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Original Article

Differences between an accelerometer and a heart rate monitor in monitoring non-training-related load in adolescents: an opportunity to distinguish between the physical and mental load

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Abstract:
Apart from the knowledge of training load, managing the training process also requires information on non-training related load, together with distinguishing between the physical and mental load. However, verified objective measurement methods are lacking. The objective was to assess whether the differences between an accelerometer and heart-rate monitor in non-training related load measurement could be interpreted as a proportion of the physical load or mental load to the total load in the meaningful segments of a school day in adolescents. The sample comprised of 573 girls (mean age of 16.47 ± 1.06 years) form Czech and Polish secondary schools. The ActiTrainer device (including the accelerometer and heart-rate monitor) was used to measure the percentage of selected day time segments in which the load intensity was classified at a given level. Statistically significant differences between the accelerometer and heart-rate monitor derived data were observed, which ranged from -22.8% to 12.9% in the physical education lesson and -6.3% to 8.1% in the remaining segments. The observed differences are in relation to the nature of the segments. The study indicates that some of specific differences between accelerometer and heart-rate monitor derived data can be utilized to distinguish between the non-training related physical and mental load in adolescents.
Key words: athletic performance, physical exertion, mental fatigue, methods, motor activity.

Introduction

Sport training is a comprehensive, sophisticated, systematic, and controlled process of work with an individual or group of athletes (Issurin, 2010). The training effects are perceived as an outcome of the influence of a set of physical and mental stressors to which an athlete is exposed (Lloyd et al., 2015). These stressors influence athletes not only during training but also throughout the whole day. Therefore, the training effects should be observed as an outcome of the influence of overall training load and its interactions with all other stressors that affect an individual throughout the day and night. It is evident, in this regard, that the accumulation of non-training (all of load arising throughout day except those arising on sport training session) and training related load and the simultaneous deficiency of rest time might lead to a long-term increase of excessive fatigue and overtraining risk or even result in various health complications (Issurin, 2010; Smith, 2003). Additionally, the actual physical and mental status of an athlete at the beginning of the training session is one of the fundamental factors that influences its course (Kvintová, & Sigmund, 2016; Nakamura et al., 2015). It refers to a certain readiness for training. While the methods of training load monitoring and assessment are well established and have been further developed (Botek, Krejčí, Neuls, & Novotný, 2013; Halson, 2014; Nunes et al., 2014; Roos, Taube, Brandt, Heyer, & Wyss, 2013; Sannicandro, Cofano, & Rosa, 2016; Saw, Main, & Gastin, 2016), the current practice and research lacks a robust tool for the objective monitoring of non-training related load.

In sport training, the techniques that are applied to quantify the training load are mostly focused on the estimation of energy expenditure (EE), which is considered an appropriate indicator of load intensity and volume (Ekelund et al., 2001). Self-reports (questionnaires, diaries, logs, and recalls) as well as objective measures (motion sensors ACC, pedometers, and HRM), direct observation, and double-labelled water) are usually used for EE estimation (Warren et al., 2010). Currently, many wearable devices are available, which include both the sensors, i.e., the ACC and HRM. Combination of ACC and HRM (as one device) enables an improved accuracy and precision with which EE can be predicted (Brage et al., 2004; Butte, Ekelund, & Westerterp, 2012). However, the non-training related load monitoring is conducted in field conditions, which significantly hinders the possibilities of employing precise measurement techniques. Because of the construction and nature of these devices, the accuracy of an EE estimate using the ACC and HRM substantially varies, depending on the actual conditions and situations during monitoring (Eston, Rowlands, & Ingledew, 1998). Inaccurate EE estimation determined by ACC is especially associated with inadequate recording of load intensity during non-locomotor activities, exercising in static positions, and in underwater conditions (Ainsworth, Cahalin, Buman, & Ross, 2015). The transfer of the counts, the primary ACC-derived unit, to kcal or MET as an EE unit is another source

