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A Standardized Buffalo Concussion Treadmill Test After Sport-Related Concussion in Youth: Do ActiGraph Algorithms Matter?

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Context: Current guidelines for recovery after sport-related concussion (SRC) recommend 24 to 48 hours of rest, followed by a gradual return to activity with heart rate (HR) maintained below the symptom threshold. In addition, monitoring physical activity (PA) after SRC using ActiGraph accelerometers can provide further objective insight into the amounts of activity associated with recovery trajectories. Cutpoint algorithms for these devices allow minute-by-minute PA to be classified into intensity domains; however, researchers have shown that different algorithms used to evaluate the same healthy participant dataset can produce various classifications.

Objective: To identify the more physiologically appropriate cutpoint algorithm (Evenson or Romanzini) to analyze ActiGraph data among concussed adolescents in comparison with their HR responses on the Buffalo Concussion Treadmill Test (BCTT).

Design: Prospective cohort study.

Setting: University sport concussion clinic.

Patients or Other Participants: Eleven high school students (5 boys, 6 girls; median [range] age = 16 years [15–17 years], height = 177.8 cm [157.5–198.1 cm], mass = 67 kg [52–98 kg], body mass index = 22 [17–31]) involved in high-risk sports who sustained a physician-diagnosed SRC.

Main Outcome Measure(s): Evenson and Romanzini algorithm PA intensity domains via ActiGraph data and HR during the BCTT.

Results: We observed differences in PA time classified as moderate ($P = .003$) and vigorous ($P = .004$) intensities between algorithms but no difference in PA time classified as light intensity ($P = .48$). The Evenson algorithm classified most of the time as moderate-intensity PA (mean = 57.03%, range = 0.00%–94.12%), whereas the Romanzini algorithm classified virtually all PA as vigorous intensity (mean = 88.25%, range = 2.94%–97.06%]). Physical activity based on HR (stages 1–7 = 20%–39% HR reserve [HRR], stages 8–13 = 40%–59% HRR, stages $\geq$14 = 60%–85% HRR) indicated the BCTT primarily involved light to moderate intensity and, therefore, was better represented by the Evenson algorithm.

Conclusions: The Evenson algorithm better characterized the HR response during a standardized exercise test in concussed individuals and, thus, should be used to analyze ActiGraph PA data in pediatric populations with concussion.

Key Words: mild traumatic brain injuries, adolescents, athletes, actigraphy

Key Points

- The Evenson algorithm classified most of the time during the Buffalo Concussion Treadmill Test (BCTT) as moderate physical activity, whereas the Romanzini algorithm classified most of the time as vigorous activity.
- The BCTT primarily exists as a light- to moderate-intensity protocol in concussed adolescents based on the physiological heart rate response and confirmed using the Evenson algorithm.
- The Evenson algorithm is more representative of the heart rate response during the BCTT and should be used to analyze ActiGraph data in pediatric populations after concussion.

Sport-related concussion (SRC) is a mild traumatic brain injury resulting from biomechanical forces that are transmitted to the head.[1] Current recovery guidelines[1] recommend an initial 24 to 48 hours of physical and cognitive rest, followed by a gradual return to activity with heart rate (HR) maintained below the clinical symptom threshold. Therefore, appropriate monitoring of physical activity (PA) after SRC using HR and ActiGraph (ActiGraph, LLC) accelerometer measures has the potential to provide objective data regarding optimal amounts of activity associated with symptom resolution and return-to-play (RTP) trajectories.

