Metabolic Power in the Men's European Handball Championship 2020

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Abstract

Introduction: Analyzing metabolic power of horizontal movements may contribute to the understandings of physical and metabolic demands in professional handball.

Purpose: To ascertain the typical metabolic power characteristics of elite handball players of different positions, and whether changes occur within matches during the European Championship 2020.

Design: Prospective cohort study.

Methods: 414 elite male handball players were included. During all 65 matches of the EURO 2020, local positioning system data were collected (16.6 Hz), yielding in 1853 datasets. Field players were categorized in six positional groups: centre backs (CB), left and right wings (LW/RW), left and right backs (LB/RB) and pivots (P). Metabolic power, total energy expenditure, high-power energy and the equivalent distance index was calculated from the position data and further processed as dependent variables. We used linear mixed models with players as random and positions as fixed effects models. Intensity models included time played to account for a time-dependency of the intensity.

Results: LW/RW spent most time on the pitch, expended most total energy, and most relative energy per kg body weight in the high intensity categories. CB played at the highest mean intensity (highest mean metabolic power). Playing intensity decreased with longer playing time in a curvilinear manner with a stronger decrease in the short playing time areas.

Conclusion: Metabolic power intensity profiles are modulated by playing positions and players' time on the pitch. Analysis of metabolic intensity in handball should take these parameters into account for optimizing training and performance during matches.

Keywords: energy expenditure, exercise volume, intensity, external load, activity profile, local positioning system, mixed models.

Introduction

Handball is a highly intermittent team sport with fast transitions between offensive and defensive phases (Manchado et al., 2013). To improve training prescriptions, it is important to understand the physical position-specific on-court demands, e.g. volume and intensity, beside technical-tactical actions (Manchado et al., 2013; Fasold & Redlich, 2018). Beside handball-specific movements like collisions, jumps, passes, and shots, physical demands include horizontal movements of the players. Previously used analyses of physical demands during handball matches mainly used distance and speed and revealed position-depending differences between players. For example, wings covered more total distance (Büchel et al., 2019; Manchado et al., 2021), spent more time and covered more distance in high speed and sprinting zones compared to backs and pivots (Cardinale et al., 2017). Total distance is important because it determines energy expenditure regardless of movement speed (Carling et al., 2008), and is thus often used as an indicator for exercise volume. Movement speed has been assumed to represent exercise intensity (Bangsbo et al., 1991).

To capture volume and intensity of an intermittent sports game like handball, however, it is not sufficient to only assess distance and speed. Accelerations and decelerations are also physiologically relevant in handball even at submaximal speed (Akenhead et al., 2014) and are thought to be the most energetically demanding elements in team sports directly contributing to energy cost (Polglaze et al., 2018). Further, accelerating is energetically even more demanding than maintaining velocity (Varley & Aughey, 2013). Therefore, distance alone is not sufficient to represent volume and speed alone cannot signify exercise intensity in handball. The focus on accelerations alone, however, neither is sufficient, because the energetic demand for a given acceleration varies when starting speed is taken into account (Osgnach et al., 2010). Therefore, one should rather account for the interplay between velocity and acceleration when analyzing metabolic demands in handball. The respective parameter considering both is metabolic power. Metabolic power is the product of the energy cost of running and the running speed itself (instantaneous values or time courses) (Osgnach & Di Prampero, 2018). To the best of our knowledge, metabolic power has not been analyzed so far during top-level handball matches for the determination of the energetic costs of horizontal movement patterns.

The specific rules in handball enable the teams to interchange their players any number of times resulting in different playing times of single players and between positions. Therefore, playing time has to be taken into account for any detailed analysis of physical demands in handball. Previous studies reported that there is a decrease in total distance covered during the second half and also that the distance covered at high speed is lower as the game went on (Michalsik et al., 2014; Büchel et al., 2019). Knowledge of the time-dependency of metabolic power-derived parameters in handball is missing.

Thus, the first aim of this study was to assess the volume and intensity of top-level handball match-play at different positions using the energy-based metabolic power approach by Osgnach et al. (2010). The second aim was to analyze the time course of intensity in dependence of playing time. We hypothesized that (1) positional differences in the volume and intensity parameters exist and that (2) intensity decreases throughout the game.

Methods

Study design and ethical aspects

A prospective cohort observational study was performed. Data were obtained from players participating in European Handball Federation (EHF) EURO 2020 held in Austria / Norway / Sweden.

The participating players provided informed consent before inclusion. The study was planned and performed in line with the Declaration of Helsinki and approved by the Ethics Committee of the University of Alicante (registration number UA-2020-09-10).

Participants

Data were collected from 414 male elite handball players. A total of 1853 datasets out of 65 games were obtained. We excluded goalkeepers and observations from field players with less than 1 minute playing time. The remaining 1596 datasets from 352 players were analysed with regard to playing position (Figure 1).