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of error (Crouter, DellaValle, Haas, Frongillo, & Bassett, 2013; Pate, O'Neill, & Mitchell, 2010). Furthermore, the ACC does not reflect the mental load (ML) (Tanaka, Monahan, & Seals, 2001). In contrast, the inaccuracy of an EE estimate determined by HRM is mainly associated with age (Beckers, Ramaekers, & Aubert, 2002; Dugas, Noakes, Lambert, Van Der Merwe, & Odendaal, 2005), physical fitness level (Beckers et al., 2002; Dugas et al., 2005), motion specifics of physical activity (PA) (movements of the upper and lower limb lead to different heart rates while oxygen consumption values remains the same) (Clausen, Trap-jensen, & Lassen, 1970), gender specificities (Acharya, U R, Joseph, K P, Kannathal, N, Lim, C M, Suri, 2006) and the fact that heart rate response is delayed when PA intensity is suddenly changing (i.e., heart rate stabilization takes about three minutes) (James, Munson, Maldonado-Martin, & De Ste Croix, 2012). Moreover, it is unclear to what the extent the heart rate is affected by a PL or ML during PA (Freedson & Miller, 2000; Trost, 2001). Despite various limitations, the ACC and HRM are mostly considered accurate and well applicable methods to estimate EE in free-living conditions (Ainsworth et al., 2015; Butte et al., 2012; Dyrstad & Hausken, 2014; Warren et al., 2010). In adolescents, there can be several regular discrete periods (segments) in the structure of a school day, during which accuracy of the EE estimate determined by the ACC is typically lower in comparison to the HRM and vice versa. Such inaccuracy is associated with the character of dominant activities during the periods in which the EE estimate is determined by the ACC or HRM (because of the nature of an activity). As mentioned, in non-training related load assessment, the simultaneous usage of ACC and HRM enables quite accurate EE estimates by branched equation models (Butte et al., 2012; Zakeri, Adolph, Puyau, Vohra, & Butte, 2008). On the other hand, in a comprehensive approach to sport training, serious non-training related load assessment is not possible without further knowledge about volume, intensity and proportion of the PL and ML. To our knowledge, no studies have been published presenting a method to enable us to distinguish between PL and ML and their quantification (monitoring) for a longer period. It may be expected that some differences between ACC- and HRM-derived EE estimates in selected meaningful segments of a day can highlight a proportion of PL and ML to the total load. It would be beneficial to know whether and to what extent additional information can be extracted from the differences. Therefore, the purpose of this study was to assess whether differences between the two sensors, i.e., ACC and HRM, in non-training related load measurement could be interpreted as a proportion of the PL or ML to the total load in the meaningful segments of a school day in adolescents.

Material & methods

Experimental approach to the problem

In this study, the school day was divided into three meaningful segments (assessment time frame): "*pre-school*", "*school*", and "*post-school*". Moreover, the school segment was structured into three sub segments: "*lessons*", "*recesses*", and "*physical education lesson*" (PEL). The selection of mentioned segments is based on the following criteria: traits of major activities in a segment, expected volume and intensity of ML and PL in a segment, and expected volume of physical inactivity in a segment. It has not been determined whether sport training was part of the *pre-school* or *post-school* segment.

To compare the ACC- and HRM-derived values, we defined a derived parameter, Given Load Intensity in the Segment of a Day (GLIS), as the percentage of the segment in which the load intensity was classified at a given level (e.g., low, medium, vigorous, and very vigorous). We split the load intensity into four categories according to (Ekelund et al., 2001): low (<60% HRmax; <4 METs), moderate (60-70% HRmax; 4-6.99 METs), vigorous (71-80% HRmax; 7-9.99 METs), and very vigorous (≥80% HRmax; ≥10 METs). The GLIS values were calculated separately for each load in each intensity category. To compute them, we used the following formula: GLIS (in %) = 100 * Σ (DI) / DS, where DI (duration of a given intensity) represents the time periods when the load measured by the ACC or HRM was classified at a given load intensity and DS (duration of a segment) is the time period of a segment.

