to Exercise Science

- *Course Laboratory Assistant,* Fall 2009-Summer 2013
  - PET 4076 Physical Dimensions of Aging

The Florida State University
Center of Advancing Exercise and Nutrition Research on Aging
- *Graduate Student Associate*, 1/11/2012 – Current
- *Founding Student Member*

Tallahassee Community College
- *Invited Lecturer,* Spring 2012
  - PEM 1101: Theory and Practice of Adult Fitness

California State University, Fullerton
Department of Kinesiology
- *Teaching Assistant*, Fall 2006-Spring 2009
  - KNES 100: Physical Conditioning
  - KNES 146: Weight Training

- *Graduate Assistant*, Fall 2006-Summer 2009
  - CSUF Exercise Testing Laboratory
  - CSUF Employee Wellness Program

California State University, Long Beach
Department of Kinesiology
- *Undergraduate Research Assistant*, Fall 2005-Spring 2006
  - Human Performance Laboratory
  - Exercise Physiology Laboratory

PUBLICATIONS AND CURRENT PROJECTS

1. **Jo E.** Validation of the Fitbit Charge HR and Surge wearable fitness monitors. (in progress)

2. **Jo E**. The effects of intersession recovery supplementation of MusclePharm GAINZ™ on the metabolic, morphometric, and performance adaptations to an 8-week high-volume resistance training program. (in progress)

3. Galpin A, Bagley J, **Jo E**, and McLeland K. Influence of lifelong endurance training on health, fitness, and performance variables: a middle-aged monozygous twin case study. (in progress)

4. **Jo E.** and Fischer M. The effects of a two-week nitrate supplementation loading phase on time trial performance and muscle oxygenation using near infrared spectroscopy. (completed)

5. Liang M, **Jo E**, Spalding T, and Moustafa M. Effects of whole-body vibration training on bone density and bending strength in premenopausal women. (in progress)

6. **Jo E**, Osmond A, and Wong A. The effects of pre-exercise protein or carbohydrate consumption on metabolic rate and substrate oxidation after a bout of high-volume resistance exercise. (completed)

7. **Jo E.** and Dolezal BA. Validation of the Basis Peak™ Smart Watch. (completed)

8. **Jo E**, Directo D, Keong J, Wong M, Higuera D, and Osmond A. The acute effects of accommodating elastic resistance on electromyographic activity during the back squat, bench press, and deadlift exercises. (in preparation)

9. **Jo E**. A single-blinded randomized, controlled study of the effects of stretch refle air on flexibility and posture. (in preparation)

10. Liang M, **Jo** E, Gavin J, and Kwoh Y-L. Low body mass index and osteoporosis risk in young females. (in preparation)

11. Lee S-R, Grant SC, **Jo E**, Khamoui AV, Kim J-S. The effects of conjugated linoleic acid and omega-3 polyunsaturated fatty acid administration on age-related muscle loss in sedentary or resistance trained mice (in preparation)

12. **Jo E**, Arjmandi B, Cain A, Khamoui AV, Kim D-H, Ormsbee MJ, Prado CM, Smith D, Snyder K, Yeh M-C, and Kim J-S. A single-center evaluation of a clinical proprietary hypocaloric treatment for morbid obesity. (in review)

13. Zourdos MC, **Jo E**, Khamoui AV, Park B-S, and Kim J-S. The effects of a sub-maximal warm-up on endurance performance in trained male runners during a 30-minute time trial. (in review)

14. Zourdos MC, Klemp A, Dolan C, Quiles JM, Schau KA, **Jo E**, Helms E, Esgro B, Duncan S, Garcia Merino S, and Blanco R. Novel resistance training-specific rating of perceived exertion scale measuring repetitions in reserve. Journal of Strength and Conditioning Research. (1): 267-75 (2016)

15. **Jo E**, Kim J-S, Ormsbee MJ, Prado CM, and Khamoui AV. The physiological basis for weight recidivism following severe caloric restrictive diet therapies: A molecular rationale for exercise- and nutrition-based treatment optimization. Journal of Advanced Nutrition and Human Metabolism. (in press) (2016)

16. **Jo E**, Lewis K, Higuera D, Hernandez J, and Osmond A. Dietary caffeine and polyphenol supplementation enhances overall metabolic rate and lipid oxidation at rest and after a bout of sprint interval exercise. Journal of Strength and Conditioning Research (in press) (2015)

17. Zourdos MC, Dolan C, Quiles J, Klemp A, **Jo E**, Loenneke JP, Blanco R, and Whitehurts M. Efficacy of daily 1RM training in well-trained powerlifters and weightlifters. Nutricion Hospitalaria (in press) (2015)

18. Zourdos MC, **Jo E**, Khamoui AV, Lee S-R, Park B-S, Kim J-S. Modified daily undulating periodization model produces greater performance than a traditional configuration in powerlifters. Journal of Strength and Conditioning Research (in press) (2015)