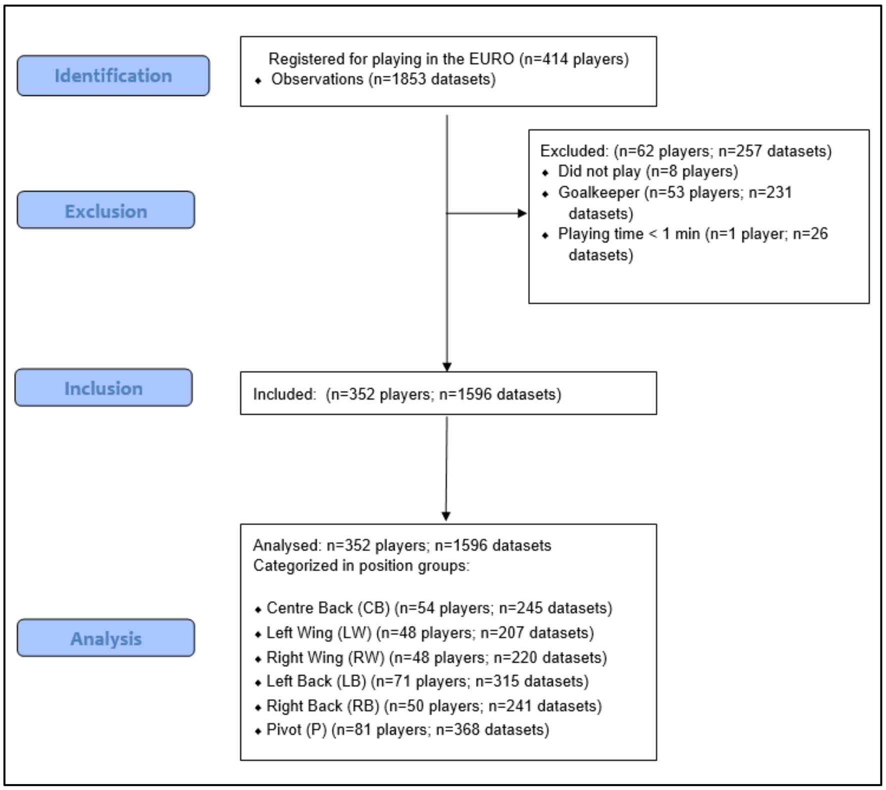

Figure 1 Flow diagram

Instruments

Position data were continuously monitored using a local positioning system (LPS) (Kinexon Precision Technologies, Munich, Germany). Nine antennas were placed around the playing field which were connected to 10 anchor antennas distributed at 3 different levels above the ground in the arena. For a closer look at the setup, the reader is referred to Manchado et al. (2021). Player's position was recorded with a 16.6 Hz frequency by calculating the time-of-flight of ultra-wide-band radio signals from the transmitter to the base stations. These time-of-flight measurement signals are smoothed with an Unscented Kalman Filter. Subsequently, the position was determined through triangulation. Speed and acceleration are calculated subsequently and filtered with a zero-phase shifting low pass Butterworth-filter of 3rd order with cut-off frequencies of 1 and 0.5 Hz, respectively. Recently the system has been validated (Hoppe et al., 2018; Fleureau et al., 2020; Alt et al., 2020) and was used for the analysis of movement patterns in ice-hockey and handball (Link et al., 2019; Manchado et al., 2020).

Data processing

To automate the calculation of net playing time the player's position had to be at least 1 second and 0.8 meter on the field to count as active. For substitutions, it had to be 0.4 meter outside of the field for 1 second or more. The time in which the ball was not on the pitch or no team had possession of the ball was not included. Further, playing phases (offence/defence) were distinguished based on ball possession and overall player movement. The net playing time was calculated as the accumulated time of the offense and defence phases. LPS data of each single player were analysed for the periods of his individual net playing time and summed up for further analysis. Total run distance was determined accordingly.

Energy costs and metabolic power data were calculated using previously outlined equations (Osgnach et al., 2010; Di Prampero et al., 2015). Instead of 3.6 J/kg/m energy cost of running at constant speed on flat terrain, which had originally been determined in endurance mountain runners (Minetti et al., 2002), however, we used 4.46 J/kg/m for the handball players included in this study. Handball players, as football players and further generally active men not specialized in straight-forward running, are running in a less economic way compared to endurance runners and, therefore, need slightly more energy (Buglione & Di Prampero, 2013; Savoia et al., 2020). Further, the constant (KT) for running on a grassy terrain in analyses of football match play and training sessions (Osgnach et al., 2010; Gaudino et al., 2014) was not included.