Participants

The research was conducted at 29 Czech and nine Polish secondary schools in which organization of education is same. Stratified sampling was employed for subject selection. The schools were selected in three regions (Olomouc and Plzen, Czech Republic and Katowice, Poland). Two classes were selected per school according to the availability of computer classrooms. This method of participant selection was selected due to the organizational demands of the research. The sample included 573 girls with a mean age of 16.47 ± 1.06 years, mean body mass index of 21.12 ± 2.90 kg·m-2 and mean resting heart rate of 64.35 ± 7.40 beats per min. Only the girls who did not report swimming as a part of their daily PA records were included in the study. The participants and their parents provided written informed consent after they were given information about the study. The Ethics Committee of the Faculty of Physical Culture, Palacký University, Olomouc approved the study design on May 4, 2012 (no. 24/2012).

Procedures

The ActiTrainer monitoring device, which is a combination of ActiGraph (ACC) and Polar S610 TM (HRM), (ActiGraph, LLC; Pensacola, FL 32502, USA) was used for data collection. The methods used are described in the previous studies by Frömel, Svozil, Chmelík, Jakubec, and Groffik (2016). The record sheet (see Frömel et al. (2016)) was used to determine the segments of a day. The ACC and HRM recordings were segmented based on the reported data.

The IntPa13 software, developed specifically for this purpose, (available only in Czech; http://www.cfkr.eu), was used to process data from the ActiTrainer device in 15-second recording intervals. For more details on the methods, please refer to our previous study Frömel et al. (2016). To estimate the load intensity (in METs) using an ACC, the basic ACC-derived unit (count) was converted to kcals/min using the work-energy theorem formula *kcal/min = 0.0000191 * counts / (min * body mass)*. Individually determined HRmax was used to categorize the load using a HRM (as percentage of HRmax). Despite well-known limitations (Tanaka et al., 2001) due to the demands associated with field monitoring, we used a universal formula for girls: *HRmax = 226 – age*. We included only those individuals who wore the device 1) for at least 15 minutes before school, 2) for at least 180 minutes during school time, 3) for at least 120 minutes after school, and 4) for at least 600 minutes during the whole day.

Statistical analysis Descriptive statistics, Wilcoxon signed-rank test, Cohen's d, and Bland–Altman method (Bland & Altman, 1986) were used for overall assessment of agreement between the ACC- and HRM-derived data (ACC-GLIS and HRM-GLIS). These were applied to measure the time spent in a given zone of load intensity. Statistical significance was verified at the level of $\alpha = 0.01$. The effect size was computed according to Cohen's d statistic and interpreted in line with Cohen (1988). The Statistica v12 statistical package program (StatSoft, Inc., Tulsa, OK, USA) and GraphPad Prism (GraphPad Software, Inc., La Jolla, CA, USA) were used to process the data.

Results

The girls were physically active (sum of the time during which an individual was physically active; ≥25 counts per 15 seconds; based on ACC) for slightly over 1/3 of the overall monitoring time (866.5 ± 110.8 minutes; based on ACC). The ratio of the *pre-schoo*l, *school*, and *post-school* segments were 8.6:40.4:50.9. The *lessons*, *recesses*, and *PEL* segments accounted for 30.6%, 7.8%, and 6.0% of the total day monitored by ACC, respectively. The highest ratio of PA vs. inactivity was observed only in the pre-school segment (53.3% of the segment classified as active) and the *PEL* segment (72.9% of the segment classified as active). The ratio was almost equal during the recesses segment (approximately 1:1). The differences between the ACC-GLIS and HRM-GLIS (ACC-HRM difference) were found to be statistically significant ($p < 0.01$) for all the segments of the day, as well as for all the intensity levels, except for the medium-load intensity in the *post-school* segment (Table 1). A medium effect size was observed in more than ¾ of the differences. The decrease of valid cases n in Table 1 occurred because some individuals did not reach the given load intensity in a particular segment of the day.