ActiGraph accelerometers are small devices that are worn by participants and objectively measure acceleration. They have been demonstrated to be a valid, reproducible, and appropriate method of assessing PA in people aged 2 to 18 years.[2–4] ActiGraph counts, the unit of measure for activity, enable PA to be classified into different intensity domains or bin levels (ie, sedentary, light, moderate, or vigorous) by applying cutpoint algorithms. Multiple algorithms have been established for a pediatric population[5]; however, researchers[6–11] have shown that different algorithms used on the same dataset can produce various classifications of PA as a result of how the data are processed. For example, when using activity cutpoints on actigraphy data from Latino children (age range = 7–11 years) in low-income families, Banda et al[11] reported differences ($P < .001$) in minutes per day and the percentage of time spent in sedentary behavior, light PA, moderate PA, vigorous PA, and moderate-to-vigorous PA according to the Evenson,[12] Romanzini,[13] Treuth,[14] Puyau,[15] and Mattocks[16] algorithms. Specifically, the Evenson[12] algorithm classified 64.63% of the time as spent in sedentary behavior, 29.58% in light PA, 4.09% in moderate PA, 1.69% in vigorous PA, and 5.78% in moderate-to-vigorous PA.[11] On the other hand, the Romanzini[13] algorithm classified 69.33% of the time as spent in sedentary behavior, 20.30% in light PA, 5.57% in moderate PA, 4.79% in vigorous PA, and 10.36% in moderate-to-vigorous PA.[11] Smith et al[8] suggested that population-specific PA patterns may contribute to the disparity of estimated PA intensities among algorithms, so investigators need to select the most appropriate algorithm for their population of study. Migules et al[5] recommended that researchers follow the same data-collection and data-processing criteria used in the original algorithm calibration study when applying cutpoints to a dataset; however, a limitation of the previous ActiGraph research was that no algorithm cutpoints have been specifically based on a pediatric population with concussion. Therefore, the evaluation of common algorithms using standardized physiological data from this population is warranted. The purpose of our study was to identify the more physiologically appropriate algorithm for analyzing ActiGraph data in adolescents with concussion using 2 common algorithms (Evenson[12] and Romanzini[13]) by comparing ActiGraph activity bin levels with physiological HR responses throughout a standardized exercise protocol, namely, the Buffalo Concussion Treadmill Test[17] (BCTT).

METHODS

Study Design and Participants

This was a prospective cohort study. We recruited high school students who participated in a sport associated with a high risk of concussion and had sustained a physician-diagnosed SRC during the 2019–2020 academic year. They were part of the broader Surveillance in High Schools to Reduce Concussions and Consequences of Concussions in Canadian Youth (SHRed Concussions) project at the University of Calgary. Adolescents were included if they were enrolled in high school in Calgary, Canada, and involved in a high-risk sport (ie, rugby, ice hockey, football, wrestling, basketball, lacrosse, soccer, volleyball, ringette, or cheerleading) at the interscholastic, community, or club level. Exclusion criteria were a history of systemic disease (eg, cancer, arthritis, heart disease), neurologic disorder (eg, head injury, cerebral palsy), or bone fracture or surgery in the year before the study that would interfere with sport participation. Parental or guardian consent and participant assent were obtained, as aligned with SHRed Concussions, and the Conjoint Health Research Ethics Board at the University of Calgary (REB18-2017) approved the study.

Procedures

We collected demographic information at baseline or initial physician assessment, or both, after a suspected SRC when the diagnosis was confirmed, consistent with SHRed Concussions. Participants completed a BCTT at the first follow-up physician assessment and at RTP. They reported performing an average of $\geq$20 minutes of moderate-to-vigorous PA throughout their recovery period. An initiated and fully charged ActiGraph device (model GT9X Link; ActiGraph, LLC) was worn above the right anterior-superior iliac spine during the BCTT and paired with a chest-worn HR monitor (model H10; Polar Electro).

Buffalo Concussion Treadmill Test

The BCTT is a graded exertional test and was administered by a certified exercise physiologist (L.N.M.) using a treadmill (model T635M; SportsArt). The initial minute, or stage,[18] began at a speed of 3.2 mph (5.1 km/h) and 0% incline.[17] The treadmill grade was increased by 1% each minute for the first 15 minutes, after which the speed was increased by 0.2 mph/min.[17] Manual blood pressure and HR were collected immediately before and approximately 5 minutes after the test. The Borg Rating of Perceived Exertion (RPE; scale range = 6–20),[19] overall condition (visual analog scale range = 0–10),[17] and HR were monitored every minute of the exertion test. The BCTT was terminated when there was a >2-point increase over presymptom levels on the overall condition scale, RPE of >18, or HR of >180 beats/minute (bpm) or volitional fatigue occurred.[17–19]

Data Analysis

We used ActiLife software (version 6.13.4; ActiGraph, LLC) following the standard operating procedure for ActiGraph GT3X+ Accelerometer for SHRed Concussions to analyze ActiGraph data in 15-second epochs. (The GT3x and GT9x devices have the same internal accelerometer.)

Physical activity intensity cutpoints were determined using the previously established Evenson[12] and Romanzini[13] algorithms. These algorithms were selected because they have been demonstrated to be appropriate for assessing PA in pediatric populations.[12,13] Physiologically based exertional levels were categorized as *light* (20%–39% HR reserve [HRR]), *moderate* (40%–59% HRR), or *vigorous* (60%–85% HRR).[20] The HRR is the difference between predicted maximum HR and resting HR.[20] We calculated HRR as the difference between maximum HR (220 − age)[20] and immediate pre-exercise resting HR and intensity zones using the Karvonen formula[21] as the sum of the percentage of HRR and pre-exercise resting HR. We used the Karvonen formula[21] instead of the traditional percentage of maximal HR for establishing light, moderate, and vigorous workloads as it enabled us to account for individual variations in resting HR and vagal tone when identifying individual activity thresholds. We used pre-exercise resting HR because true supine resting HR data were not available.