19. Zourdos MC, Klemp AK, Dolan C, Quiles JM, Schau KA, **Jo E**, Helms E, Esgo B, Merino SG, Blanco R. Novel resistance training-specific RPE scale measuring repetitions in reserve and corresponding velocities. Journal of Strength and Conditioning Research (in press) (2015)

20. Lee S-R, Khamoui AV, Jo E, Park B-S, Zourdos MC, Panton LB, Ormsbee MJ, and Kim J-S. Effects of chronic high fat feeding on skeletal muscle mass and function in middle-aged mice. Aging Clinical and Experimental Research (in press) (2015)

21. Kim J-S, Zourdos MC, Henning PC, **Jo E**, Khamoui AV, Lee S-R, Park Y-M, Naimo M, Nosaka K. The repeated bout effect in muscle-specific exercise variations. Journal of Strength and Conditioning Research (in press) (2015)

22. Feresin R, Johnson S, Elam EL, **Jo E**, Arjmandi BH, Hakkak R. Effects of obesity on bone mass and quality in ovariectomized female zucker rats. Journal of Obesity. 2014(690123) (2014)

23. Huang C-J, Zourdos MC, **Jo E**, Ormsbee MJ. Influence of Physical Activity and Nutrition on Obesity-related Immune Function. The Scientific World Journal. 2013(752071) (2013)

24. Kim J-S, Park Y-M, Lee S-R, Masad IS, Khamoui AV, **Jo E**, Park B-S, Arjmandi BH, Panton LB, Lee W-J, Grant SC. Beta-Hydroxy-Beta-Methylbutyrate did not enhance high intensity resistance training-induced improvements in myofiber dimensions and myogenic capacity in aged female rats. Molecules and Cells. 34(5): 439-48 (2012)

25. Kim J-S, Khamoui AV, **Jo E**, Park B-S, Lee W-J. Beta-Hydroxy-Beta-Methylbutyrate as a countermeasure for cancer cachexia: A cellular and molecular rationale. Anti-Cancer Agents in Medicinal Chemistry. 13(8) (2012)

26. **Jo E**, Lee S-R, Park B-S, Kim J-S. Potential mechanisms underlying the role of chronic inflammation in the atrophy of aging muscle. Aging Clinical Experimental Research. 24(5): 412-422 (2013)

27. Wilson JM, Marin PJ, Duncan N, **Jo E**, Loenneke JP, Miller A, Brown LE. Meta-Analysis of post activation potentiation and power: effects of conditioning activity, volume, gender, rest periods, and training status. Journal of Strength and Conditioning Research. 27(3): 854-9 (2013)

28. Wilson JM, Loenneke JP, **Jo E**, Wilson GJ, Zourdos MC, Kim J-S. A brief review: The effects of endurance, strength, and power training on muscle fiber shifting. Journal of Strength and Conditioning Research. 26(6): 1724-1729 (2012)

29. **Jo E**, Judelson DA, Brown LE, Coburn JW, Dabbs N. Influence of Rest Duration Following a Potentiating Stimulus on Muscular Power. Journal of Strength and Conditioning Research. 24(2): 343-347 (2009)

BOOK CHAPTERS

1. Brown LE, **Jo E**, Khamoui AV. Test Administration and Interpretation. In: *Conditioning for Strength and Human Performance* 2nd Edition. Chandler TJ, Brown LE (Eds.) Philadelphia, PA: Lippincott Williams & Wilkins, 2010

LAY PUBLICATIONS

1. Dacuma M and **Jo E** (interview). How to Fall in Love with your Workout (and Ditch One you Hate). Brit+Co, November 8, 2015. www.brit.co/find-perfect-workout

2. **Jo E**, Ormsbee MJ. Yes or No? The Final Answer on Nitric Oxide (NO) Supplements. Sports Nutrition Insider, October 24, 2011. http://sportsnutritioninsider.insidefitnessmag.com/2631/yes-or-no-the-final-answer-on-nitric-oxide-no-supplements

3. Khamoui AV, **Jo E**, Brown LE. Postactivation Potentiation and Athletic Performance. NSCA, Hot Topics Series, September 24, 2009. http://www.nsca.com/HotTopic/download/Postactivation%20Potentiation.pdf

ABSTRACTS / FORMAL PRESENTATIONS

1. Lewis K, Directo D, Dolezal B, Fischer M, Higuera D, Osmond A, Wes R, Wong M, and **Jo E**. Validation of wearable multi-sensor biofeedback technology for heart rate tracking. NSCA National Conference, New Orleans, LA, June 6-9, 2016

2. Higuera D, Lewis K, Directo D, Osmond A, Wong M, and **Jo E**. The acute effects of a caffeine and polyphenolic compound on anaerobic performance and energy expenditure following high intensity interval exercise. NSCA National Conference, New Orleans, LA, June 6-9, 2016

3. Bathgate K, Bagley J, **Jo E**, Segal N, Brown L, Coburn J, Gulick C, Ruas C, and Galpin A. Physiological profile of monozygous twins with 35 years of differing exercise habits. NSCA National Conference, Boston, MA, June 6-9, 2016