According to Osgnach et al. (2010), the following five power categories were used: low power (LP from 0 to 10 W/kg), intermediate power (IP, from 10 to 20 W/kg), high power (HP; from 20 to 35 W/kg), elevated power (EP; from 35 to 55 W/kg), and max power (MP; > 55 W/kg). In order to describe high intensities in a more general manner, we additionally summarized both highest intensities (EP+MP; > 35 W/kg) and named this combined category high intensity power (HIP). For each of these power categories, time, distance, and estimated net energy expenditure (above resting) were quantified.

Additionally, equivalent distance and the equivalent distance index were calculated. The equivalent distance represents the distance that the player would have run at a steady pace on the field using the total energy spent over the match. The equivalent distance index is the ratio between equivalent distance and total distance and reflects the erraticness of running (Osgnach et al., 2010). All data were processed in Matlab (R2020b).

Statistical analyses

All statistical analyses and plots were performed with R (4.0.4) (R Core Team, 2021).

We have applied and compared different linear regression models for the analysis of the relationships between various parameters: Metabolic power, energy expenditure, equivalent distance index and summed high metabolic power energy (EP+MP) were dependent variables (DV), while position and time played were defined as independent variables. To account for the nested data structure (repeated measures for players in teams), we used linear mixed models via the {lme4} package (Bates et al., 2015) (see our markdown script for dependencies and versions). Volume (DV: Energy expenditure) models did not include time because we were interested in total time-independent exertion (random intercept). Intensity distribution analysis did not include time as well (random intercept). The intensity (DV: average MP) models included time played and position as fixed effects and players nested in teams as random effects to account for multiple observations for players who played more matches (random intercept & random intercept/slope over time). Erracticness (DV: Equivalent distance index) models also included time played and position as fixed effects and player nested in teams as random effects (random slope). Sensitivity was checked via a reduced data set (preliminary round) and a spline model with the {mgcv} (Wood, 2011). We compared models via several criteria (p-value, Akaike-Information-Criterion, Bayesian-Information-Criterion) and their coefficients. Further, we compared the estimated means with 95% confidence intervals of our models for the positions (and time in intensity models). Heterogeneity was inspected via random slope/intercept coefficients. Assumptions were checked graphically via model residual plots (Q-Q, residuals vs. fit) – see our repository for further details (https://osf.io/zqpt2/).

Results

In sum, 352 of 414 observations met our inclusion criteria (Figure 1). Descriptive values are shown in our repository (https://osf.io/zqpt2/).

Wings weight the least on average, followed by Centre Backs, outer Backs and Pivots (Table 1). Additionally, there were more observations for Left Backs and Pivots. Time played seems to be higher for Wings, especially Left Wings (Table 1).

Table 1 Number of players and observations included, anthropometric characteristics, and playing time for the single positions.

Position	n_{pl}	n_{obs}	Weight (kg)		Height (cm)		Time (min)	
			Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Centre Back	54	245	90.6	6.9	189.7	5.8	24.9	13.6
Left Wing	48	207	84.4	7.9	186.9	5.7	32.1	17.0
Right Wing	48	220	83.1	6.3	184.6	5.4	30.0	18.4
Left Back	71	315	97.1	6.5	196.1	4.2	23.8	12.6
Right Back	50	241	95.8	8.9	194.4	5.8	24.5	13.3
Pivot	81	368	105.4	8.4	196.8	4.6	24.5	13.8
Total sample	352		94.3	10.5	192.4	6.7		

n_{pl} = number of players; n_{obs} = number of observations

Volume – total energy expenditure and equivalent distance

Energy expenditure relative to body weight was higher in left wings, followed by right wings, centre backs and left/right backs and pivots – see Figure 2A. Neglecting body weight, absolute total energy expenditure was, still, highest in left wings followed by pivots, centre backs, right wings, and left and right backs. However, likewise in our intensity models, the interindividual variability was high.

Since the equivalent distance is calculated from the energy expenditure by multiplying with a fixed value, equivalent distance was also highest in left wings, followed by right wings, centre backs, left backs, right backs and pivots. Data of mean total distances run in the matches are given in our repository (https://osf.io/zqpt2/).

Intensity – Metabolic Power

Our random intercept and slope model performed best among other models (random intercept/slope vs. random intercept, AIC: 3635 vs. 3769, BIC: 3710 vs. 3823, p<.001) and yielded a plausible distinction between positional groups: Centre Backs had the highest mean metabolic power, followed by right and left wings, left and right backs and pivots (Figure 2C).

Erraticness – Equivalent distance index

Wings had highest equivalent distance index values, followed by the centre backs, the pivots, the left backs and the right backs (Figure 2D).