Table 1. Characteristics of 11 Canadian Adolescents With Sport-Related Concussion

Characteristic	Athletes		
	Males (n = 5)	Females (n = 6)	Total (n = 11)
Primary sport[a]	Basketball (n = 1)	Basketball (n = 2)	Basketball (n = 4)
	Football (n = 2)		Football (n = 3)
	Hockey (n = 2)		Hockey (n = 2)
		Ringette (n = 1)	Ringette (n = 1)
	Rugby (n = 1)	Rugby (n = 1)	Rugby (n = 2)
		Soccer (n = 1)	Soccer (n = 1)
		Volleyball (n = 1)	Volleyball (n = 1)
	Wrestling (n = 1)	Wrestling (n = 2)	Wrestling (n = 3)
Age, y[b]	17 (15–17)	16 (15–17)	16 (15–17)
Height, cm[b]	185.4 (165.1–198.1)	167.0 (157.5–185.4)	177.8 (157.5–198.1)
Mass, kg[b]	75 (57–98)	63 (52–67)	67 (52–98)
Body mass index[b]	22 (21–31)	22 (17–26)	22 (17–31)

[a] Some participants took part in multiple sports.
[b] Values are median (range).

Statistical Analysis

We compared light, moderate, and vigorous PA intensities between the Evenson[12] and Romanzini[13] algorithms via the 2-tailed paired *t* test (Excel version 16.0.11929.20836; Microsoft Corp) and the Wilcoxon signed rank test. Data are presented as median (range). The α level was set a priori at .05. We also performed a regression analysis to compare HR and BCTT stage for each participant throughout the exercise protocol.

RESULTS

Twelve adolescents were recruited for our study; however, we removed 1 participant during analysis because of abnormal variations in ActiGraph measures (Romanzini ActiGraph activity values were ≥3 SDs greater than the mean for moderate activity). Therefore, 11 adolescents (5 boys, 6 girls) were included in our study. Participant characteristics are presented in Table 1. The first follow-up assessment was at a median of 18 days (range = 6–40 days) after SRC, and RTP was at a median of 18 days (range = 10–57 days). Most (91%) of the acutely concussed participants were tested in the expected symptomatic period (<30 days) after the SRC. Only 2 participants reported medication use before performing the BCTT; 1 had used albuterol sulfate for asthma, and the other had used paroxetine hydrochloride for anxiety. Yet because the Evenson[12] and Romanzini[13] algorithms were processed on the same bout of exercise, these medications would have had minimal effects on the results with respect to PA intensities.

Pre-exercise resting HR levels were comparable for the initial follow-up assessment (76 bpm; range = 62–84 bpm) with those of the RTP assessment (70 bpm; range = 54–84 bpm; $t_{13} = 0.549$, $P = .59$; Wilcoxon $Z = -0.465$, $P = .64$). The Evenson[12] algorithm indicated that 3.13% (range = 1.09%–10.00%) of the time spent during the BCTT was in light-intensity PA, and the Romanzini[13] algorithm showed that 5.00% was in light-intensity PA (range = 0.00%–28.95%, $t_{12} = -0.730$, $P = .48$; Wilcoxon $Z = -0.905$, $P = .37$; Figure 1). The Evenson[12] algorithm determined that 51.56% (range = 0.00%–83.33%) of the time was spent in moderate-intensity PA, and the Romanzini[13] algorithm demonstrated that 4.69% was spent in moderate-intensity PA (range = 0.00%–52.78%, $t_{12} = 3.745$, $P = .003$, Wilcoxon $Z = -2.765$, $P = .006$; Figure 1). Lastly, 42.19% (range = 0.00%–97.06%) of the time was spent in vigorous-intensity PA according to the Evenson[12] algorithm, and 92.11% (range = 31.58%–97.06%) was spent in vigorous-intensity PA according to the Romanzini[13] algorithm ($t_{12} = -3.547$, $P = .004$; Wilcoxon $Z = -2.787$, $P = .005$; Figure 1). The group mean physiological results indicated that stages 1 to 7 of the BCTT were spent in light-intensity PA (20%–39% HRR), stages 8 to 13 were spent in moderate-intensity PA (40%–59% HRR), and stages 14 to 23 were spent in vigorous-intensity PA (60%–85% HRR; Figure 2; Supplementary Table 1).