4. Meeks L, Reynaga A, **Jo E,** Wein MA, Worland C, Burns-Whitemore B. The effects of perdometer-metered walking on body composition, blood glucose, diet alterations, blood pressure, and waist-to-hip ratios in college-aged participants: A pilot study. Experimental Biology, San Diego, CA, April 3, 2016

5. **Jo E**, Ormsbee MJ, Cain A, Snyder K, Elam M, Yeh M-C, Worts P, Khamoui AV, Kim D-H, Prado CM, Smith D, Brown AF, Kim J-S. The clinical application of periodized resistance training during a 12-week hypocaloric treatment for obesity. 2015 ACSM Southwest Chapter Annual Meeting, Costa Mesa, CA, October 16, 2015

6. Wong M, **Jo E**, Cain A, Kim J-S. A single-center evaluation of a proprietary hypocaloric treatment for morbid obesity. 2015 ACSM Southwest Chapter Annual Meeting, Costa Mesa, CA, October 16, 2015

7. Higuera D, Lewis K, Directo D, Osmond A, Wong M, and **Jo E**. The acute effects of caffeine and polyphenol supplementation on metabolic and fat oxidation rate at rest and following a bout of sprint interval exercise. 2015 ACSM Southwest Chapter Annual Meeting, Costa Mesa, CA, October 16, 2015

8. Osmond A, Higuera D, Lewis K, and **Jo E**. The acute effects of a caffeine and polyphenolic compound on metabolic rate and substrate oxidation at rest and following a bout of sprint interval exercise. 2015 CPP College of Science Research Symposium, May 29, 2015

9. Wong M and **Jo E**. A single-center evaluation of a proprietary hypocaloric treatment for morbid obesity. 2015 CPP College of Science Research Symposium, May 29, 2015

10. **Jo E**, Ormsbee MJ, Cain A, Snyder K, Elam M, Yeh M-C, Worts P, Khamoui AV, Kim D-H, Prado CM, Smith D, Brown AF, and Kim J-S. The clinical application of periodized resistance training during a 12-week hypocaloric treatment for obesity. 2015 ACSM National Conference, San Diego, CA, May 29, 2015

11. Khamoui AV, Kim D-H, Yeh M-C, Park B-P, Oh S-L, Elam ML, Worts PR, **Jo E**, Myers CM, Arjmandi BH, Salazar G, McCarthy DO, and Kim J-S. Aerobic and resistance training effects on skeletal muscle plasticity in colon-26 tumor-bearing mice. 2015 ACSM National Conference, San Diego, CA, May 29, 2015

12. Gavin JM, Kwoh N, **Jo E**, and Liang MTC. Low body mass index affects bone health in young women. 2015 ACSM National Conference, San Diego, CA May 29, 2015, May 29, 2015

13. Zourdos MC, Dolan C, Quiles JM, Klemp A, Blanco R, Krahwinkel AJ, Goldsmith JA, **Jo E**, Loenneke JP, and Whitehurst M. Efficacy of daily 1RM squat training in well-trained lifters: Three case studies. 2015 ACSM National Conference, San Diego, CA, May 29, 2015

14. Yeh M-C, **Jo E**, Worts P, Cain A, Elam M, Khamoui AV, Kim D-H, Ormsbee MJ, Prado CM, Smith D, Snyder K, and Kim J-S. The clinical application of periodized resistance training during a 12-week hypocaloric treatment for obesity. 2015 ACSM Southeast Chapter Annual Meeting, Jacksonville, FL, February 12-14, 2015.

15. Dolan C, Quiles JM, Klemp A, Schau KA, Esgro B, **Jo E**, and Zourdos MC. Evaluating squat attempt velocities of collegiate and open powerlifters as a marker of performance and indicator of success during competition. NSCA National Conference, Las Vegas, NV, July 9-12, 2014.

16. Klemp A, Dolan C, Quiles JM, Schau KA, Esgro B, **Jo E**, and Zourdos MC. The usefulness of average velocity of opening deadlift attempts in open and collegiate powerlifters during competition as a predictor of performance. NSCA National Conference, Las Vegas, NV, July 9-12, 2014.

17. **Jo E**, Cain A, Prado CM, Ormsbee MJ, Arjmandi B, Snyder K, Smith D, Khamoui AV, Yeh M-C, Kim D-H, Park B-S, Oh S-L, and Kim J-S. A single-center evaluation of a proprietary hypocaloric treatment for morbid obesity. Annual Meeting, ACSM, Orlando, FL, May 27-31, 2014.

18. Oh S-L, Lee S-R, Khamoui AV, **Jo E**, Park B-S, Ormsbee MJ, Kim D-H, Yeh M-C, and Kim J-S. Effects of CLA/n-3 and resistance training on muscle quality in middle-aged mice during high-fat diet. Annual Meeting, ACSM, Orlando, FL, May 27-31, 2014.

19. Zourdos MC, **Jo E**, Khamoui AV, Park B-S, Lee S-R, Panton LB, Ormsbee MJ, Thomas D, Ward E, Contreras RJ, and Kim J-S. Novel daily undulating periodization model produces greater performance gains than a traditional configuration in powerlifters. Annual Meeting, ACSM, Indianapolis, IN, May 30, 2013.