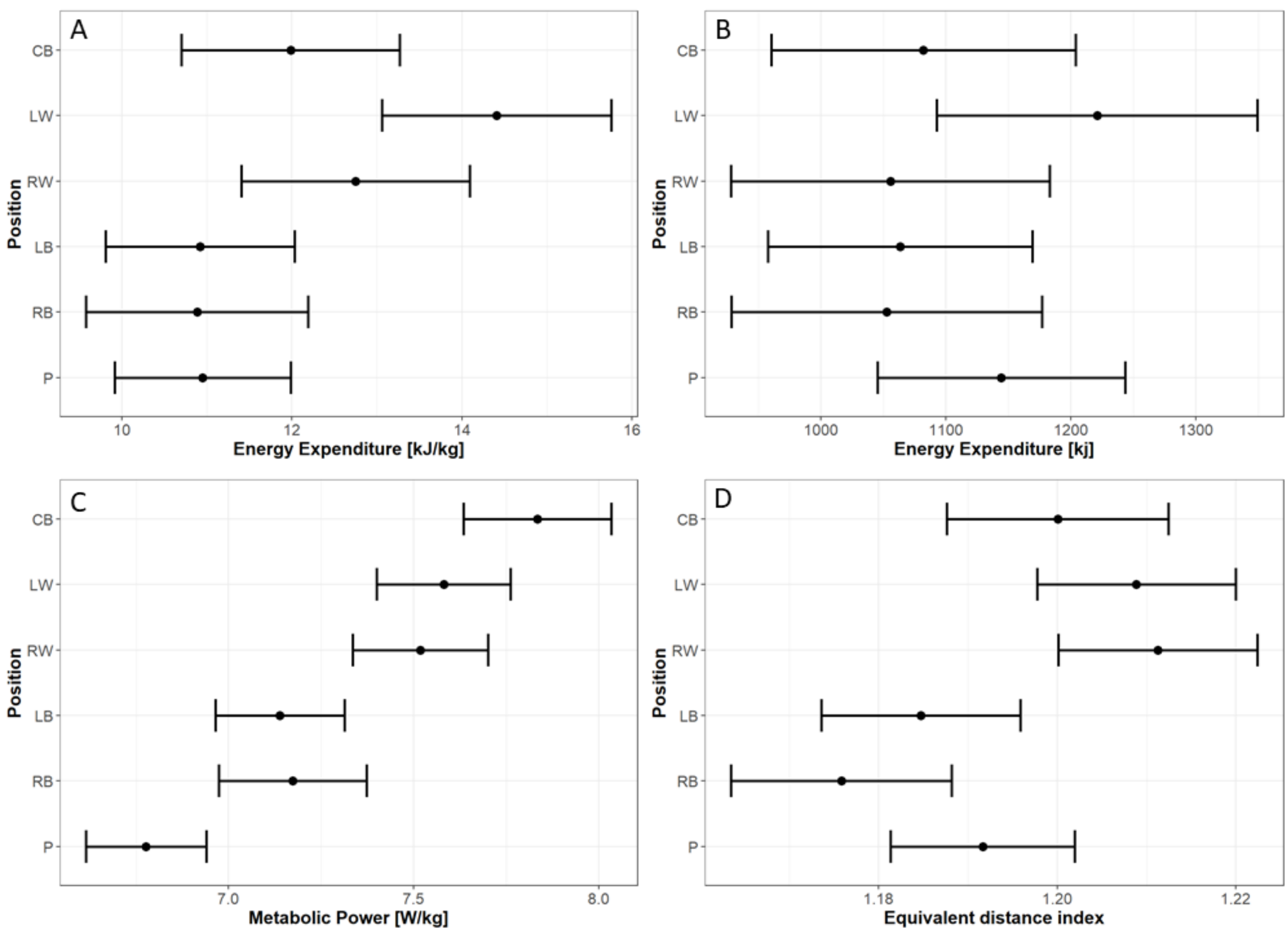

Figure 2 TIE-fighter plots of estimated means with 95% confidence intervals
Relative (A) and absolute (B) total energy expenditure (random intercept), mean metabolic power (C) (random intercept/slope) and equivalent distance index (D) (random slope)

Intensity distribution – metabolic power categories

Intensity distribution analysis revealed that all position groups expended similar energy in low to mid intensity zones (< 35 W/kg). Position-specific differences occurred in the higher intensity zones and especially in the combined high intensity power category (> 35 W/kg). Left wings expended most energy in the high intensity category, followed by right wings, centre backs, left backs, right backs and pivots (Figure 3).