Table 1. Differences between the volume of a given load intensity in the segment of a day (in %) determined by ACC and HRM; results of a Wilcoxon signed-rank test.

Segment	**LI**	*n**	**ACC** (mean±*SD*)	**HRM** (mean±*SD*)	$\Delta_{HRM-ACC}$	*Z*	*p*-value	*d*
Pre-school	L	573	91.6 ± 8.5	85.3 ± 16.4	-6.3	8.136	<0.001	0.34††
	M	562	8.2 ± 8.2	10.4 ± 10.1	2.2	3.951	<0.002	0.17
	V	331	0.6 ± 2.1	5.2 ± 6.8	4.6	13.696	<0.001	0.65††
	V-V	104	0.3 ± 1.7	8.4 ± 15.6	8.1	8.412	<0.001	0.52††
School	L	573	98.0 ± 2.4	95.1 ± 7.8	-2.9	8.751	<0.001	0.36††
	M	551	1.8 ± 2.1	3.1 ± 3.7	1.3	6.557	<0.001	0.31††
	V	360	0.2 ± 0.5	1.8 ± 2.6	1.6	13.096	<0.001	0.60††
	V-V	186	0.2 ± 0.3	2.6 ± 6.8	2.4	8.286	<0.001	0.35††
Post-school	L	573	95.0 ± 4.5	91.2 ± 11.1	-3.8	6.117	<0.001	0.32††
	M	560	4.4 ± 3.7	5.4 ± 5.6	1.0	2.145	0.032	0.15
	V	460	0.6 ± 1.4	2.4 ± 3.6	1.8	12.653	<0.001	0.47††
	V-V	312	0.3 ± 1.2	2.8 ± 6.4	2.5	10.346	<0.001	0.38††
Lessons	L	573	98.9 ± 2.0	97.0 ± 7.1	-1.9	7.077	<0.001	0.26†
	M	476	1.2 ± 2.0	2.0 ± 2.8	0.8	5.041	<0.001	0.23†
	V	240	0.2 ± 0.4	1.6 ± 2.6	1.4	10.591	<0.001	0.53††
	V-V	99	0.1 ± 0.3	4.2 ± 10.1	4.1	7.187	<0.001	0.41††
Recesses	L	573	96.5 ± 4.8	93.9 ± 9.8	-2.6	4.657	<0.001	0.24†
	M	514	3.7 ± 4.6	4.8 ± 6.4	1.1	2.665	0.008	0.14
	V	203	0.5 ± 1.1	3.3 ± 4.7	2.8	9.710	<0.001	0.58††
	V-V	85	0.2 ± 0.5	4.4 ± 8.9	4.2	5.816	<0.001	0.47††
PEL	L	175	90.5 ± 8.9	67.7 ± 29.5	-22.8	11.177	□0.001	0.74††
	M	165	7.4 ± 6.5	20.3 ± 17.5	12.9	11.14	<0.001	0.69††
	V	135	2.1 ± 2.7	11.3 ± 11.8	9.2	11.73	<0.001	0.76††
	V-V	104	1.6 ± 2.5	7.4 ± 13.4	5.8	7.240	<0.001	0.43††

Note. ACC = accelerometer; HRM = heart rate monitor; $\Delta_{HRM-ACC}$ = mean differences between the values determined by HRM and ACC; LI = load intensity; L = low load intensity; M = medium load intensity; V = vigorous load intensity; V-V = very vigorous load intensity; Z = test criterion of Wilcoxon's test; * non-zero pairs of values (ACC and HRM); † small effect size; †† medium effect size.

Bland-Altman plots (Fig. 1 and 2) represent the level of agreement between the ACC-GLIS and HRM-GLIS in the six segments. The comparison of the ACC-GLIS and HRM-GLIS is presented separately for the three segments and split by the four levels of load intensity.