20. Park B-S, Henning PC, Khamoui AV, **Jo E**, Lee S-R, Zourdos MC, Kim D-H, Yeh M-C, and Kim J-S. HMB attenuates a loss of myofiber cross-sectional area during prolonged exercise with calorie restriction by Enhancing Regenerative Capacity. Experimental Biology, Boston, MA, April 20-24, 2013.

21. Lee S-R, Jo E, Khamoui AV, Park B-S, Zourdos MC, Grant SC, and Kim J-S. Fatty Acid and Resistance Exercise Administration Improve Muscle Wasting by Impaired Myogenic Capacity in High Fat Diet-Fed Mice. Experimental Biology, Boston, MA, April 20-24, 2013.

22. Zourdos MC, **Jo E**, Khamoui AV, Park B-P, Lee S-R, Panton LB, Contreras RC, Ormsbee MJ, Wilson JM, and Kim J-S. Time course of hormonal responses with two different models of daily undulating periodization in trained powerlifters. Annual Meeting, SEACSM, Greenville, SC, February 14-16, 2013.

23. **Jo E,** Zourdos MC, Wilson JM, Nosaka K, Lee S-R, Naimo M, Henning PC, Park Y-M, Khamoui AV, Park B-P, Panton LB, and Kim J-S. Varying muscle-specific exercise between consecutive training sessions does not diminish the repeated bout effect. Annual Meeting, ACSM, San Francisco, CA, May 29-June 2, 2012.

24. Zourdos MC, Khamoui AV, **Jo E**, Park B-P, Lee S-R, Panton LB, Contreras RC, Ormsbee MJ, Wilson JM, and Kim J-S. Changes in maximal strength with two different models of daily undulating periodization in trained powerlifters. Annual Meeting, ACSM, San Francisco, CA, May 29-June 2, 2012.

25. Lee S-R, Khamoui AV, **Jo E**, Park B-P, Zourdos MC, Bakhshalian N, Grant SC, Arjmandi BH, Ormsbee MJ, Kim J-S. Anti-catabolic Effects of CLA/n-3 In Resting And Loaded Muscles of High Fat Diet-fed Mice. Annual Meeting, ACSM, San Francisco, CA, May 29-June 2, 2012.

26. Kim J-S, Lee S-R, Grant SC, **Jo E**, Khamoui AV, , Park B-P, Zourdos MC, Hooshmand S, Ormsbee MJ, Arjmandi BH. Fatty Acid Intake and Exercise Improve Body Composition and Functionality in High Fat Diet-Fed Mice. Annual Meeting, ACSM, San Francisco, CA, May 29-June 2, 2012.

27. Wilson JM, Marin PJ, Duncan N, Loenneke JP, **Jo E**, Zourdos MC, Brown LE. Post Activation Potentiation: A Meta-Analysis Examining The Effects Of Volume, Rest Period Length, And Conditioning Mode On Power. Annual Meeting, ACSM, San Francisco, CA, May 29-June 2, 2012.

28. Park B-S, Henning PC, Lee S-R, Wilson JM, Park Y-M, **Jo E**, Khamoui AV, Zourdos MC, and Kim J-S. β -hydroxy-β-methylbutyrate (HMB) improves myogenesis and maintains strength in male mice during a 6-wk catabolic condition. Experimental Biology, Washington D.C, April 8-13, 2011.

29. Lee S-R, Wilson JM, Henning PC, Ugrinowitsch C, Park Y-M, Zourdos MC, Park B-S, Khamoui AV, **Jo E**, Grant SC, Panton LB, and Kim J-S. Β-hydroxy-β-methylbutyrate (HMB) improves relative grip strength and sensorimotor function in middle aged and old rats. Annual Meeting, ACSM, Baltimore, MD, June 2-5, 2010.

30. Park Y-M, Lee S-R, Wilson JM, Henning PC, Bakhshalian N, Ugrinowitsch C, Zourdos MC, Park B-S, **Jo E**, Khamoui AV, and Kim J-S. Influence of β-hydroxy-β-methylbutyrate (HMB) on body composition and neuromuscular function in old rats during resistance training. Annual Meeting, ACSM, Baltimore, MD, June 2-5, 2010.

31. **Jo E**, Martinez M, Brown LE, Coburn JW, Biagini M, Gochioco M, Judelson DA. Effects of caffeine on resistance exercise performance, mood, heart rate, and rating of perceived exertion. Annual Meeting ACSM, Baltimore, MD, June 2-5 2010.

32. Lee SR, Park YM, Wilson JM, Henning PC, Zourdos MC, Bakhshalian N, Ugrinowitsch C, Park BS, Khamoui A, **Jo E**, Kim JS. Effects of β -hydroxy-β-methylbutyrate (HMB) on body composition in old Sprague-Dawley female rats during 10-week resistance training Lee. Annual Meeting, SEACSM, Greenville, SC, February 11-13, 2010.