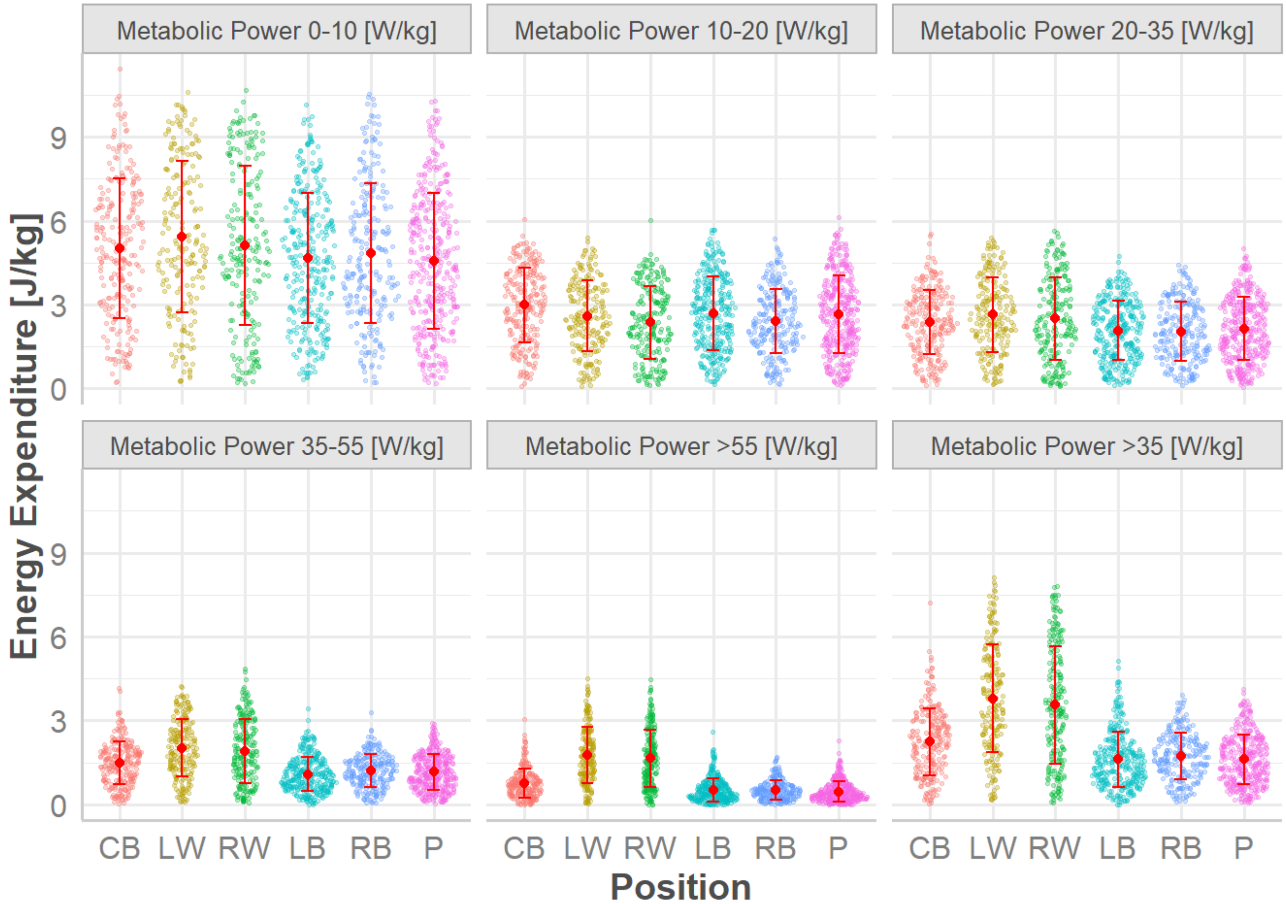

Figure 3 Energy expended (J/kg) in metabolic power zones in the different playing positions; estimated means with 95% confidence intervals

Time dependency of metabolic power and related parameters

The linear model predicted a decrease in intensity of 2.5% (0.2 kJ/kg/s; $CI_{95\%}$ [0.17, 0.23]) per 10 minutes played. However, the decrease seems to be rather curvilinear with a stronger decrease in short playing times accompanied by higher variability (Figure 4). The random effects for teams suggest less variability between teams (range: -0.26 to 0.25) but a rather high variability in individuals (range: -3.23 to 3.84) – see our repository for details (https://osf.io/zqpt2/).