To facilitate easier comparison, the same scale in used for all three segments on the Y axis. In graphs, positive values demonstrate an overestimation of the HRM-GLIS compared to the ACC-GLIS. It should be noted that the graphs depict only values from participants that have been recorded in all four load intensity levels. For proper interpretation of the results, it is necessary to mention that an association exists between intra-individual GLIS values displayed in the graphs throughout all four levels of load intensity. For each individual, the sum of the percentages is equal to 100% in all the intensity levels (separately for ACC-GLIS and HRM-GLIS).

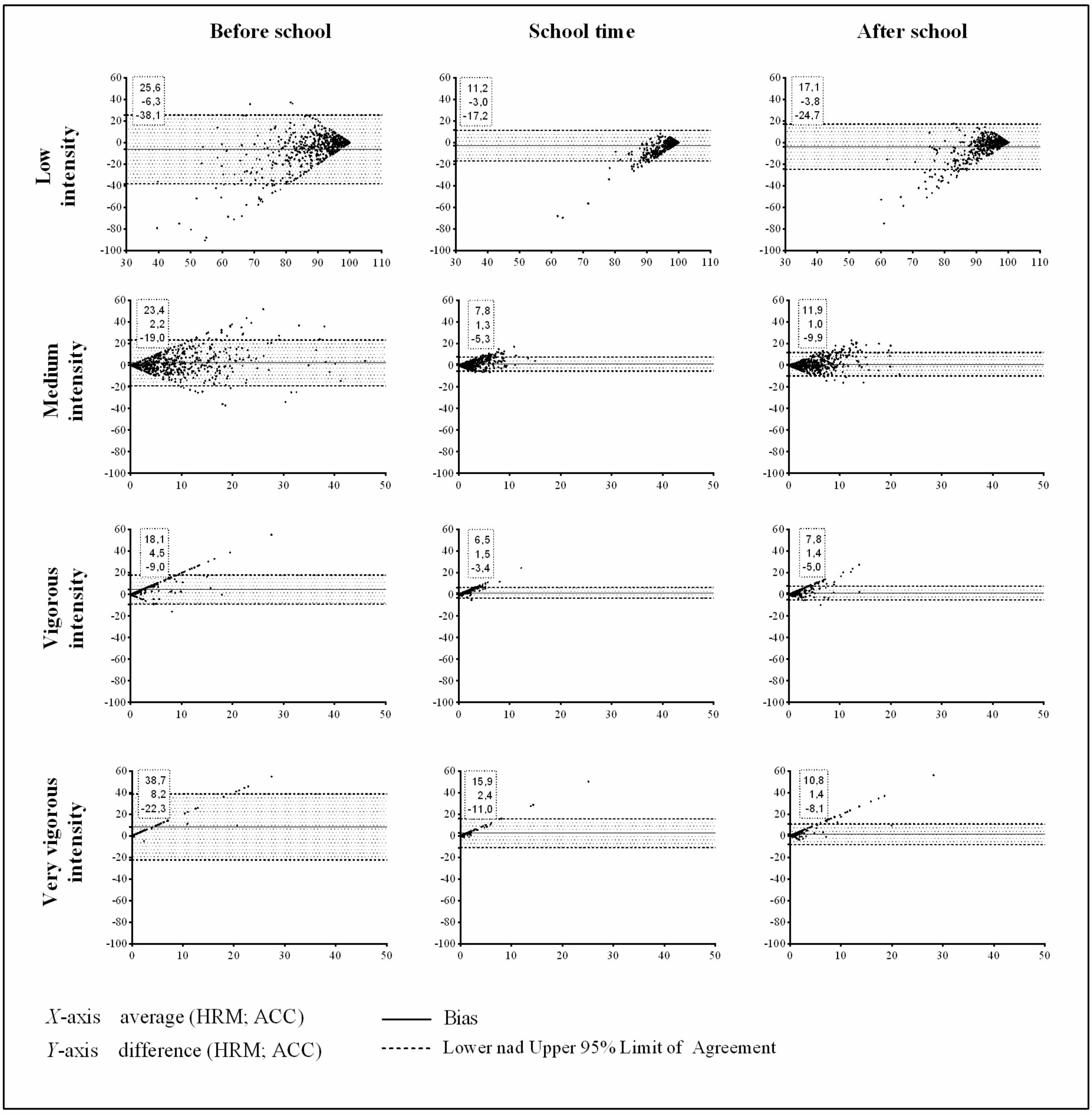

Fig. 1. Bland-Altman's plots (difference vs average): Agreement between the HRM and the ACC used to estimate the volume of a given load intensity in the segment of a day (in %) in the pre-school, school, and post-school segments. The values displayed in the frame represent (in descending order) the upper 95% limit of agreement, bias, and the lower 95% limit of agreement.