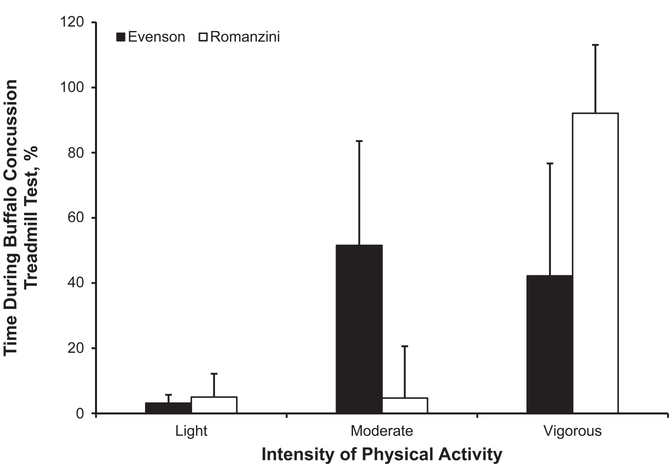

Figure 1. Clustered bar graph depicting the median (SD) percentage of time spent during the Buffalo Concussion Treadmill Test in light, moderate, and vigorous physical activity intensity as determined via the Evenson and Romanzini cutpoint algorithms using ActiGraph data from 11 Canadian adolescents. *P* values were determined via paired *t* tests. [a] Indicates a difference ($P < .05$).

DISCUSSION

The key findings from our study were that the Evenson[12] algorithm classified more PA as moderate intensity, the Romanzini[13] algorithm classified more PA as vigorous intensity, and HR primarily represented light- to moderate-intensity PA during the BCTT in adolescents after SRC. We aimed to identify whether the Evenson[12] or the

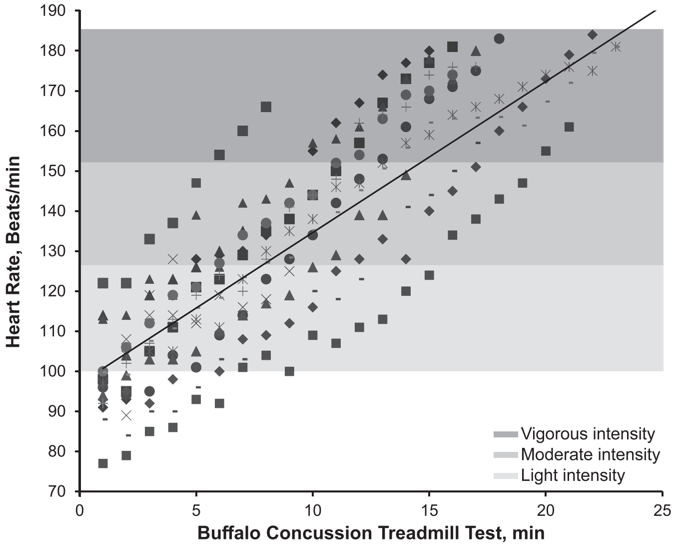

Figure 2. Individual plots of heart rate (HR) from a chest-worn heart rate monitor (model H10; Polar Electro) of 11 Canadian adolescents for each stage of the Buffalo Concussion Treadmill Test. Each stage of the exertion test was 1 minute in duration. Stages 1 to 7 were spent in light-intensity (20%-39% HR reserve [HRR]), stages 8 to 13 in moderate-intensity (40%–59% HRR), and stages 14 to 23 in vigorous-intensity physical activity (60%–85% HRR). The solid black line denotes the mean.

Romanzini[13] algorithm was more appropriate for analyzing ActiGraph data in adolescents with concussion by evaluating objective HR data obtained during a standardized exercise protocol. We found that the Evenson[12] algorithm best aligned with the physiological HR data throughout the BCTT.

Our results showed no difference in light-intensity PA between the Evenson[12] and the Romanzini[13] algorithms; however, the Evenson[12] algorithm classified greater levels of moderate-intensity PA, whereas the Romanzini[13] algorithm classified greater levels of vigorous-intensity PA (Figure 1). This discrepancy in intensity classification between algorithms was congruent with that reported in previous studies,[6–11] suggesting that the algorithms reflect different classifications of PA as a result of the cutpoints used to process the data. With these findings, we corroborate the need for purposeful consideration of algorithm selection when analyzing actigraphy data in a pediatric population with concussion and thus justify the use of objective physiological data to inform the most relevant classification for a population of interest in the absence of an appropriate algorithm calibration study.