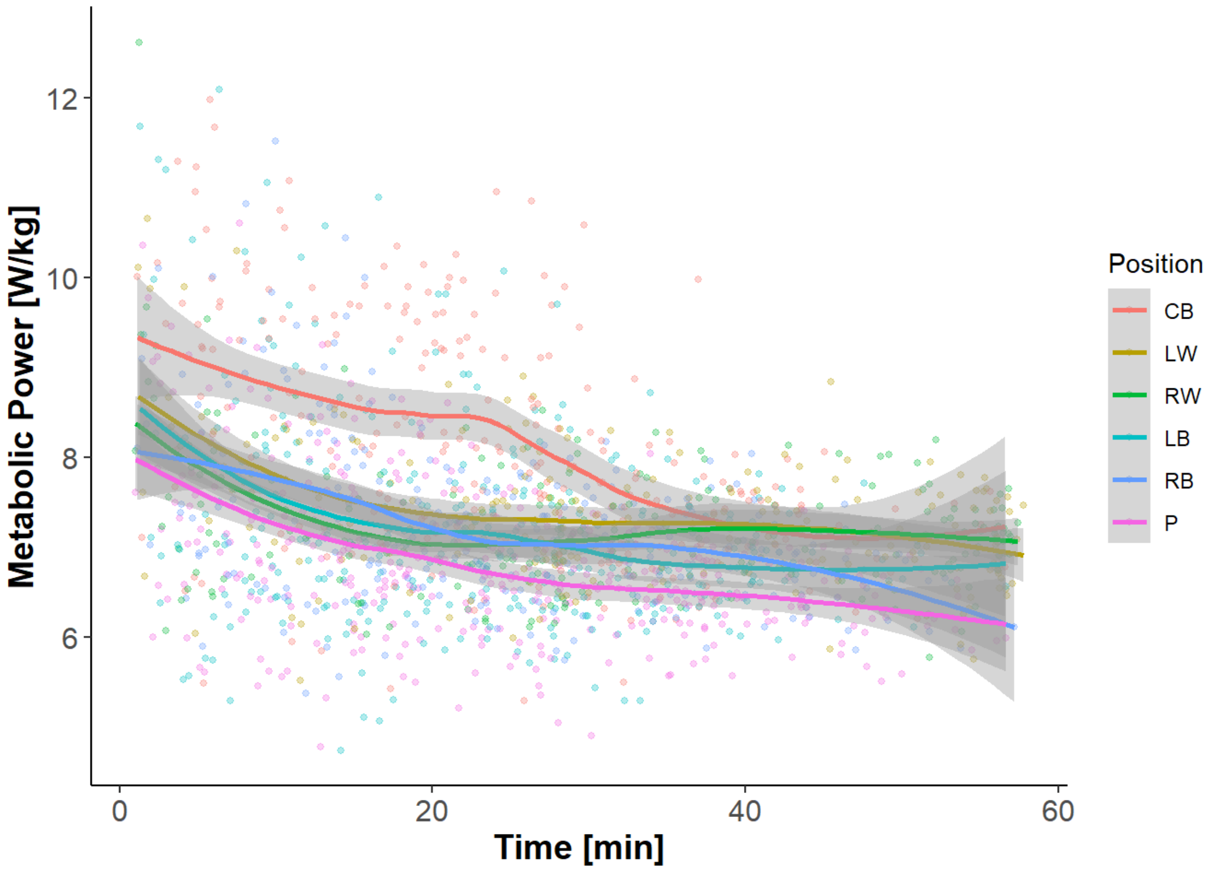

Figure 4 Mean metabolic power in dependency of time played and position

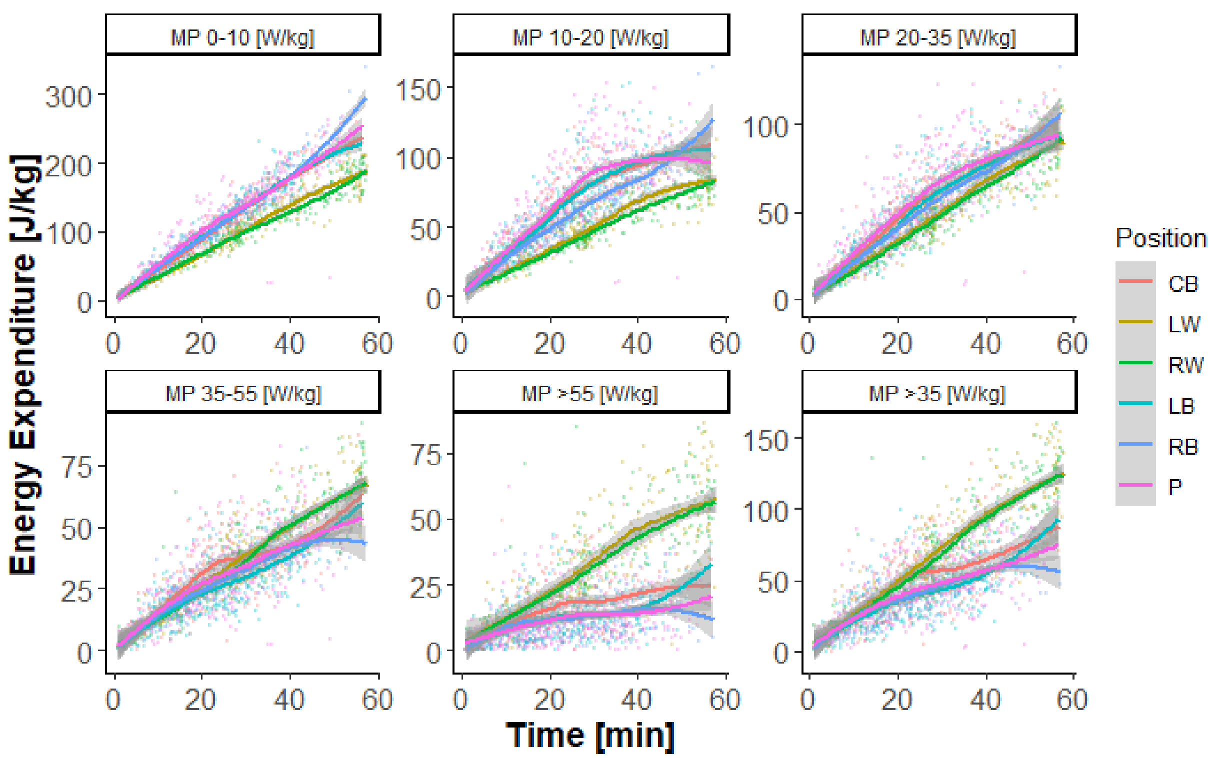

Figure 5 Energy expended in metabolic power (MP) zones in dependency of time played and position

Discussion

Hypotheses verification

The findings of differences (between positions and in dependence of the time on the court) in metabolic power, energy expenditure, equivalent distance index and high metabolic power energy lead to a verification of hypothesis (1) and a decrease of intensity verifies the secondary hypothesis.

Comparison to the handball-relevant evidence

Our results are mostly in line with other studies who reported the highest exercise volume in wing players (Cardinale et al., 2017; Büchel et al., 2019; Manchado et al., 2021) followed by centre backs (Cardinale et al., 2017; Manchado et al., 2021). In contrast to our study, Büchel et al. (2019) did not differentiate between left, right, and centre backs. Another parameter in the energy based approach reflecting volume is the equivalent distance, which represents the distance that the player would have run at a steady pace using the total energy spent over the match (Osgnach & Di Prampero, 2018). The equivalent distance shows the same ranking as metabolic power (Osgnach & Di Prampero, 2018). The total distance covered is commonly used as the parameter to describe the volume of handball match play (Póvoas et al., 2012; Cardinale et al., 2017; Manchado et al., 2021). The energy based approach uses the energy expenditure because the total distance is only a correct estimate of the volume if the speed is constant because it does not take into account acceleration and deceleration (Osgnach & Di Prampero, 2018).

The centre backs showed the highest values in average metabolic power. This is in line with Manchado et al. (2021); although they used the running pace for describing the intensity of the game instead of metabolic power. However, our model yields different conclusions for other positions than centre backs.