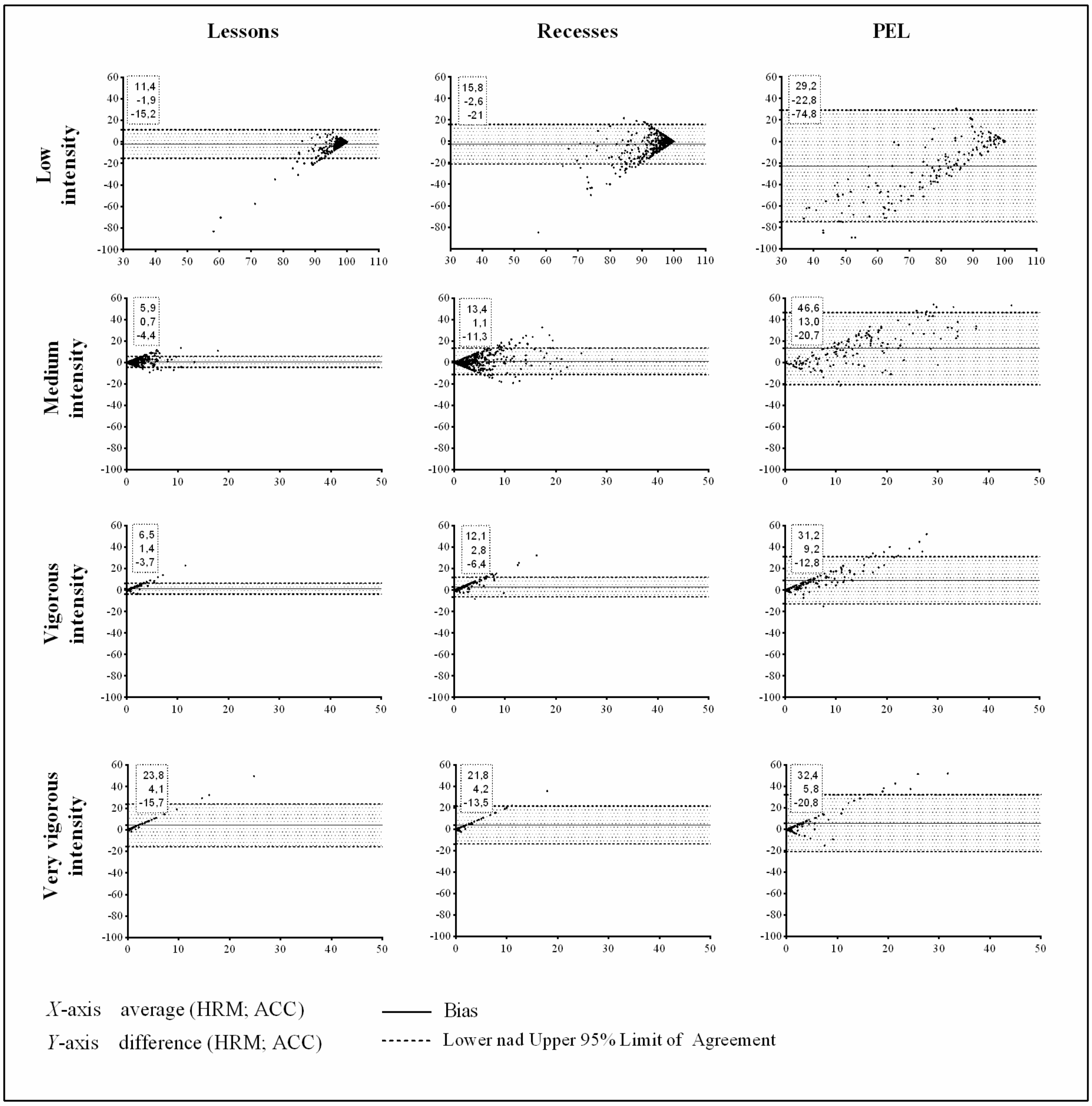

Fig. 2. Bland-Altman's plots (difference vs average): Agreement between the HRM and the ACC used to estimate the volume of a given load intensity in the segment of a day (in %) in the lessons, recesses, and PEL segments. The values displayed in the frame represent (in descending order) the upper 95% limit of agreement, bias, and the lower 95% limit of agreement.

Discussion

The results show the noteworthy discrepancy between the ACC-GLIS and HRM-GLIS in all segments of the day. Although a wide variety of differences was found in the study, certain specific features of the ACC-HRM differences can be observed.

In general, if particular segments are not considered, then the smallest ACC-HRM differences are noticeable in the vigorous-load intensity and the largest differences are observed in the low-load intensity. Similarly, if particular categories of load intensity are not considered, then the smallest ACC-HRM differences are noticeable in *school* segment lessons and the largest differences are observed in school segment *PEL*. The magnitudes of the ACC-HRM differences were inconsistent in all the segments as well as in each load intensity category; they varied from -22.8% to 12.9%. Except in one case, they were statistically significant ($p < 0.01$) in observed segments. In ¾ of all ACC-HRM differences, we registered a medium effect size. Moreover, in all the segments of the day, we found a medium effect size (the lowest value was 0.35) in the vigorous and very-vigorous intensities.