The HR data demonstrated that in the early stages (ie, stages 1–13) of the BCTT, exercise intensity was most frequently (approximately 60%) classified as either light or moderate (Figure 2), which was consistent with the Evenson[12] algorithm data (Figure 1). These classifications were not surprising given that the BCTT protocol consisted of a continuous walking speed and gradual incline starting from 0% for these stages. Walking and similar activities are often considered of light to moderate intensity[20,22] and, thus, the exercise intensities determined from HRR during these stages of the BCTT are congruent. The HRR has greater utility for determining exercise intensity than strictly basing workloads on maximum HR because it takes into account individual variability in fitness levels.[20,23] Exercise intensity at stage 14 and beyond was considered vigorous based on HR (Figure 2). Again, this result was expected, as speed increased by 0.2 mph (0.3 kph) per stage starting after stage 15. A linear relationship exists between workload and HR[24]; therefore, as speed increased, HR also increased to match the elevated metabolic demands. Given that participants did not reach vigorous-intensity PA on the BCTT until stage 14 based on the physiological HR (Figure 2) and test cessation occurred on average at stage 15 in our investigation and that of Atrand and Ryhming,[25] it was reasonable to conclude that the BCTT exists primarily as a light-to-moderate intensity exercise protocol in a pediatric population with concussion. This finding was confirmed by the Evenson[12] algorithm (Figure 1). Intensity classifications as determined by the Evenson[12] algorithm appear to better represent the physiological response during the BCTT as the protocol primarily involves light-to-moderate intensity PA. This is clear from the Evenson[12] algorithm's classification of most of the time spent during the BCTT in moderate-intensity PA (Figure 1), which aligns with the HR data classifying the early stages (ie, stages 1–13) of the BCTT as either light- or moderate-intensity PA (Figure 2). On the other hand, the Romanzini[13] algorithm classified most of the BCTT time (approximately 90%) as vigorous-intensity PA (Figure 1), which does not reflect the physiological HR reaching vigorous intensity until later stages (ie, stage 14 and later) toward the end of the exercise protocol (Figure 2). As a consequence, researchers[26] who used the Romanzini[13] algorithm to analyze data in a youth population with concussion may have overestimated the total time spent in vigorous-intensity PA, leading to potentially erroneous interpretations. Based on our findings, we recommend that investigators use the Evenson[12] algorithm to analyze ActiGraph data collected from a pediatric population with concussion.

Our study had limitations. The sample size was relatively small ($n = 11$). Participants attended a sports medicine clinic that was affected by COVID-19 shutdown protocols, which affected recruitment. Despite a small sample size, we found differences (moderate-intensity PA: $P = .001$; vigorous-intensity PA: $P = .002$) when considering the absolute difference in PA intensities between algorithms. These findings were verified using a nonparametric statistical method, thereby confirming power despite a relatively small sample size. All participants were able to act as their own controls because the Evenson[12] and Romanzini[13] algorithms were used on the same within-subject ActiGraph data. This allowed us to control for various between-subjects confounders, which would not have been possible if we had used a matched case-control design. Another limitation was the application of pre-exercise resting HR as a surrogate for a true supine resting HR. Pre-exercise resting HR is slightly elevated compared with the most accurate representation of supine resting HR, and it should be indexed as an average across 3 early-morning measures performed immediately after awakening and before beginning any activity. Lastly, the pediatric participants completed only 1 type of exertional test (ie, BCTT), which was mostly a walking protocol. How our findings apply to other forms of exercise or to an older athlete population with SRC has yet to be determined.

CONCLUSIONS

We identified the most appropriate ActiGraph algorithm to use for analyzing actigraphy data in a pediatric population with concussion by evaluating the physiological HR response during a standardized exercise protocol. Our results showed differences in moderate and vigorous classifications of PA between the Evenson[12] and the Romanzini[13] algorithms. The Evenson[12] algorithm classified most of the time spent during the BCTT as moderate-intensity PA, which aligned with HR data classifying the early BCTT stages (ie, stages 1–13) as light (20%–39% HRR)- or moderate (40%–59% HRR)-intensity PA. However, the Romanzini[13] algorithm indicated that most of the time was spent in vigorous-intensity PA, which did not align with the HR response during the exercise protocol because vigorous-intensity PA (60%–85% HRR) was not achieved until the later stages (ie, stages 14 and later). Therefore, we conclude that the Evenson[12] algorithm is more representative of the physiological HR response to a standardized exercise test in adolescents with concussion and should be used to analyze ActiGraph data in these populations.

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