33. **Jo E**, Martinez M, Brown LE, Coburn JW, Biagini M, Gochioco M, Judelson DA. Effects of caffeine on resistance exercise performance, mood, heart rate, and rating of perceived exertion. Annual Meeting, SEACSM, Greenville, SC, February 11-13, 2010.

34. Khamoui AV, Brown LE, Tran TT, Uribe BP, Nguyen D, Gochioco MK, Schick EE, **Jo E**, Coburn JW, Noffal GJ. Comparison of methods to calculate vertical jump displacement. Annual Meeting, SEACSM, Greenville, SC, February 11-13, 2010.

35. Khamoui AV, Nguyen D, Uribe BP, Tran T, **Jo E,** Brown LE, Coburn JW, Judelson DA, Noffal GJ. Relationship between Dynamic Kinematics and Isometric Force-Time Characteristics. NSCA National Conference, Las Vegas, NV, July 8-11, 2009.

36. Dabbs NC, Khamoui AV, Nguyen D, Uribe BP, Tran T, **Jo E,** Brown LE, Coburn JW, Judelson DA, Noffal GJ. Difference in Vertical Jump Performance by Force Production. NSCA National Conference, Las Vegas, NV, July 8-11, 2009.

37. Tran T, Faulkinbury K, Stieg J, Khamoui AV, Uribe BP, Dabbs NC, **Jo E,** Brown LE FNSCA, Coburn JW FNSCA, and Judelson DA. Effect of 10 Repetitions of Box Jumps on Peak Ground Reaction Force. NSCA National Conference, Las Vegas, NV, July 8-11, 2009.

38. **Jo E**, Judelson DA, Brown LE, Coburn JW, Dabbs N, Uribe BP. Influence of Rest Duration Following a Potentiating Stimulus on Muscular Power in Recreationally Trained Individuals. Annual Meeting, ACSM, Seattle, WA, May 27-30, 2009.

CONTRACTS, GRANTS, AND DONATIONS

1. **Jo E** (PI) and Dolezal BA. Validation of Fitbit Surge and Charge HR Fitness Trackers. Funding Source: Lieff, Carbraser, Heimann, and Bernstein. Amount: $10,100 (Funded 1/29/16)

2. **Jo E** (PI). The effects of a two-week nitrate supplementation loading phase on time trial performance and muscle oxygenation using near infrared spectroscopy. Funding Source: Shaklee Corporation. Amount: $7,000 in-kind value of supplies (Funded 9/25/15)

3. **Jo E** (PI) and Dolezal BA. Validation of the Basis Peak™ Smart Watch. Funding Source: Basis, an Intel Company. Amount: $6,000 in-kind value of supplies (Funded 9/10/15)

4. **Jo E** (PI). Acquisition of Ultrasonic Imaging System. Funding Source: 2015-2016 SPICE Classroom Modernization Program- Cal Poly Pomona. Amount: $15,396.97 (Funded 6/2/15)

5. **Jo E** (PI). The effects of intersession recovery supplementation of MusclePharm GAINZ™ on the metabolic, morphometric, and performance adaptations to an 8-week high-volume resistance training program. Funding Source: International Society of Sports Nutrition and MusclePharm Corp. Amount: $10,000+$2,400 in-kind value of supplies= $12,400 (Funded 2/25/15)

6. **Jo E** (PI). A single-blinded randomized, controlled study of the effects of stretch refle air on flexibility and posture: a research proposal. Funding Source: NCC Co. Ltd. Amount: $120,537 (Funded)

7. Liang M, **Jo E** (Co-PI), Spalding T, and Moustafa M. Effects of whole-body vibration training on bone density and bending strength in premenopausal women. Funding Source: NIH-SCORE S3. Amount: $150,000 (not funded)

8. **Jo E** (PI). Exercise and Nutrition Research for Obesity Treatment. Funding Source: Kellogg FuTURE Program, Cal Poly Pomona Office of Undergraduate Research. Amount: $2,000 (Funded 2/4/2015)

9. **Jo E** (PI). Human Health and Performance Research. Funding Source: 2015 Faculty Center for Professional Development, Cal Poly Pomona. Amount: $1,000 (Funded 1/15/2015)

10. **Jo E** (PI). Cal Poly Human Performance and Nutrition Research. Funding Source: Dymatize Nutrition. Amount: $1,272.23 in-kind value of supplies (Funded 12/2/14)

11. Liang M and **Jo E** (Co-PI)**.** Low body mass index affects bone health in young females. Funding Source: Research, Scholarly and Creative Activities (RSCA) Grant Program, Cal Poly Pomona. Amount: $5,000 (Funded 10/13/15)

12. **Jo E** (PI). Effects of Thermogenic Supplementation on Muscular Performance during a Bout of High Intensity Interval Training and Pre-, Mid- and Post- Exercise Metabolic Rate in Overweight, College-aged Males and Females. Funding Source: 2014 Faculty Center for Professional Development, Cal Poly Pomona. Amount: $1,000 (Funded)