According to the magnitude of the ACC-HRM difference (*Δ*HRM-ACC in Table 1), the *PEL* segment appears unusual, in comparison to others. In *PEL*, we found that the ACC-HRM differences, the effect size values, and the 95% limits of agreement are largest in each load intensity category across observed segments, except for the very-vigorous load intensity in the *pre-school* segment (the second largest). However, the highest discrepancy between the ACC- and HRM-GLIS in *PEL* is evident in the low and moderate-load intensities. A similar character of differences appeared in *pre-school*. When considering the order of observed values in respective segments and load intensity categories, the second highest discrepancies between ACC and HRM appeared in *pre-school*. In the same way, the smallest discrepancy between ACC and HRM was observed in *school* and *lessons*. Specifically, in those two segments, very small ranges of 95% limits of agreement are evident, which could be understood as a specific feature for "mostly physically inactive segments". Not considering the concrete segments, the ACC-GLIS are steadily high in low-load intensities in comparison to the HRM-GLIS and are distinctly smaller in the very-vigorous load intensity. It is caused by the fact that ACC determines load intensity much more often to be "low", compared to HRM. This fact corresponds to the findings of other authors (Dyrstad & Hausken, 2014; Freedson & Miller, 2000; Hills, Mokhtar, & Byrne, 2014) who have demonstrated disagreement between PA assessment derived by the ACC and HRM in the low, as well as very high, PA intensity.