Regarding the running pace, pivots and left backs ran with higher intensity than the wing positions and the right back (Manchado et al., 2021), while the average metabolic power was higher for the wing positions, followed by Left/Right Back and then the Pivots. Further, the wing position players' movements seems to be more erratic compared to the backs and pivots indicated by a higher Equivalent Distance Index. A higher Equivalent Distance Index indicates that activities are more intermittent in nature. Wings often reach high accelerations (Font et al., 2021) and velocities (Manchado et al., 2021). This could be due to wings having greater spatial limitation probably need those accelerating changes to succeed, in addition they run more counter-attacks.

Centre Backs playing at the highest average metabolic power due to the highest number of accelerations overall (Font et al., 2021). As we were interested in the intensity throughout the whole match, we did not distinguish between offensive and defensive game phases and, thus, cannot conclude if this separation may be of explanative values for the differences observed. Metabolic power data showed that wings play at a higher intensity compared to both half back positions and the pivot backed up by a higher Equivalent Distance Index. The positional order between both intensity parameters differs because the running pace does not take into account the weight of the specific player and does not include acceleration which substantially increases energy demands (Polglaze et al., 2018). Further, our model took into account decreasing intensity throughout the game and different playing time.

Left wings spent most energy over the high intensity thresholds, followed by right wings. This is consistent with the results from Manchado et al. (2021) and Cardinale et al. (2017), who used a speed based classification of determining the playing intensity. We chose to describe the high intensity volume as energy over a certain metabolic power threshold compared to the mentioned studies because a speed based classification omits activities at lower speed but very high acceleration (Polglaze et al., 2018). In handball matches, athletes hardly reach their level of top speed and the ability to frequently change velocity is more important to successful performance (Upton, 2011). The metabolic power approach takes both into account.