13. **Jo E** (PI). The clinical application of periodized resistance training and HMB free acid supplementation during a 12-week hypocaloric treatment for obesity: A multicenter clinical trial. Metabolic Technologies Inc. (in review)

14. **Jo E** (PI; Primary Grant Writer) and Ormsbee MJ. Periodized resistance training and whey protein intake during weight-loss treatment. Funding Agency: National Strength and Conditioning Association Foundation. Amount: $10,000 (Funded)

15. Kim JS (PI), Cain AF, Ormsbee MJ, Prado C, Snyder K, Smith D, and **Jo E** (Co-PI; Primary Grant Writer). The independent and combined effects of Programmed resistance training and whey protein supplementation on body composition, resting metabolic rate, neuromuscular function, and Biochemical Regulators of lean tissue Morphology in clinically obese subjects undergoing weight-loss treatment. Funding Agency: Nestlé HealthCare Nutrition. Amount: ~$120,000 in product support (scored; not funded)

16. Kim JS (PI), Arjmandi BH, Grant SC, and **Jo E** (Primary Grant Writer). Efficacy of Anti-Inflammatory Fatty Acids in Attenuating Inflammation-Mediated Musculoskeletal Impairments during Lifelong High Fat Diet. Funding Agency: USDA. Amount: $500,000 (not funded)

17. Kim JS (PI), Arjmandi BH, Grant SC, Levenson CW, and **Jo E** (Primary Grant Writer). Reversing Obesity-Accelerated Aging: Mechanisms of Diet and Exercise Amount: Funding Agency: NIH-R01. Amount: $1,702,917 (scored; not funded)

18. Kim JS (PI), Arjmandi BH, Grant SC, and **Jo E** (Primary Grant Writer). Efficacy of Anti-Inflammatory Fatty Acids in Attenuating Inflammation-Mediated Musculoskeletal Impairments during Lifelong High Fat Diet. Funding Agency: USDA. Amount: $500,000 (scored; not funded)

CERTIFICATIONS / LICENSES

International Society of Sports Nutrition

- Certified Sports Nutritionist (CISSN), 6/17/14 - Current

California Department of Public Health, Radiologic Health Branch

- X-Ray Technician Bone Densitometry Permit (DXA) (#RHP00098002), 8/31/14 - Current

The Foundation of Osteoporosis Research and Education

- Limited Permit X-Ray Technician, 3/2/14 - Current

National Strength and Conditioning Association

- Certified Strength and Conditioning Specialist (CSCS), 11/8/07 - Current
- Certified Personal Trainer (CPT), 11/13/04 – Current

American Heart Association

- Adult and Child CPR and AED, Current

PROFESSIONAL MEMBERSHIPS

International Society of Sports Nutrition, 1/14 - Current
American Physiological Society, 6/11 - Current
American College of Sports Medicine, 6/15/10 - Current
Southeast Chapter of American College of Sports Medicine, 2/10 - Current
National Strength and Conditioning Association, 11/13/04 – Current

PROFESSIONAL AND ACADEMIC SERVICES

One More Round Documentary Advisory Board
Advisory Board Member, Fall 2014-Current

Editorial Review Panel
NSCA Coach Publication, Summer 2014-Current

Kellogg Honors College Application Reviewer
California State Polytechnic University, Pomona, Winter 2014

Student Health Advisory Committee
California State Polytechnic University, Pomona, Winter 2014-Current

International Society of Sports Nutrition (ISSN) West Coast Representative
International Society of Sports Nutrition, Spring 2014-Current

Invited Peer Reviewer
Applied Physiology, Metabolism and Nutrition
Sports Medicine
NSCA Performance Training Journal
Journal of Strength and Conditioning Research
NSCA Coach

College of Human Sciences Graduate Show Case 2012
Florida State University
Graduate Student Panel, 10/18/2012

College of Human Sciences Dissertation Award Program
Florida State University
Invited Reviewer, 10/2012

Center of Advancing Exercise and Nutrition Research on Aging
Florida State University
Graduate Student Assistant
Founding Student Member, 1/11/2012 - Current

Optimizing Performance: Training and Nutritional Adaptations Symposium
Florida State University and Florida A&M University
Organizer, 10/14/2012

LABORATORY SKILLS AND ANALYTICAL TECHNIQUES

Analysis of human health and performance

- Maximal VO_2 testing, cardiopulmonary stress testing, and indirect calorimetry using metabolic measurement system (ParvoMedics TrueOne)
- Isokinetic dynamometry using Biodex system
- Body composition analyses: Hydrodensitometry, multi-site skinfold caliper test, whole body air-displacement plethysmography (BODPOD)
- Cycle ergometry performance analysis using Monark Sports and Medical system
- Force plate analysis of human performance kinetics
- Maximal and submaximal graded exercise and strength testing administration
- Muscle oximetry utilizing NIRS and photoplethysmography

Small animal model research techniques

- Basic small animal handle and care
- Administration of exercise and dietary interventions for rodent models
- Small animal euthanasia and surgical techniques for hindlimb muscle and multi-organ isolation
- Post-surgery tissue sample treatment, care, and storage
- In vivo analysis of small animal body composition using dual x-ray absorptiometry
- In vivo measurement of small animal physical function: muscular contractile properties and sensorimotor coordination