In this context, some facts should be considered for proper interpretation of the previous findings. First, *PEL* is a segment with a typically high frequency of PL; second, lessons is primarily “physically inactive (sedentary) segment” in which ML dominates; third, the ACC does not reflect the ML effect and does not measure accurately enough in specific conditions or situations such as static exercise, cycling, exercise in the water, etc.; and fourth, the HRM underestimates the EE in low intensity PA. Segments in which individuals are often or predominantly under mental stress, together with a negligible volume of PA, one can expect ACC-GLIS values to mostly score in the category of low and medium-load intensity while HRM-GLIS values often score in categories of higher load intensity. This would lead to high discrepancy between the ACC- and HRM-GLIS values, more specifically, higher ACC-GLIS values in the low-load intensity can be expected, in comparison to HRM-GLIS. Furthermore, in those segments, smaller ACC-HRM differences in comparison to physically active segments can be expected in the very-vigorous load intensity. These facts together with the results from this study offer some suggestions about how to identify PL and ML on the basis of data from the ACC and HRM.

An analogous character of the observed ACC-HRM differences (Table 1, Fig. 1 and 2) across the four load intensities in the *PEL* and *pre-school* segments suggests that there exist some specific similarities in the nature of the two segments. As described above, the highest ratio of PA to inactivity was observed in the two segments. Therefore, it can be assumed that a high proportion of PL in overall load in a segment could be identified based on four specific features: first, extra-large ACC-HRM differences in the low-load intensity; second, large ACC-HRM differences in the moderate-, vigorous-, and the very-vigorous load intensities; third, very high 95% limits of agreement between the ACC- and HRM-GLIS in the low-load intensity; and fourth, large effect size (related to ACC-HRM difference) in the moderate-load intensity. Furthermore, the study results lead to a hypothesis that (1) a very low level of 95% limits of agreement between the ACC- and HRM-GLIS in the categories of moderate- and vigorous-load intensity together with (2) a very large ACC-HRM difference, primarily in the very-vigorous load intensity and partly in the low-load intensity, could be considered as indicators of an increased amount of ML in a respective daily segment. Such character of GLIS was obvious chiefly in lessons and school segments. We suppose most of the similarly structured segments (structure of the ACC-HRM differences) could be considered as a “low physically active segment with high percentage of ML”. Within all such segments, we expect that an ACC-HRM difference in category of the very-vigorous load intensity could be perceived as certain measure of amount of ML.

There are, however, some limitations that need to be acknowledged. The present findings have to be interpreted in the view of the fact that the sample comprised of mostly inactive girls, which is apparent in the results. For this reason, the frequencies in the respective categories of load intensity level were not homogeneous. The highest frequency of GLIS was observed in the low-load intensity in all the segments (see Fig. 1 and 2). Next, the observed ACC-HRM differences (or agreement) may be partly biased by input parameters such as, the device setup, the formula for calculating HRmax, the categorization of load intensity according to heart rate and MET. We acknowledge these eventual sources of error, bearing in mind that the present study results will always be interpreted only in the light of these input parameters. However, despite the considerable limits, the study demonstrates specific guidelines for the combination of the ACC and HRM to distinguish between PL and ML in non-training related load.

In future research, more details corresponding to a participant’s activities performed throughout given segments are needed to better understand the ACC-HRM differences. Specifics of daily activities should clarify concrete differences in a segment and load intensity category. The goal of future research should verify the above mentioned signs of ACC-HRM differences (suggested to determine ML and PL in the segment) experimentally, in specific situations.

Conclusions

In summary, there is a disagreement between the ACC and HRM in determining the time during which the load intensity is classified at a given category, i.e., low, medium, vigorous, and very vigorous. The study indicates that some of the ACC-HRM differences could be utilized to distinguish between the PL and ML. The results from this study lead us to a hypothesis that an increase of PL or ML can be deduced based on a combination of three parameters: magnitude of the ACC-HRM difference in the respective categories of load intensity, magnitude of 95% limits of agreement between the ACC- and HRM-GLIS, and magnitude of effect size corresponding to the ACC-HRM difference.

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