Comparison to other team sports

The mean total energy expenditure (approx. 11.6 kJ kg^{-1} body weight) showed lower values compared to other team sports like football (61.1 kJ kg^{-1}, Osgnach et al., 2010), Australian football (63.3 kJ kg^{-1}, Coutts et al., 2015), rugby league (39,2 kJ kg^{-1}, Kempton et al., 2015) and field hockey (31.8 kJ kg^{-1}, Polglaze et al., 2018). A reason for this may be found in the fact that handball is an indoor sport with much smaller field size than football. Furthermore, the possibility to interchange (players can play only on the offensive side of the field and be substituted when the phase changes) may be another reason. In comparison, field hockey players, who also have the possibility to interchange, tend to play more (47:28 ± 5:34 min:s) (Polglaze et al., 2018).

Average metabolic power showed lower values compared to other studies investigating other sports (Gaudino et al., 2014; Coutts et al., 2015; Kempton et al., 2015; Polglaze et al., 2018) Mostly, and unlike in our study, a correction factor for the surface was used. So the energy cost and average metabolic power in this study are about 29% higher compared to our data. Handball is defined by various movements which take place on a fixed point of the field like jumping, throws and passes (Póvoas et al., 2012) which are not reflected in the calculated energy expenditure and average metabolic power but require a certain amount of energy as well.

Impact of the time on the field

Our model shows a decrease of intensity of 2.5 % per 10 minutes played. This is in line with Büchel et al. (2019) who reported a 7% higher mean speed for low playing-time players compared to high playing-time players. Similar results were reported in changes in average speed, relative time spent running and high-intensity running between halftimes in handball (Michalsik et al., 2014; Büchel et al., 2019) and field hockey (MacLeod et al., 2007). Bradley et al. (2014) showed that substitute players in soccer covered more distance at high intensity and performed more sprints which supports the thesis that the less you play the more intense you move.

Further, our model shows that for low playing time players the expended energy over the high metabolic power threshold seems to be similar in wings and centre backs but the longer the players play, the higher the volume of high intensity energy of wing players compared to centre backs. A reduction in distance or speed is considered to indicate fatigue (Polglaze et al., 2018) which we cannot support. We observed the greatest decrease in intensity for low playing time players but we also found the greatest variability in the intensity. The highest intensity for lower playing time players could also be due to the nature of substitution itself as Büchel et al. (2019) proposed. Players need to act accordingly to the situation in the match in which they are needed to rush on and off the court as quick as they can.

Practical relevance

The differences in intensity and volume between positions throughout handball match-play suggest that it is important to adapt the training work to the positional profile. Players change their position frequently during a match, especially, the back positions which makes it even more necessary to individualize training work based on the individual profile of movement. An implication of metabolic power in team sport match play is useful and necessary because it allows high-intensity activity to be expressed in proportion to the total energy expenditure and not playing time or distance covered (Gray et al., 2018). Especially in handball those high intensity efforts are rather short little bouts where time and distance can not reflect this bouts accurately, where adenosine triphosphate (ATP) turnover can be extremely high (Polglaze & Hoppe, 2019).

Methodological considerations

Although we evaluated positional differences, it has to be stated that in handball, players change their position frequently in the offense phases of the match and we did not account for different tactical behaviour, for example, players in different defensive systems (4-2; 5-1; 6-0) could have different values. Further, the metabolic power approach assumes movement of the centre mass and is neglecting any movements from the limbs. Also, the sensor device was placed in a little bag between the shoulder blades, therefore, amplified movements from the trunk from tackling or other handball specific movement patterns could overestimate metabolic power (Polglaze et al., 2018). Volume and intensity of handball match-play are characterized by many jumps, throws, passes and tacklings. All these actions could yield a certain amount of energy and therefore a higher volume and also a higher average intensity of match-play. These actions are not considered in the metabolic power approach yet and are needed to be investigated and added to the approach

Perspective

With our analyses, we show ways to model the physical demands (i.e., exercise volume and intensity) in handball using the metabolic power model, a phase-by-phase model to extract net playing time and linear mixed models to account for the observational character, which can be conceptionally used in other studies. However, the metabolic power model is far from being perfect in modelling the physical and physiological demands; future research should implement demands of sport-specific actions like passing, jumping, side-steps, body contact, etc. Despite this, we yet see advantages over the commonly speed/distance approach. Those metrics can give an insight into the locomotion of handball players, metabolic power seems to reflect the load and intensity more accurate because it takes into account the cost of acceleration in activity comprising perpetual changes in speed. We suggest using intensity models incorporating time to account for decreasing intensity throughout the game, especially in sports where interchange is allowed.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Author Contributions

Conceptualization, J.V., R.S. and P.P.; Methodology, J.V., R.S. and D.N.; Software, R.S.; Formal Analysis, J.V. and R.S.; Resources, C.M.; Writing – Original Draft, J.V.; Writing – Review & Editing, J.V., R.S., D.N., C.M. and P.P.; Visualization, J.V. and R.S.; Supervision, P.P.

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