Wet laboratory techniques

- Skeletal muscle immunohistochemistry and histology: Tissue fixation, cryostat operation, Avidin Biotin Complex (ABC) staining method, light microscopy, image acquisition, histological analysis (CSA, nuclei and protein quantification, etc)
- Reverse Transcriptase Polymerase Chain Reaction
- Western Blot
- RT-PCR and western blot band amplification and densitometric analysis (ChemiDoc and densitometry software)
- Enzyme Linked Immunosorbent Assay (ELISA)
- Protein assay using BCA method
- Automated serum analyzer (Sigma) operation
- Microplate reader (BioRad Model 680 and BioTek) operation
- General phlebotomy techniques (venipuncture)
- Blood lactate, glucose, and lipid measurement and analysis

AWARDS AND HONORS

2015 Science Council Club Advisor of the Year
California State Polytechnic University, Pomona

2015 College of Science Distinguished Teaching Award Finalist
California State Polytechnic University, Pomona

2014-2015 Cal Poly Pomona Intercollegiate Athletics Recognition of Appreciation
California State Polytechnic University, Pomona, Department of Athletics

Minority Scholarship 2011
National Strength and Conditioning Association Foundation

Glenn Society Inductee 2011
College of Human Sciences, Florida State University
Recognition of scholarly achievements and outstanding leadership

Outstanding Teaching Assistant Award Nominee 2011
Program for Instructional Excellence, Florida State University
University-wide recognition of outstanding performance as teaching assistant

Challenge Scholarship 2010
National Strength and Conditioning Association Foundation

Frances / Ricardo Moreno Scholarship Award 2009
College of Health and Human Sciences, California State University, Fullerton

Dean's List 2007-2009
College of Health and Human Services, California State University, Long Beach

Undergraduate Kinesiology Student of the Year 2006
Dept. of Kinesiology, College of Health and Human Services, California State University, Long Beach

NON-ACADEMIC PROFESSIONAL EXPERIENCE

Private Strength and Conditioning, Orange County and Los Angeles, CA
2001-2009
Private Certified Strength and Conditioning Specialist

Private Personal Training, Orange County and Los Angeles, CA
2001-2009
Private Certified Personal Trainer

Michael Seril Fitness, Inc., Whittier, CA
2004-2008
Certified Strength and Conditioning Specialist and Certified Personal Trainer

LA Fitness: Pro Results, La Habra, CA
2003-2005
Personal Fitness Trainer / Fitness Manager

Premier Results, Diamond Bar, CA
2003-2005
Personal Fitness Trainer

Body of Change, La Habra, CA
2001-2003
Personal Fitness Trainer

INTERNSHIPS

Care House, Anaheim, CA
Summer 2009

2 FAST 4 U, Fullerton, CA
Fall 2007-Spring 2008

YMCA Older Adult Fitness, Long Beach, CA
Spring 2005-Summer 2005

Bright Medical Center: Health education courses, Whittier, CA
Spring 2005-2007

Seal Beach Boeing, Seal Beach, CA
Spring 2005-Summer 2005

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EXHIBIT B

BRETT ANDREW DOLEZAL, PH.D.

PUBLICATIONS (SINCE 2006)

PUBLICATION/BIBLIOGRAPHY

<u>Research Papers – Peer Reviewed</u>

1. Cooper, CB, **Dolezal, BA**, Riley, M, and PB Shieh. Reverse Fiber Type Disproportion: A Distinct Metabolic Myopathy. *Muscle and Nerve*, 2016.

2. **Dolezal, BA**, Waite, J, Neufeld, E, Boland, D and CB Cooper. Remotely-guided feedback enhances exercise training adherence and physical performance in firefighters. *International Journal of Sports Science,* 5(6), 221-227, 2015.

3. Rawson, RA, Chudzynski, J, Mooney, L, Gonzales, R, Ang, A, Dickerson, D, Penate, J, Salem, B, **Dolezal, BA** and CB Cooper. Impact of an exercise intervention on methamphetamine use outcomes post-residential treatment care. *Drug and Alcohol Dependence,* 156, 21-28, 2015.

4. Robertson, C, Ishibashi, K, Chudzynski, J, Mooney, L, Rawson, R, **Dolezal, BA**, Cooper, C, Brown, A, Mandelkern, M and ED London. Effect of Exercise Training on Striatal Dopamine D2/D2 Receptors in Methamphetamine Users during Behavioral Treatment. *Neuropsychopharmacology*, XX, 1-8, 2015.

5. Abrazado, M, **Dolezal, BA**, Storer, TW and CB Cooper. Effect of added weight on metabolic and cardiovascular responses to graded treadmill exercise in men. *International Journal of Sports Science,* 5(5), 187-191, 2015.

6. Rawson, RA, Chudzynski, J, Gonzales, R, Mooney, L, Dickerson, D, Ang, A, **Dolezal, BA** and CB Cooper. The impact of exercise on depression and anxiety symptoms among abstinent methamphetamine-dependent individuals in a residential treatment setting. *Journal of Substance Abuse Treatment,* 57, 36-40, 2015.

7. Haglund, M, Ang, A, Mooney, L, Gonzales, R, Chudzynski, J, Cooper, CB**, Dolezal, BA**, Gitlin, M and RA Rawson. Predictors of depression outcomes among abstinent methamphetamine-dependent individuals exposed to an exercise intervention. *The American Journal on Addictions*, 24, 246-251, 2015.

8. **Dolezal, BA**, Barr, D, Boland, DM, Smith, DS and CB Cooper. Validation of the firefighter WFI treadmill protocol for predicting VO2max. *Occupational Medicine,* 65(2), 143-6, 2015.

9. **Dolezal, BA**, Boland, D, Carney, J, Abrazado, M and CB Cooper. Validation of a physiological status monitor-embedded compression shirt against a criterion laboratory ECG-derived heart rate. *Journal of Occupational and Environmental Hygiene,* 2014.

10. **Dolezal, BA**, Chudzynski, J, Dickerson, D, Rawson, R, Garfinkel, A, and CB Cooper. Exercise Training Increases Heart Rate Variability after Methamphetamine-Dependency. *Med Sci Sport Exercise,* 46(6), 1057-1066, 2014.

11. **Dolezal BA**, Abrazado M, Batalin MA, Smith D and Cooper CB. Deployment of Remote Advanced Electrocardiography for Improved Cardiovascular Risk Assessment in Career Firefighters. *Journal of Telemedicine and e-Health*, 20(7), 1-4, 2014.

12. Smith, DL, Haller, JM, **Dolezal, BA**, Cooper, CB and PC Fehling. Evaluation of a wearable physiological status monitor during simulated firefighting activities. *Journal of Occupational and Environmental Hygiene*, 11, 427-433, 2014.

13. Storer, TW, **Dolezal, BA**, Berenc, M, Timmins, JE, and CB Cooper. Effect of supervised, periodized exercise training versus self-directed training on lean body mass and other fitness variables in health club members. *Journal of Strength and Conditioning Research*, 28(7), 1995-2006, 2014.

14. Mooney, LJ, Cooper, C, London, E, Chudzinski, J, **Dolezal, BA**, Dickerson, D, Brecht, M, Penate, J and R Rawson. Exercise for methamphetamine dependence: Rationale, design, and methodology. *Contemporary Clinical Trials*, 37, 139-147, 2014.

15. Storer, TW, **Dolezal, BA**, Abrazado, M, Smith, DL, Batalin, M, Tseng, C, Kaiser, W, and CB Cooper. Firefighter health and fitness assessment: A call to action. *Journal of Strength and Conditioning Research,* 28(3), 661-671, 2014.

16. **Dolezal, BA**, Lau, M, Abrazado, M, Storer, TW and CB Cooper. Validity of two commercial grade bioelectrical impedance analyzers for measurement of body fat percentage. *Journal of Exercise Physiology online,* 16(4), 74-83, 2013.

17. **Dolezal, BA**, Chudzynski, J, Storer, TW, Abrazado, M, Mooney, L, Dickerson, D, Rawson, R, and CB Cooper. Eight weeks of exercise training improves fitness measures in methamphetamine-dependent individuals in residential treatment. *Journal of Addiction Medicine*, 7(2), 122-128, 2013.

18. Batalin, M, Yuen, E, **Dolezal, BA**, Smith, D, Cooper, C and J. Mapar. PHASER: Physiological Health Assessment System for Emergency Responders. Body Sensor Networks, 2013.

Research Papers – Peer Reviewed (Submitted)

1. Carney, JJ, **Dolezal, BA**, Neufeld, E, Boland, DM, Martin, J, and CB Cooper. Characterization of sleep quality and cardiovascular reactivity measure via heart rate variability in emergency medical technicians.

2. **Dolezal, BA**, Storer, TW, Smooke, S, Tseng, C and CB Cooper. A systematic method to detect the metabolic threshold from gas exchange during incremental exercise. *BMC Pulmonary Medicine.*

3. **Dolezal, BA**, Sirichana, W and CB Cooper. Correlation of wrist-worn accelerometry with oxygen uptake.

4. Boland, D, **Dolezal, BA**, Chang, A, Lee, J and CB Cooper. Reliability of standing static posture analysis using a mobile application.

Research Papers – Non-Peer Reviewed

1. **Dolezal, BA**, Boland, D and CB Cooper. Digitizing the Ivory Tower of Academia. *iHealthBeat*, October 2014.

2. **Dolezal, BA**, Boland, D and CB Cooper. Marrying Academia and Industry to Validate the Wild Wild West of Wearables. *Nuviun,* October 2014.

Book - Chapter

1. Cooper CB, **Dolezal BA**. Chronic obstructive pulmonary disease. In: American College of Sports Medicine. *Exercise management for persons with chronic diseases and disabilities, 4th ed.* Champaign: Human Kinetics, 2016.